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Digital twin applications for indoor environmental quality in healthy building research: a systematic review of indicators, methods and computational paradigms

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ABSTRACT

Digital Twin (DT) technologies are increasingly adopted in Healthy Buildings research to monitor and optimise Indoor Environmental Quality (IEQ). However, their implementation remains heterogeneous, with substantial variability in indicator selection, methodological configurations and computational architectures. This study presents a systematic review of 62 peer-reviewed contributions to analyse how DTs are operationalised across IEQ-domains and to identify structural integration patterns within the field. Through combined bibliometric mapping and qualitative content analysis, the review classifies DT-based IEQ applications according to three interconnected dimensions: (i) indicator typologies (dose-related, building-related and occupant-related), (ii) methodological approaches (quantitative, qualitative and hybrid), and (iii) computational paradigms, including scripting-based workflows, visual programming environments, machine-learning models, simulation-driven frameworks and semantic graph-based systems. Rather than ranking individual studies, the analysis examines dominant configurations and emerging trajectories of integration across these dimensions. The results reveal a strong prevalence of dose-related environmental indicators and quantitative sensor-driven methods, typically associated with monitoring-oriented and predictive architectures. In contrast, building semantics and occupant-centred variables remain comparatively under-integrated, limiting the representation of behavioural variability and long-term exposure dynamics. By systematically mapping how indicators, methods and computational architectures intersect, this review clarifies the current structural orientation of DT-research for IEQ and outlines research directions toward more integrated, interoperable and health-aware digital building ecosystems.

1. Introduction

Indoor Environmental Quality (IEQ) plays a fundamental role in shaping human health, comfort and cognitive performance, positioning the built environment as a critical determinant of individual and collective well-being [1,2]. Over the last decades, research has progressively shifted from energy-centred building performance toward occupant-centred paradigms, emphasising that indoor spaces must not only minimise fossil energy source consumption but also actively support physical and psychological health [3]. Within this broader transition, the concept of Healthy Buildings has emerged as an integrative framework that links environmental exposure, user perception and building operation within a systemic perspective.

IEQ, however, is intrinsically multi-domain and dynamic. Thermal conditions, indoor air quality (IAQ), visual comfort and acoustical parameters interact continuously, influenced by building envelope characteristics, HVAC (Heating, Ventilation and Air Conditioning) strategies, occupant behaviour and outdoor climatic drivers [4,5]. These domains cannot be treated as independent variables: ventilation strategies affect both thermal comfort and pollutant concentration; façade design simultaneously shapes daylight availability and solar heat gains; occupancy patterns influence CO_2 levels, internal loads and acoustical conditions. Moreover, IEQ variables exhibit spatial and temporal heterogeneity, with localised gradients and time-dependent fluctuations that challenge simplified, steady-state representations. Despite this complexity, many assessment frameworks still rely on threshold-based or dose-related indicators, often detached from behavioural adaptation and cumulative exposure dynamics.

In parallel with the evolution of Healthy Buildings research, Digital

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Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
BIM	Building Information Modelling
BMS	Building Management System
CO_2	Carbon dioxide
DT	Digital Twin
FM	Facility Management
GNN	Graph Neural Network
HVAC	Heating, Ventilation and Air Conditioning
IAQ	Indoor Air Quality
IEQ	Indoor Environmental Quality
IoT	Internet of Things
ML	Machine Learning
MPC	Model Predictive Control
PM	Particulate Matter
PMV	Predicted Mean Vote
POE	Post-Occupancy Evaluation
PPD	Predicted Percentage of Dissatisfied
VR	Virtual Reality
VOC	Volatile Organic Compounds
WSN	Wireless Sensor Network

Twin (DT) technologies have gained prominence in the built environment domain. Broadly defined as dynamic digital representations of physical assets that integrate real-time data streams, simulation models and analytical algorithms, DTs promise to enable continuous monitoring, predictive analytics and adaptive control of building performance. The rapid diffusion of low-cost IoT sensors, cloud-based infrastructures and artificial intelligence techniques has accelerated their application to IEQ monitoring and optimisation [6].

However, the operationalisation of Digital Twins within IEQ research remains heterogeneous and, at times, conceptually ambiguous. In building science, the term "Digital Twin" is applied to a wide spectrum of configurations, ranging from real-time dashboards connected to sensor networks, to simulation-based co-models, machine-learning predictors, and ontology-driven knowledge graphs. These implementations differ substantially in their degree of integration between environmental sensing, Building Information Modelling (BIM), simulation workflows and occupant-related feedback. As a result, the extent to which current DT systems function as fully integrated cyber–physical ecosystems, rather than advanced monitoring platforms, remains an open question.

While the concept of Digital Twin originated primarily in manufacturing and industrial applications, its implementation in civil buildings introduced substantially different requirements and objectives [7]. In this context, the term civil buildings refers to the broad spectrum of occupied living and working environments, including residential, educational, office, healthcare and public buildings, which constitute the primary focus of Healthy Building research [7,8]. Industrial DTs are typically designed to represent physical assets, machinery and production processes, with the primary goals of process optimisation, predictive maintenance and operational efficiency. These systems generally rely on deterministic behaviours and well-defined performance parameters. In contrast, DTs applied to civil buildings must account for the dynamic interactions between building systems, environmental conditions and human occupants. Indoor environments are characterised by spatial and temporal variability, behavioural adaptation and subjective responses that cannot be fully represented through deterministic models alone. Consequently, DTs for civil buildings require the integration of environmental monitoring, building information, occupant-related data and predictive analytics within unified socio-technical frameworks, supporting not only operational optimisation but also the assessment and management of IEQ and occupant wellbeing [7,9].

Despite the growing number of DT applications addressing IEQ, current research remains fragmented across disciplinary and technological perspectives. Existing reviews have predominantly focused on specific components of DT ecosystems, including energy optimisation, HVAC control, sensor technologies, artificial intelligence techniques, or BIM-enabled workflows [6,7,10–15]. As a result, limited attention has been devoted to understanding DT systems as integrated configurations in which monitored indicators, methodological approaches, computational paradigms and operational objectives interact. In particular, the relationships between the categories of IEQ indicators considered, the methods adopted to collect and analyse data, and the DT architectures used to support monitoring, prediction, adaptation and decision-making remain insufficiently explored. Consequently, the literature still lacks a systematic framework capable of linking DT objectives with the indicators, methods and computational paradigms required to achieve them [7,10].

This limitation is particularly evident in relation to the typology of indicators embedded within DT-workflows. Most applications prioritise dose-related environmental variables such as temperature, CO_2 concentration, relative humidity and illuminance, which are readily measurable and compatible with established comfort indices. Building-related parameters (e.g. geometry, envelope properties, zoning logic and HVAC configuration) are often included as contextual inputs, while occupant-related indicators such as subjective votes, behavioural responses or physiological signals are less systematically integrated. This uneven distribution raises critical questions: How do different indicator categories shape methodological choices? To what extent do sensing strategies influence the computational architecture of DT-systems? How aligned are current DT-implementations with health-oriented, rather than purely comfort-driven, representations of IEQ?

These three dimensions represent the main layers through which DTs operationalise IEQ information: what is measured (indicators), how information is collected and processed (methods), and how it is computationally implemented (paradigms).

Addressing these questions is essential for clarifying the current maturity level of DT-applications in IEQ research and for identifying pathways toward more holistic, interoperable and health-informed digital ecosystems. Beyond technical implementation, such clarification contributes to a broader epistemological shift: from viewing DTs as tools for environmental monitoring toward conceptualising them as adaptive infrastructures capable of representing spatial variability, behavioural diversity and exposure dynamics in indoor environments.

Against this background, this study conducts a systematic review of peer-reviewed literature to map and interpret the current landscape of DT-applications for Healthy Buildings. Specifically, the review aims to:

- Identify and classify the indicators employed in DT-based IEQ applications, distinguishing between dose-related, building-related and occupant-related variables [5].
- Analyse the methodological approaches adopted for measurement, integration and validation, including quantitative, qualitative and hybrid configurations.
- Examine the computational paradigms underpinning DT-implementations, ranging from scripting-based pipelines to machine-learning, simulation-driven and semantic frameworks.
- Analyse how different computational paradigms support distinct DT operational objectives, including monitoring, prediction, adaptive control, interoperability and occupant-centred decision support.

This study analyses how indicator typologies, methodological approaches and computational paradigms interact within DT-based IEQ applications, proposing an integrated interpretative framework for understanding current Digital Twin implementations in Healthy Buildings. Through a combined bibliometric and qualitative content analysis, the review examines the relationships between indicators, methods, computational paradigms and DT operational objectives. By identifying dominant implementation patterns, methodological gaps and emerging hybrid configurations, the study provides insights into the transition from monitoring-oriented DTs towards more adaptive, interoperable and health-aware digital ecosystems for IEQ. It further establishes a conceptual basis for aligning DT architectures with specific assessment, control and decision-support objectives.

2. Materials and methods

The present systematic literature review examines how indicators, sensing infrastructures and computational approaches are implemented within DT-frameworks for Healthy Buildings. The review process followed a structured, multi-step protocol combining database searches, eligibility screening, and bibliometric analysis. The procedure aligns with PRISMA 2020 recommendations and builds upon established guidelines for systematic reviews in the built environment [16].

2.1. Database selection and search strategy

The literature search targeted four major scientific databases (Scopus, Web of Science, PubMed, and Google Scholar) selected for their complementary coverage of engineering, environmental health, architecture, and computer science.

Search strings were organised around five conceptual dimensions covering IEQ-domains, DT/BIM workflows, IoT sensing technologies, Healthy Buildings and occupants, and monitoring or predictive objectives (Table 1).

This multi-block strategy ensured that selected studies addressed not only DT–BIM–IoT (Internet of Things) integration but also explicit links to IEQ-indicators, healthy building objectives, and occupant-related evaluation.

2.2. Screening and eligibility criteria

The initial database search yielded a total of 186 records. After removing duplicates and documents that did not fall within the expected scientific categories, 182 studies were retained for preliminary screening. The selection process then proceeded through three consecutive filtering phases, moving from broader to increasingly refined criteria, as illustrated in the PRISMA diagram (Fig. 1). In the first phase, titles and author keywords were examined to remove contributions that clearly lacked relevance to DTs, BIM–IoT integration, or IEQ. This step substantially reduced the pool to 91 records, mainly by excluding works focused on unrelated engineering sectors, generic IoT applications without building relevance, or studies addressing environmental monitoring without any connection to DT frameworks. The second phase consisted of reading abstracts and conclusions to evaluate the presence of explicit IEQ indicators, DT or BIM-based modelling, and measurable environmental or occupant-related variables. Studies that mentioned digital technologies only superficially, lacked quantitative or qualitative data, or focused exclusively on energy or facility management objectives were excluded at this stage. This review resulted in 70 papers eligible for full-text assessment. The final selection was based on an in-depth examination of the full texts. Papers were excluded if they addressed building systems or HVAC-control without any link to IEQ-indicators, if they did not rely on sensor-based measurements or lacked experimental or field validation, or if their focus remained strictly on energy management or FM workflows without contributing to healthy building assessment. Through this process, nine studies were removed from the dataset due to insufficient alignment with the objectives of the review. To ensure completeness, a complementary snowballing strategy was carried out by screening the reference lists of the retained publications; this led to the identification of one additional relevant study. At the end of the screening process, 62 studies fulfilled all methodological and thematic requirements and were included in the systematic review. This multi-stage approach ensured both breadth and specificity, capturing the diversity of existing DT-applications while maintaining a consistent focus on IEQ and Healthy Building criteria.

A specification must be made on the topic of the DT: given the broad and sometimes inconsistent use of the term "Digital Twin" in the literature, explicit inclusion criteria were applied during the screening phase. For this review, a contribution was considered a DT-application only if it satisfied at least one of the following conditions:

- Dynamic integration of real-time or near-real-time data streams with a digital building model.
- Bidirectional interaction enabling simulation-informed control, feedback or decision support.
- Model-based predictive capabilities directly coupled with sensor-driven environmental monitoring.

Studies limited to static BIM representations, stand-alone monitoring dashboards or data visualisation systems without model-based interaction were excluded. This criterion ensured that the analysed contributions reflected operational DT architectures rather than generic smart monitoring frameworks.

2.3. Bibliometric analysis

A bibliometric analysis was performed to complement the systematic selection and identify dominant themes, clusters, and temporal trends in

Table 1
Keywords for the literature review.

	Combined with AND Concept 1	Concept 2	Concept 3	Concept 4	Concept 5
Combined with OR	Comfort	BIM	Control system*	Building*	AI
	IAQ	Building Information Modelling	Device*	Built environment	Algorithm
	IEQ		Internet Of Buildings	Green building*	Artificial Intelligence
	Indoor Air	Digital Twin	Internet Of Things	Health	Control Strategy
	Indoor Environmental Quality		IoB	Healthy buildings	Data Environment
			IoT	HVAC	Machine Learning
	Thermal comfort		Sensor*	Occupant*	Model Predictive Control
	Thermal health		Smartphone*	Smart building*	Monitoring
	Visual		Smartwatch*		Neural
	Acoustics		Wearable		PMV
					Predictive Control
					Prediction
					Sampling

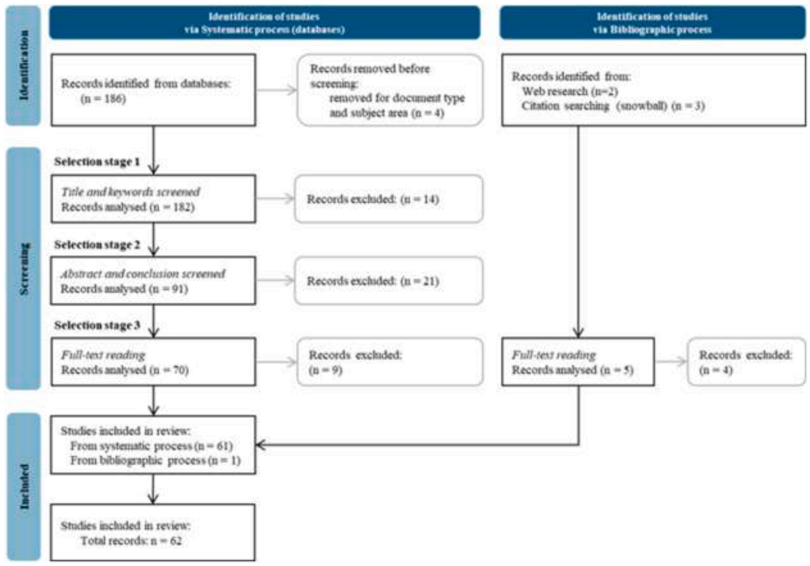


Fig. 1. Flow diagram of the systematic and bibliographic methodology for the selection of documents.

DT-related IEQ research. VOS viewer [17] was used to perform the analysis and two techniques were applied: (i) co-citation analysis and (ii) co-occurrence analysis of author-supplied keywords. After thesaurus cleaning, keywords with a minimum of two occurrences were considered for the initial mapping, and those with at least three occurrences were included in the network visualisation. Node size reflects term frequency, link thickness indicates co-occurrence strength, and colours represent modularity-based clusters. This mapping provided a structured overview of the thematic domains emerging from the literature.

3. Results

The results section is presented following a multi-layered analytical structure that integrates quantitative bibliometric mapping and qualitative content analysis. As illustrated in Fig. 2, the analysis progresses from the identification of bibliometric clusters to the interpretation of research groups, and subsequently to the examination of indicators, methods, and DT- applications. First, five bibliometric clusters describing the DT–IEQ research landscape are identified (Section 3.1). These clusters are subsequently interpreted through seven recurrent research groups (Section 3.2). The analysis then examines indicators (Section 3.3), methodological approaches and sensor infrastructures (Section 3.4), and DT computational paradigms (Section 3.5), providing an integrated interpretation of current DT applications for IEQ.

3.1. Bibliometric analysis

The geographical and temporal distribution of the 62 reviewed papers highlights clear regional research concentrations and the evolution of scientific attention over time. The geographical distribution of the reviewed studies shows a strong concentration in Europe and Asia, led by Italy (13 studies) and China (12 studies), followed by Canada (6) and

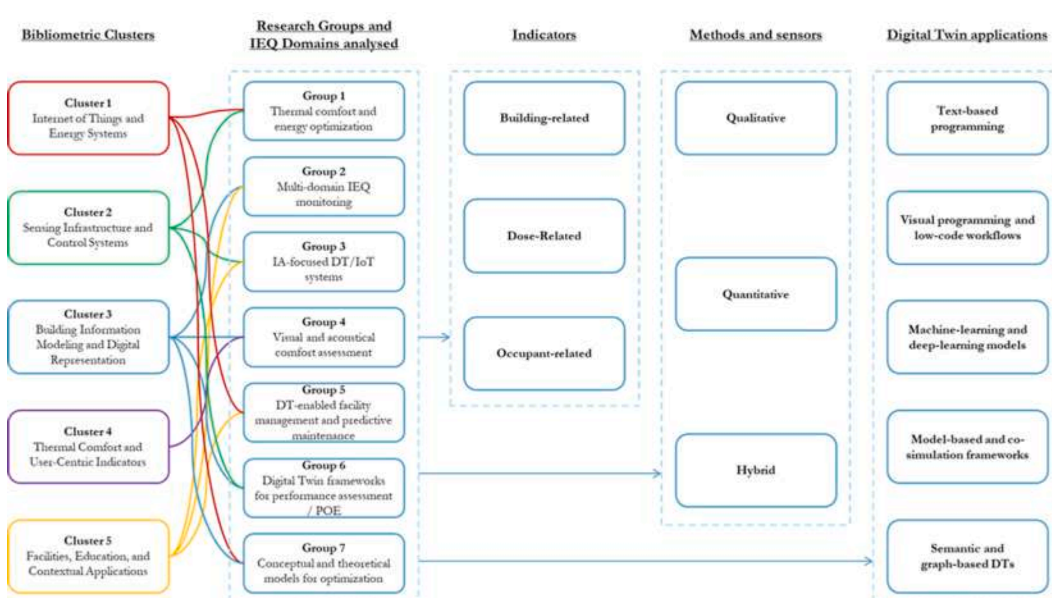


Fig. 2. Multi-layered analytical structure of the review: The five bibliometric clusters (left) were identified through keyword co-occurrence analysis. The seven research groups emerge from qualitative content analysis and describe recurrent IEQ-oriented research configurations across and within clusters. Indicators, methods and DT-applications were subsequently analysed across all groups, enabling cross-sectional interpretation of IEQ-domains and DT-functionalities.

Spain (4). Additional contributions originate from North America, the Middle East and Southeast Asia, confirming the international diffusion of DT-research for IEQ and Healthy Buildings (Fig. 3A).

Fig. 3B shows a substantial increase in publications after 2020, with peaks in 2021–2023. This growth reflects the increasing adoption of DT technologies for IEQ monitoring and control, accelerated by heightened attention to indoor environmental conditions and health-related issues.

The result of the bibliometric analysis is a neural network (Fig. 4) built on author-supplied keywords ($\geq$ 3 occurrences, after thesaurus cleaning) reveals a highly interconnected landscape in which DT sits at the centre of five well-defined thematic clusters. Node size reflects frequency, line thickness reflects co-occurrence strength, and colour denotes modularity-based cluster membership.

Cluster 1 – internet of things and energy systems (Red) The largest and most interconnected cluster centres around IoT and includes closely related terms such as energy efficiency, energy management, artificial intelligence (AI), big data, and sustainability. This cluster reflects a predominant research focus on the integration of IoT-enabled sensor networks for energy monitoring and optimization within building environments. The convergence of AI and edge computing within this domain further emphasizes the growing interest in decentralized and intelligent control systems for real-time performance management. The presence of healthcare and retrofit suggests an emerging attention toward sector-specific implementations and interventions in existing building stocks.

Cluster 2 – sensing infrastructure and control systems (Green) A second cluster, built around terms like sensor, building management system (BMS), monitoring systems, and model predictive control (MPC), highlights the technological backbone enabling DT implementations. Here, artificial neural network (ANN) and HVAC appear as critical nodes, indicating the increasing reliance on machine learning models to support adaptive control strategies for IEQ. This cluster emphasizes the operational dimension of DTs, with sensors functioning as the foundational layer for data-driven decision-making processes aimed at optimizing building energy efficiency.

Cluster 3 – building information modelling and digital representation (Blue) The third cluster is centred around BIM and includes terms such as building performance, ontology, and comfort. This area foregrounds the representational and semantic components of DTs, where BIM acts as the digital backbone that integrates heterogeneous data types, including sensor data, occupancy patterns, and environmental metrics. The linkage to ontology reflects ongoing efforts to formalize and structure building-related knowledge to support interoperability and automated reasoning within DT-ecosystems.

Cluster 4 – thermal comfort and user-centric indicators (Purple) This cluster gravitates around thermal comfort, PMV/PPD (Predicted mean Vote/Percentage of Dissatisfied), personal thermal comfort models, and graph neural networks (GNN). It signifies a research direction that prioritizes occupant-centric approaches to healthy buildings, focusing on subjective comfort assessment and personalization. The inclusion of virtual reality (VR) and Arduino indicates exploratory or experimental research avenues where user feedback and prototyping are employed to refine comfort-related metrics and sensor-based interventions.

Cluster 5 – facilities, education, and contextual applications (Orange) The final cluster includes keywords such as facility management (FM), educational building, and air quality. This group represents applied research contexts where DT technologies are deployed for performance monitoring, IEQ assessment, and lifecycle management. The presence of wireless sensor network and built environment reinforces the importance of scalable and context-aware sensor infrastructures for enabling real-world implementations of Healthy Building frameworks.

The temporal dynamics of keywords indicate a gradual shift from BIM-based modelling and performance assessment towards sensor-driven monitoring, predictive control and AI-enabled DT applications. Recent terms such as IoT, MPC, ANN and GNN reflect increasing attention to real-time data integration, personalised comfort and intelligent decision-support, highlighting the evolution of DTs from static representations towards dynamic systems. This trajectory underscores the increasing maturity of the DT-concept, transitioning from static representations to dynamic systems capable of enhancing IEQ through continuous feedback loops. Moreover, the prominence of healthcare, educational building, and air quality as recent terms indicates a growing contextualization of DTs within healthy building paradigms, where sensor-informed interventions are tailored to specific occupant needs and building typologies.

3.2. Research groups and IEQ-domains analysed

The five bibliometric clusters identified represent data-driven thematic aggregations within the DT–IEQ research landscape. However, while clusters highlight keyword proximity and citation structures, they do not fully capture how IEQ-domains are operationalised within DT-applications. To clarify this dimension, a qualitative content analysis was conducted across all reviewed studies. This analysis identifies seven recurrent research groups that emerge within and across the five clusters. These groups describe dominant research configurations and IEQ-domain orientations that may be concentrated within a single cluster or distributed across multiple clusters. The seven groups are embedded within and often span across multiple bibliometric clusters. They were identified through qualitative content analysis considering research objectives, investigated IEQ-domains and methodological approaches (field, laboratory or theoretical). This analysis (Table 2) reveals the variety of approaches adopted for integrating BIM and IoT-technologies within DT-environments, IEQ assessment, and control.

Group 1: Thermal comfort and energy optimization represents the largest group, encompassing almost half of the reviewed studies [18,28,29,35,46]. These works focus on predicting and optimizing thermal comfort and energy efficiency through data-driven or AI-assisted models, often integrating IoT sensor networks with BIM-based control frameworks. Most studies in this cluster are field-based and concern educational or office buildings, confirming the operational maturity of

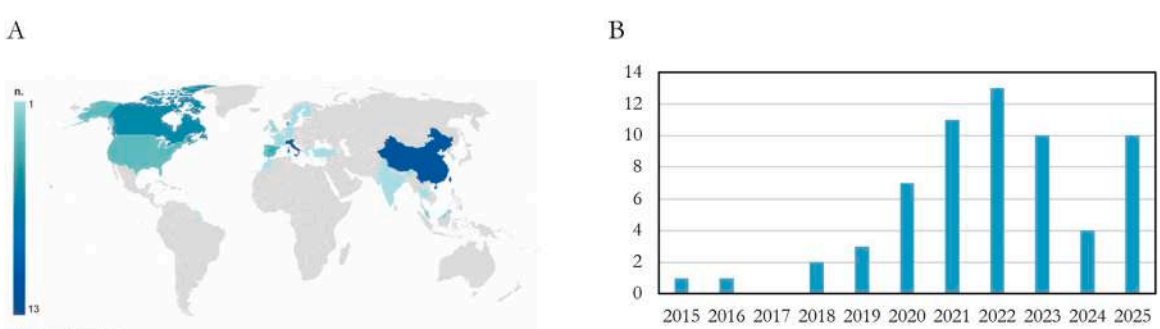


Fig. 3. Geographical (A) and temporal (B) distribution of the reviewed studies.

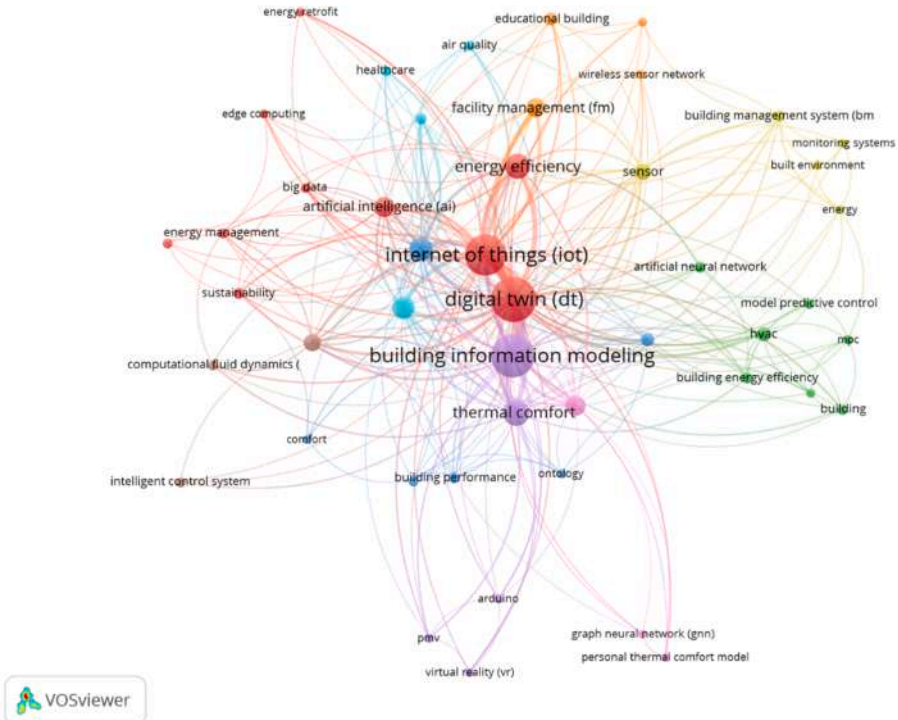


Fig. 4. Network Visualization map of keywords occurrences.

adaptive control strategies for thermal comfort in real contexts (e.g., [32,33,47]). This group is primarily associated with Cluster 1 (IoT and Energy Systems) and partially overlaps with Cluster 2 (Sensing Infrastructure and Control Systems), reflecting the strong link between thermal regulation and energy optimisation strategies.

Group 2: Multi-domain IEQ monitoring gathers studies addressing multiple comfort domains simultaneously, combining thermal, IA, visual, and acoustical variables within integrated sensor platforms (e.g., [48,50,52,53]). These investigations frequently employ laboratory or Living-Lab settings, focusing on interoperability and user interaction via feedback systems [49,76]. Such works demonstrate a clear shift from single-domain optimization toward holistic IEQ evaluation frameworks. This group is mainly distributed between Cluster 3 (BIM and Digital Representation) and Cluster 5 (Facilities and Contextual Applications), where integration and interoperability are central themes.

Group 3: IA-focused DT/IoT systems includes research primarily devoted to indoor air monitoring and pollutant prediction (e.g., [54–58]). Most of these are field studies carried out in educational and office buildings, reflecting the increased emphasis on IAQ after the COVID-19 pandemic and the technological maturity of low-cost sensors integrated with BIM and DT-environments. These works align predominantly with Cluster 2 (Sensing Infrastructure and Control Systems) and partially with Cluster 5 (Facilities and Contextual Applications).

Group 4: Visual and acoustical comfort assessment remains comparatively under-represented, comprising laboratory-based studies focused on lighting, glare, and acoustical stimuli (e.g., [59–61]). These works rely on controlled lab experiments to validate specific parameters, indicating that visual and acoustical domains still represent emerging frontiers within DT-based IEQ-research. This group appears mainly within Cluster 3 (BIM and Digital Representation) and partially within Cluster 4 (Thermal comfort and user-centric indicators), where user experience metrics are central.

Group 5: Facility management and predictive maintenance comprise contributions exploring IoT–BIM systems for maintenance and operational management (e.g., [62,64,77]). Such approaches are predominantly field-oriented, demonstrating how real-time IEQ data can enhance facility management (FM) workflows, preventive maintenance, and asset performance tracking. This group is strongly associated with Cluster 5 (Facilities, Education, and Contextual Applications) and intersects with Cluster 1 where energy optimisation strategies are embedded in operational workflows.

Group 6: DT frameworks for performance assessment and POE (Post-Occupancy Evaluation) groups research employing DT environments for post-occupancy evaluation or performance validation (e.g., [66, 69–71]). These studies typically combine laboratory development with field verification, exemplifying the evolution from static BIM-models to dynamic, data-driven DTs that can capture occupant–building interactions (e.g., [67,72]). This group is primarily distributed within Cluster 3 (BIM and Digital Representation) and partially overlaps with Cluster 2.

Group 7: Conceptual and theoretical models gather theoretical and modelling contributions addressing comfort or energy optimization without experimental validation [73–75,78]. These simulation-based frameworks serve as methodological foundations for subsequent field implementations and highlight the continuing need for empirical calibration. These studies are primarily located within Cluster 1 (IoT and Energy Systems) and partially within Cluster 3 (BIM and Digital Representation).

Approximately 60 % of the analysed studies were field-based, 25 % were conducted in laboratory or Living-Lab environments, and 15 % were conceptual or simulation-driven (Fig. 5). This distribution confirms that current research on BIM–IoT–DT integration for IEQ-monitoring and control is increasingly application-oriented and data-driven, progressively moving from theoretical developments toward real-world deployment in operational buildings. The five bibliometric clusters define the macro-structure of the DT–IEQ research landscape, while the seven groups clarify how IEQ-domains and DT-functionalities are concretely operationalised. The groups are therefore embedded within and often span across the clusters. This alignment ensures methodological coherence between bibliometric mapping and qualitative content analysis.

Table 2
Research groups and IEQ Domains analysed.

Type of study	Brief description of objective	Main IEQ domains*	References
1- Thermal comfort and energy optimization	Studies focused on predicting and optimizing thermal comfort and/or energy efficiency through IoT–BIM or DT models.	TH (+ occasional IA)	[18–47]
2- Multi-domain IEQ monitoring (integrated TH–IA–VIS–ACU)	Integrated systems for simultaneous monitoring of multiple IEQ domains and user interaction or feedback systems.	TH, IA, VIS, ACU	[47–53]
3- IA-focused DT/IoT systems	Approaches specifically oriented to the control, prediction, or improvement of indoor air quality.	IA (+ TH)	[54–58]
4 - Visual and acoustical comfort assessment	Studies focusing on visual and/or acoustical comfort, often in experimental or Living Lab environments for targeted validation.	VIS, ACU	[59–61]
5 - DT-enabled facility management and predictive maintenance	BIM–IoT or Digital Twin applications for predictive maintenance, operational management, or facility management support.	TH, IA	[62–65]
6- DT-frameworks for performance assessment / POE	DT-frameworks for post-occupancy evaluation, integrated performance analysis, or model–reality validation.	TH, IA, VIS	[66–72]
7- Conceptual and theoretical models for optimization	Theoretical or modelling studies simulating comfort or energy efficiency, generally without direct field applications.	TH (+ IA)	[73–75]

* IEQ Domains: TH = Therman; IA = Indoor Air; VIS = Visual; ACU = Acoustical.

3.3. Indicators

The analysis of the 62 studies identified a heterogeneous, yet recurrent set of indicators used to characterise indoor environmental and occupant-related conditions within DT applications for Healthy Buildings. As summarised in Table 3 and visualized in Fig. 6, the indicators were classified into three categories: dose-related, building-related, and occupant-related variables.

Dose-related indicators are the most frequently reported across the reviewed literature. Temperature and CO_2 concentration appear in more than two-thirds of the studies (e.g., [19,27,28,47]), typically accompanied by relative humidity, air velocity and illuminance. These variables constitute the primary environmental inputs within DT environments. Additional parameters such as $PM_{2.5}$, PM_{10} (particulate matter), TVOC (Total Volatile Organic Compounds) and sound pressure level (SPL) are reported less frequently (e.g., [46,55]).

Building-related indicators are reported in a smaller number of studies and are mainly associated with the spatial and constructive structure of the digital model. Building geometry is included in most BIM-based or simulation-driven DTs (e.g., [24,39,73]). Other recurring variables include envelope properties, HVAC-configuration and control strategies, thermal zoning, window opening status and sensor location (e.g., [37,49]). Only a limited number of studies explicitly model furniture, material properties or surface reflectance.

Occupant-related indicators represent the least frequent category. Most contributions collect subjective responses through surveys or post-occupancy evaluations (e.g., [69,71]). A smaller subset incorporates physiological sensing, including heart rate, skin temperature and wearable-based monitoring (e.g., [9,50]). PMV/PPD-based assessments are commonly used, while real-time user interaction through mobile applications or wearable devices is reported in a limited number of studies (e.g., [9,31,32]).

3.4. Methods and sensors used in DT-applications

Based on the indicator classification presented in Section 3.3, three main methodological groups were identified: quantitative, qualitative and hybrid approaches (Fig. 7). Because studies frequently combine multiple techniques, methodological occurrences exceed the total number of reviewed papers.

Quantitative approaches represent the most frequent methodological configuration. Thirty-one studies relied exclusively on sensor-based measurements, while 25 studies combined sensor data with modelling or simulation tools (Fig. 7). These studies employed fixed IoT monitoring networks to collect temperature, relative humidity, CO_2 and illuminance, often complemented by particulate matter ($PM_{2.5}$–PM_{10}) or VOC measurements [9,19,27,28,46,55,56]. In several cases, quantitative data were integrated with BIM-based models or thermal simulation environments (e.g., EnergyPlus, Modelica) [25,37,47]. Qualitative approaches were identified in nine occurrences. These were mainly based on occupant comfort surveys [34,38,39,51,69,71] and structured POE-questionnaires [65,67]. Additional methods included thermal sensation votes (e.g., “warmer/colder/same”) [18] and Likert-based satisfaction scales [32].

Hybrid approaches, combining environmental sensing with subjective or physiological data, total 27 occurrences (Fig. 7). These include PMV/PPD-based assessments integrated with real-time monitoring [19,41,52], app-based occupant feedback systems [31,32,53], and wearable-based Ecological Momentary Assessment (EMA) using heart rate or skin temperature [9,28,36,42,50].

The reviewed studies report the widespread use of low-cost IoT sensors integrated into multi-domain monitoring platforms (Table 4).

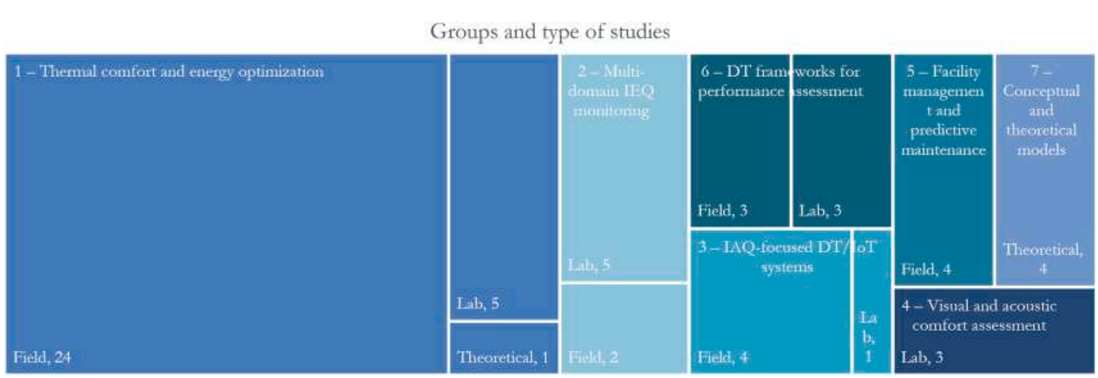


Fig. 5. Groups and type of studies, divided into: Field, Lab and Theoretical.

Table 3
Indicators analysed in previous studies.

Type	Indicator	Representative Studies
Dose-related	Air Change per Hour (h-1)	[72]
	Air pressure (Pa)	[56]
	Air temperature (°C)	[15,19–21,33,52,56,57,63,74,75,78]
	Air velocity (m/s)	[15,17,24,26,32,38,57,61,63,69,73,74]
	Airflow rate (m^3/h)	[52]
	Benzene	[69]
	CO (ppm)	[69]
	CO_2 (ppm)	[15,21,22,33,49,52,56,63,64,74,75,78]
	Discomfort Glare	[69]
	Dry bulb temperature (°C)	[69]
	Dust (ppm)	[69]
	Globe temperature (°C)	[24]
	RH (%)	[15,19–21,33,52,56,57,63,74,75,78]
	Illuminance	[15,17,32,33,56,58,60,63,72–74,76]
	Maintained luminance	[69]
	Mean radiant temperature (°C)	[17,24,26,32,38,48,57,61,69,73]
	NH_3 (ppm) - ammonia	[69]
	NO_x - nitrogen oxides	[49]
	Operant temperature (°C)	[69]
	Outdoor temperature (°C)	[20,69,71,74]
	$PM_{2.5}$ (ppm)	[29,48–50,53,55,67,73,74,76]
	PM_{10} (ppm)	[48,67,76]
	Reverberation Time (s)	[69]
	SO_2 - sulphur dioxide	[49]
	SPL (dB(A))	[15,27,33,35,44,45,56,57,63,64,66,70,73]
	TVOC (ppm)	[16,35,47,49,53,69,73,74,78]
Building-related	Building geometry	[15,19–21,33,56,63,71,74,75,78]
	Building orientation	[25]
	Envelope parameters	[16,28,35,49,56,61,64,71,73–75,78]
	Furniture	[63]
	Heat flux through the envelope	[32]
	HVAC and ventilation Type	[23,25,33,56,78]
	HVAC control type	[17,19,21,28,43,44,58,61,70,71,74]
	HVAC-layout	[15,19–21,33,52,56,57,63,71,74,78]
	IoT Sensors Location	[19–22,24,49,50,56,60,64,73,78]
	Lighting control/layout	[43,58]
	Material properties	[20,22,25,27,37,40,42,57,69,71,72]
	Occupancy (n/%/scenarios)	[20,22,25,27,37,40,42,57,69,71,72]
	Occupant proximity to HVAC	[63]
	Real-time weather API	[20]
	Servomotor-controlled windows	[76]
	Sound insulation	[69]
	Surface reflectance	[33]
	Surface temperature (°C)	[69]
	Thermal zoning	[15,19,21,28,31,71,74,75]
	Window openings and proprieties	[50,63,76]
Occupant-related	Body temperature (°C)	[20]
	Heart rate (Hz or bpm)	[30,32]
	Local comfort indexes	[24]
	Occupant comfort assessment (Survey)	[27,29,30,34,40,43,55,62,66,70]
	Occupant feedback	[26,35–37,44,45,47,53,63]
	Occupant feedback via App	[26,35–37,45,47,53]
	Occupant metabolic rate [Met]	[69]
	Occupant thermal assessment (PCS)	[17]
	Occupant thermal assessment (Survey)	[32]
	Perimetral skin temperature [°C]	[20,32]
	Personal clothing resistance [Clo]	[69]
	Personal Vote (PV)	[26]
	POE Survey	[44,45,62,66]
	Satisfaction index (0–5 Likert)	[35]
	Smartwatch-based Ecological Momentary Assessment (EMA)	[15,63]
	Thermal comfort assessment (0–1 Scale)	[42]
	Thermal comfort assessment (PMV/PDD)	[19,22,24,28,38,39,41,46,48,58,61,74]
	Thermal comfort satisfaction ("Warmer/Colder/Same")	[15]
	Thermal comfort satisfaction (1–10)	[74]
	User-controlled comfort interface	[43]

Frequently adopted devices include SHT31 and DHT22 thermo-hygrometers, SenseAir S8 and MH-Z19B CO_2 sensors, Plantower PMS7003 particulate matter sensors, CCS811 and SGP30 VOC sensors, and BH1750 or TSL2591 illuminance sensors [48,55,56]. Acoustic parameters were measured using MEMS microphones or calibrated sound level meters [50,52]. Sensor networks were generally deployed as static nodes connected via gateways, although some studies implemented portable or wearable systems to capture occupant-level measurements [9,45]. Reported temporal resolutions ranged from 1-minute to 15-minute intervals, depending on the system architecture. Connectivity infrastructures varied according to building scale and system configuration (Table 4). Wi-Fi and Bluetooth Low Energy (BLE) were commonly used in small-scale deployments such as classrooms and laboratories [35,49], while Zigbee and LoRaWAN were adopted in larger buildings [24,56]. Integration with BMS was achieved through protocols such as BACnet, KNX or Modbus TCP/IP [63,64]. Cloud-based platforms including Node-RED, ThingsBoard and AWS IoT Core were used for real-time data streaming and management [55,76].

Beyond environmental monitoring, several studies incorporated occupant-related data through questionnaires, mobile applications and wearable devices [31,71]. Standardized POE tools based on ASHRAE 55 or ISO 10,551 scales were frequently adopted (Table 5). Smartwatch and mobile-based systems (e.g., MyComfort, Cozie, custom platforms) were used to collect Ecological Momentary Assessments combining physiological and subjective inputs [9,32]. Advanced implementations integrated environmental and occupant data through middleware or cloud-based platforms ensuring semantic mapping with BIM entities [27,69]. Data exchange was often structured through IFC schemas and SensorThings API standards (Table 5).

3.5. DT- applications: coding paradigms and algorithmic approaches

Five computational paradigms were identified in the reviewed studies. These paradigms differ in terms of programming logic, modelling capabilities, automation level, and degree of integration between BIM, IoT sensing, simulation workflows and occupant-centric feedback:

(1) Text-based programming
(2) Visual programming and low-code workflows
(3) Machine-learning (ML) and deep-learning (DL) models
(4) Model-based and co-simulation frameworks
(5) Semantic and graph-based DTs.

These paradigms differ in modelling approach and integration between BIM, IoT, simulation and occupant-related data. Tables 6–10 present representative examples for each paradigm.

Fig. 8 shows the relative prevalence of the five categories. Text-based programming workflows constitute the largest group (28 studies), followed by machine-learning and deep-learning approaches (26), visual programming solutions (22), model-based simulation frameworks (21),

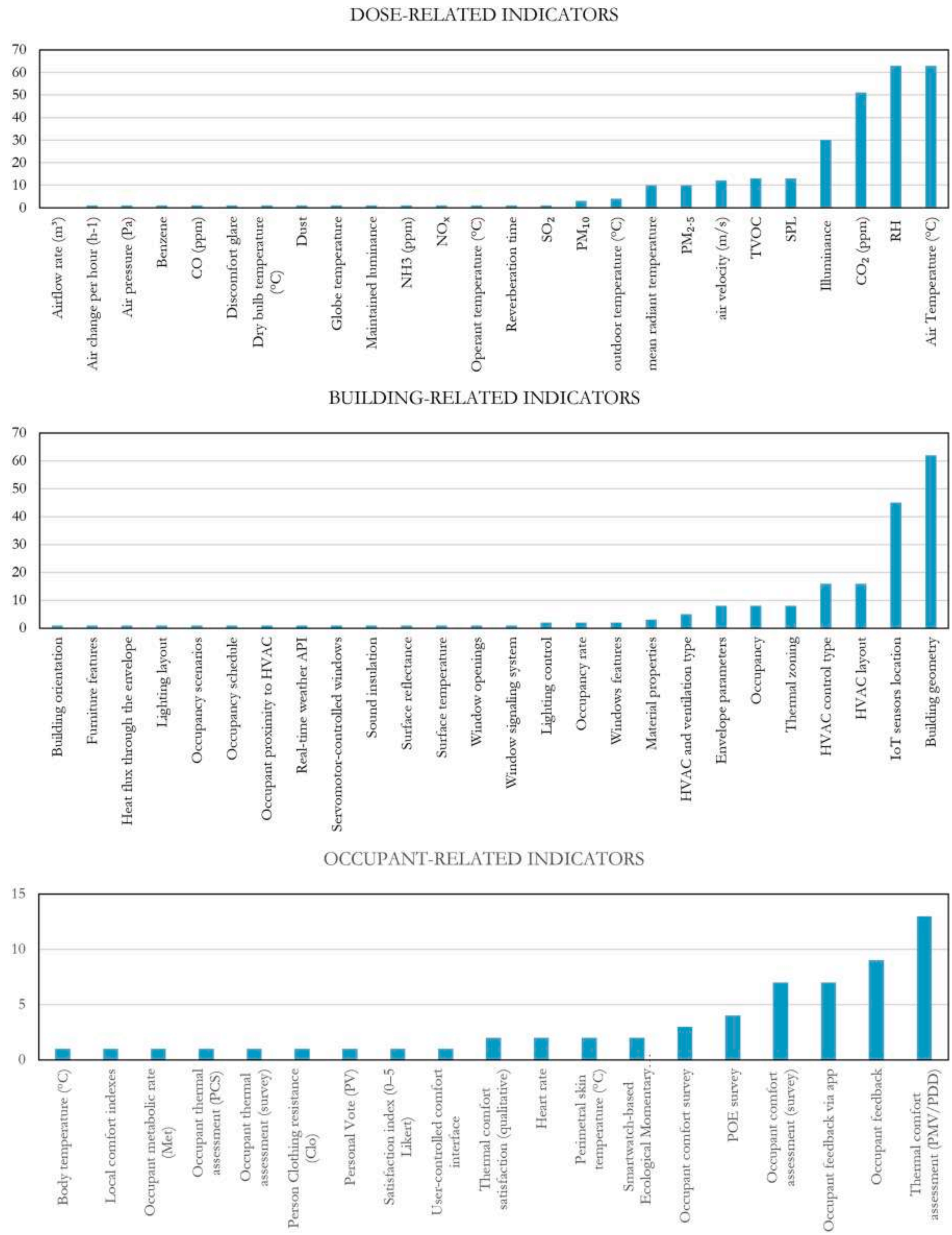
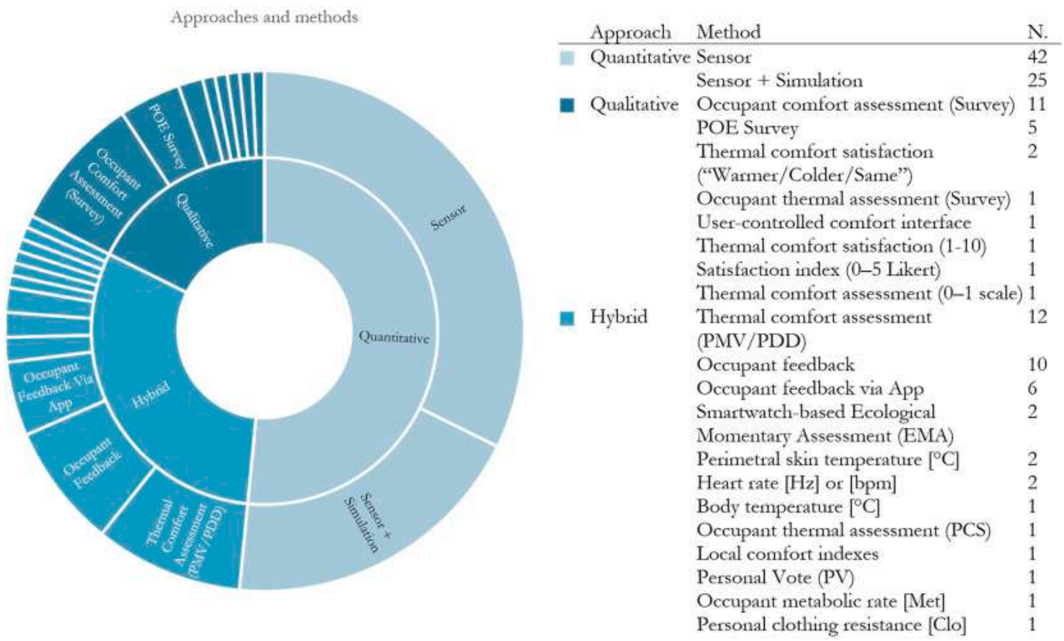


Fig. 6. Dose-related, building-related and occupant-related indicators occurrences in the analysed studies.

and semantic/graph-based DTs (5).

3.5.1. Text-based programming and scripting-based IoT–BIM integration

Text-based programming represents the most widespread computational layer (28 studies). These implementations manage tasks such as sensor data acquisition, time-series processing, BIM–sensor mapping, comfort index calculation and cloud synchronization. Python is the most frequently adopted language, supported by libraries such as Pandas, NumPy, Paho-MQTT and PyEnergyPlus [32,76]. MATLAB is used for parametric simulations and PMV/PPD modelling [19,26], while C# appears in BIM-centred applications through the Revit API [64]. Text-based DTs are applied in real-time BIM visualization systems [27], IAQ and thermal comfort monitoring pipelines [56,66], and multimodal datasets integrating environmental and occupant measurements [9]. Several studies describe modular scripting pipelines performing time-stamp alignment, spatial binding of sensors to BIM spaces, dynamic



Approach	Method	N.
Quantitative	Sensor	42
	Sensor + Simulation	25
Qualitative	Occupant comfort assessment (Survey)	11
	POE Survey	5
	Thermal comfort satisfaction ("Warmer/Colder/Same")	2
	Occupant thermal assessment (Survey)	1
	User-controlled comfort interface	1
	Thermal comfort satisfaction (1-10)	1
	Satisfaction index (0–5 Likert)	1
	Thermal comfort assessment (0–1 scale)	1
Hybrid	Thermal comfort assessment (PMV/PDD)	12
	Occupant feedback	10
	Occupant feedback via App	6
	Smartwatch-based Ecological Momentary Assessment (EMA)	2
	Perimetral skin temperature [°C]	2
	Heart rate [Hz] or [bpm]	2
	Body temperature [°C]	1
	Occupant thermal assessment (PCS)	1
	Local comfort indexes	1
	Personal Vote (PV)	1
	Occupant metabolic rate [Met]	1
	Personal clothing resistance [Clo]	1

Fig. 7. Approaches and Methods used in studies.

Table 4
Sensors and connectivity systems in DT-applications.

Parameter	Sensor Types	Common Models	Connectivity Protocol	Representative Studies
Temperature / RH	Thermo-hygrometers	DHT22, SHT31	Wi-Fi, LoRaWAN	[32,44]
CO_2	NDIR CO_2 sensors	SenseAir S8, MH-Z19B	Wi-Fi, MQTT	[48,57]
Particulate Matter ($PM_{2.5}$, PM_{10})	Optical sensors	Plantower PMS7003, SEN54	Wi-Fi, Zigbee	[55,56]
VOC / TVOC	Gas sensors	CCS811, SGP30	BLE, Zigbee	[29,76]
Illuminance	Light sensors	BH1750, TSL2591	Wi-Fi, MQTT	[35,70]
SPL	SPL meters and MEMS	A-weighted microphones	Local loggers	[50,52]
Occupancy	PIR sensors and cameras	HC-SR501, OpenCV vision	BLE, Wi-Fi	[24,40]
Wearable sensing	Smartwatch and biometric bands	Fitbit, Empatica E4	Bluetooth LE	[9,50]
Data gateways	Edge devices	Raspberry Pi, ESP32	MQTT, REST API	[55,63]

Table 5
Methods adopted in DT-applications for Healthy Buildings.

Category	Focus	Typical Tools and Protocols	Frameworks	Representative Studies
Measurement approach	Quantitative (sensor-based)	IoT nodes, fixed loggers	ISO 7726, ISO 16,000	[19,27]
	Qualitative (POE, survey)	Comfort questionnaires, ASHRAE 55 scales	ISO 10,551, ISO 28,802	[69,71]
	Hybrid (sensor + feedback)	Wearables, mobile apps, EMA	ISO 16,798–2	[9,32]
Modeling and simulation tools	Energy / thermal modelling	EnergyPlus, Modelica, MATLAB	ASHRAE 140	[25,78]
	BIM-based integration	Revit, Dynamo, IFC workflows	ISO 19,650	[27,46]
	BIM–IoT coupling	Node-RED, ThingsBoard, MQTT, REST API	IFC, SensorThings API	[49,55]
Data analysis and visualization	Real-time dashboards	Grafana, Power BI, Tableau	–	[48,76]
	Predictive models	Python, MATLAB, ANN / LSTM	ISO 50,001 (energy mgmt.)	[45,47]
Integration level	BIM–BEM–GIS	Spatial and semantic fusion	CityGML, IFC	[71]
Validation	Laboratory/ Living Lab	Controlled chamber setup	–	[50,59]
	Field / in use	Real-building case studies	–	[35,63]

updating of comfort parameters, regression or classification of comfort states, and dashboard streaming. Table 6 reports ten representative studies using text-based programming.

3.5.2. Visual programming and low-code BIM–IoT workflows

Visual programming languages (VPLs) and low-code environments are reported in 22 studies. Frequently adopted platforms include Dynamo, Grasshopper, Node-RED and ThingsBoard. These platforms support real-time visualisation, BIM interrogation, rule-based automation and rapid prototyping of DT workflows. These platforms excel in:

- Real-time visualisation: thermal, indoor air and lighting conditions
- BIM parametric interrogation: e.g., extracting room metadata, volumes, window areas
- Spatialized colour maps: representing comfort indices
- Rule-based automation: e.g., IEQ-triggered alerts or ventilation recommendations
- Rapid prototyping: DT-pipelines during early design or monitoring phases.

Dynamo emerges as the dominant paradigm for BIM–IoT integration thanks to its native interoperability with Revit [38,48,52]. It enables parametric linking of IoT nodes to BIM elements, automated comfort reporting, and interactive dashboards. Grasshopper is used primarily in

Table 6
Representative studies using text-based programming (10 selected).

Reference	DT application	IEQ domains	Study focus
[27]	Python + REST BIM–IoT pipeline	TH	Real-time comfort visualization in BIM
[64]	C# Revit API sensor integration	TH; IA	BIM plug-in for automated sensor mapping
[32]	Python + MQTT thermal pipeline	TH	Time-series forecasting + comfort analytics
[19]	MATLAB/R statistical modelling	TH; IA	Regression-based comfort analysis
[18]	Python + REST + ML	TH; IA; VIS; ACU	Adaptive sampling via graph embeddings
[66]	Python thermal modelling scripts	TH; IA	Data-driven comfort evaluation
[26]	MATLAB-based comfort pipeline	TH; IA; VIS	Early DT-like IEQ modelling
[56]	Python/MQTT IAQ pipeline	TH; IA	Classroom IAQ-to-BIM integration
[70]	Python thermal/light modelling	TH; IA; VIS	Integrated multi-domain pipeline
[76]	Python comfort analytics	TH; IA	Building-level IEQ monitoring

Table 7
Representative visual programming and low-code DT-applications (10 selected).

Reference	DT application	IEQ domains	Study focus
[48]	Dynamo dashboarding + regression	TH; IA; VIS; ACU	Multi-domain classroom comfort maps
[49]	Dynamo + ThingsBoard real-time IoT	TH; IA; VIS	User-friendly DT dashboard
[55]	Node-RED IoT orchestration	IA	Pollutant source tracking
[27]	Python + Dynamo hybrid workflows	TH	BIM-linked comfort colour maps
[51]	Grasshopper + GA optimisation	TH; IA; VIS; ACU	Early parametric-intelligence DT
[38]	Dynamo IoT workflows	TH; IA	FM-oriented IEQ DT
[68]	Dynamo parametric IEQ models	TH; VIS	Spatialized comfort visualization
[52]	Dynamo + k-means	TH; IA; VIS; ACU	Multi-domain clustering
[71]	Dynamo thermal/light workflows	TH; IA; VIS	Comfort-integrated BIM visualization
[76]	Dynamo + machine learning	TH; IA	Adaptive comfort classification

research settings involving daylighting and CFD-based analyses, combining visual programming with parametric simulation [51]. Node-RED and ThingsBoard support flexible IoT orchestration and data routing, enabling school-based and office-based monitoring DTs [49, 55]. Low-code DTs enhance interpretability for stakeholders and facilitate co-design in participatory monitoring projects. However, they may struggle with computationally demanding tasks such as simulation coupling or complex ML workflows, making hybrid approaches, visual programming plus scripting or machine learning, increasingly common [27,71]. Table 7 reports ten representative visual programming and low-code DT-applications.

3.5.3. Machine-learning and deep-learning predictive models

(ML and DL-approaches are reported in 26 studies. These models are used for thermal forecasting, IAQ-prediction, anomaly detection, zoning strategies and comfort classification. The reviewed studies employ a broad range of techniques, including:

- Regression models: linear, logistic, LASSO.

Table 8
Representative ML/DL-enabled DT applications (10 selected).

Reference	DT application	IEQ domains	Study focus
[22]	CNN + LSTM + EnergyPlus	TH; IA	Hybrid simulation–ML pipeline
[9]	GNN + embeddings	TH; IA	Spatially-aware comfort modelling
[50]	Clustering + graph analysis	TH; IA; VIS; ACU	Multi-domain, multimodal DT
[31]	Logistic regression + LSTM	TH	Thermal forecasting
[67]	Bayesian networks	TH; IA	DT-based probabilistic reasoning
[75]	Deep Q-learning + ontology	TH; IA	Intelligent HVAC control
[37]	K-means zoning	TH	Automated zoning for DT
[34]	Regression + thermal/light model	TH; IA; VIS	Multi-domain forecasting
[42]	Thermal ML modelling	TH; IA	DT-driven comfort validation
[47]	ML + Python pipeline	TH; IA	Data-driven thermal analytics

Table 9
Representative simulation-based DT applications (10 selected).

Reference	DT application	IEQ domains	Study focus
[54]	EnergyPlus + MPC	TH; IA	Predictive HVAC optimisation
[73]	EnergyPlus + IDA-ICE	TH	Calibration-driven thermal DT
[51]	IES-VE + Radiance	TH; IA; VIS; ACU	Multi-domain simulation
[20]	EnergyPlus + CFD	TH; IA	Urban–indoor airflow modelling
[79]	EnergyPlus + Modelica	TH; IA; VIS	DT for multi-domain control
[70]	Thermal + daylight models	TH; IA; VIS	School retrofit DT
[35]	Thermal + visual simulation	TH; VIS	Comfort–daylight interaction
[34]	Thermal + daylight model	TH; IA; VIS	Multi-domain school DT
[36]	Thermal + physiological integration	TH; IA; VIS; ACU	User-aware simulation
[58]	Thermal simulation	TH	Predictive indoor temperature DT

Table 10
Representative semantic/graph-based DT applications (all 5 studies).

Reference	DT application	IEQ domains	Study focus
[60]	BOT + SSN/SOSA ontology	TH; IAQ; ACU	Semantic comfort inference
[61]	BOT + SOSA	TH; VIS	Semantic integration of IEQ-data
[36]	Neo4j + embeddings	TH; IAQ	Graph-based comfort models
[75]	RDF ontology + RL	TH; IAQ	Semantic decision system
[24]	BOT; SOSA; IDMP	TH	Semantic interoperability

- Supervised classifiers: random forest, SVM, naïve Bayes.
- Unsupervised learning: k-means, DBSCAN, clustering-based zoning.
- Sequence models: LSTM, GRU [22,31].
- Convolutional neural networks: for spatiotemporal IEQ features [22].
- Bayesian networks: for probabilistic comfort reasoning [67].

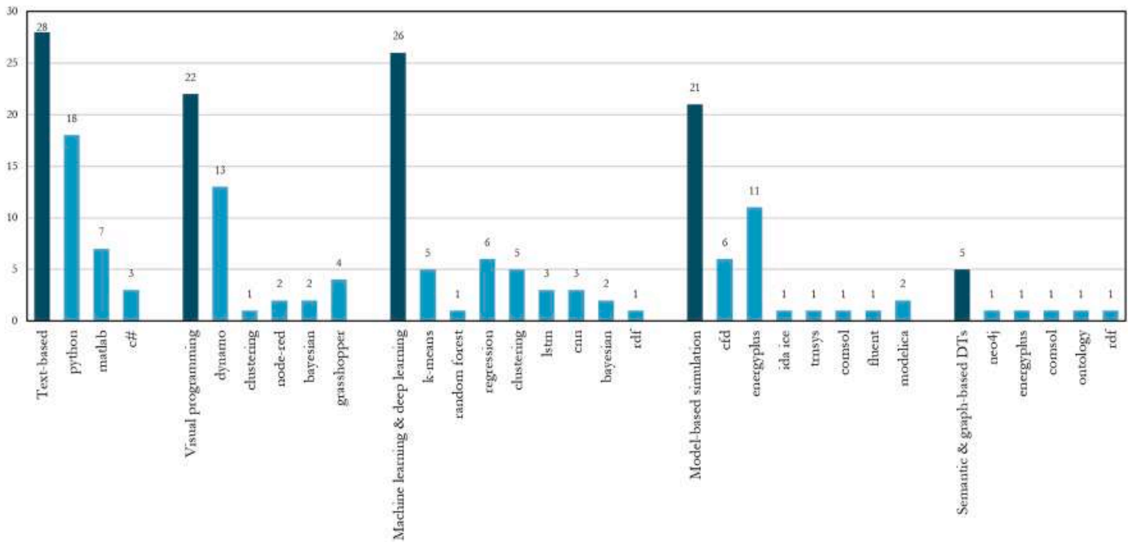


Fig. 8. Distribution of DT-application categories across the reviewed studies.

- Reinforcement learning: Deep Q-learning for intelligent HVAC-control [75].
- GNN and graph embeddings: that incorporate BIM-topology [9].

These models support forecasting of indoor temperatures [42], multi-domain environmental prediction [34] comfort classification [76] and occupant-centric analytics [50]. A significant trend is the development of hybrid ML–simulation DTs, which combine data-driven predictors with physics-based models to improve robustness [22].

A particularly innovative trend is the use of graph-based embeddings, such as Build2Vec, which learn spatial relations directly from BIM graphs to improve comfort prediction, optimize feedback sampling, or enhance zoning strategies. Graph-based models also excel at representing spatial hierarchies and adjacency relations embedded within BIM, which in turn supports more advanced analytical processes such as linking occupant feedback to environmental measurements, enabling graph-based machine learning techniques, or generating explainable inferences about building behaviour. Table 8 summarises ten representative ML/DL-enabled DT-applications.

3.5.4. Model-based simulation and co-simulation frameworks

Model-based DTs (21 studies) rely on simulation engines such as EnergyPlus, TRNSYS, IDA-ICE, Modelica, IES-VE and CFD solvers including ANSYS Fluent, OpenFOAM and COMSOL. Simulation-driven DTs are particularly valuable for evaluating design alternatives, quantifying retrofit impacts, estimating airflow and pollutant dispersion, and supporting model predictive control (MPC) strategies. These approaches are used to simulate thermal behaviour, airflow distribution, pollutant dispersion and lighting conditions [54,70]. Co-simulation frameworks (e.g., EnergyPlus–Modelica) are reported for integrated control and building physics modelling [73]. Simulation-based DTs are also combined with ML-predictors [34]. Applications include predictive HVAC-control [54], calibration-driven thermal modelling [73], school retrofit evaluation [70] and multi-domain IEQ-modelling [36,39]. Table 9 presents ten representative model-based DT-studies.

3.5.5. Semantic and ontology-based DTs

Semantic and graph-based DTs represent the smallest (5 studies) yet most conceptually advanced category. These approaches employ domain ontologies (such as BOT, SSN/SOSA, Brick or IFC—OWL), together with knowledge-graph technologies (Neo4j or RDF stores), to encode building components, sensor networks and IEQ parameters into machine-readable graph structures [60,61]. This semantic formalisation enables a level of interoperability that extends across BIM environments, IoT infrastructures, facilities management systems and simulation platforms, allowing heterogeneous datasets to be integrated within a unified and logically coherent framework [24]. Beyond interoperability, semantic DTs provide the capacity to perform complex queries and reasoning operations that go beyond simple data retrieval. Through the semantic relationships encoded in the graph, it becomes possible, for example, to identify all CO_2 sensors located in occupied classrooms, to infer comfort states from contextual information, or to explore causal dependencies between environmental conditions and occupant actions [75]. All five studies included in this category are summarised in Table 10.

4. Discussion

The results presented in Section 3 reveal a heterogeneous and rapidly evolving landscape in the application of DTs for Healthy Buildings. While the reviewed studies differ in their aims, technological maturity and experimental settings, several cross-cutting patterns emerge regarding the selection of indicators, the balance between monitoring and prediction, the integration of occupant-related information, and the computational paradigms adopted. This review does not aim to rank or hierarchically evaluate individual studies. Instead, it analyses structural patterns of integration across indicators, methods and computational paradigms to clarify dominant research configurations and identify underexplored directions within the DT–IEQ landscape. A cross-cutting analysis of methodological practices reveals heterogeneous levels of experimental robustness across the reviewed studies. Most contributions rely on sensor-based monitoring campaigns integrated with BIM or simulation environments. However, detailed reporting of sensor calibration procedures, long-term stability assessment or drift correction strategies is inconsistent. While several studies describe measurement accuracy and device specifications, fewer explicitly report recalibration intervals or uncertainty quantification methods. Similarly, monitoring duration varies considerably across studies, ranging from short-term experimental campaigns to extended seasonal deployments. Only a subset of contributions explicitly addresses cross-season variability or long-term validation, limiting the generalisability of predictive findings across different climatic conditions. In studies employing ML-approaches, validation practices are equally heterogeneous. Although train–test splits are commonly implemented, independent validation datasets, cross-season testing or transferability assessment across buildings remain comparatively limited. This suggests that predictive performance is often demonstrated within bounded experimental contexts rather than across diverse operational scenarios. Overall, the methodological landscape indicates strong innovation in integration strategies, but uneven reporting and validation depth. Future DT-based IEQ-research would benefit from more systematic documentation of calibration procedures, uncertainty propagation, longitudinal validation and cross-context testing to strengthen reproducibility and scalability. The following subsections discuss these trends by examining how current DT-applications address single and multi-domain IE-challenges, how indoor–outdoor interactions and environmental inhomogeneity are represented, and how methodological choices influence the performance and limitations of existing approaches. The discussion also integrates insights from the alluvial analyses to provide a consolidated interpretation of indicators, methods and DT paradigms, highlighting gaps and opportunities for future research.

4.1. Single-domain studies VS multi-domain studies

The classification presented in Section 3 indicates that most DT-applications for Healthy Buildings remain predominantly single-domain oriented. Thermal comfort and energy optimisation constitute the largest share of contributions, followed by IAQ-focused systems, while fully integrated multi-domain DT-frameworks are comparatively less frequent. Single-domain DTs typically concentrate on one primary performance objective, most commonly thermal comfort or IAQ, while other IEQ dimensions are treated as secondary variables or boundary conditions. Thermal-oriented DTs combine IoT sensing, BIM-integration and AI-based models to predict indoor temperatures, personalise setpoints and optimise energy use [19,28,32,47]. IAQ-focused implementations rely mainly on CO_2, VOC and particulate monitoring integrated with ventilation control or pollutant source identification workflows [54–56]. Visual and acoustical DTs appear more sporadically and are often implemented in laboratory or Living Lab contexts [59–61]. The predominance of single-domain studies reflects the methodological maturity of thermal and IAQ-modelling and the availability of standardised sensors and comfort frameworks. Focusing on one domain simplifies calibration, reduces data requirements and facilitates integration into operational building management systems. However, this configuration often assumes that non-target IEQ variables remain stable or exert limited influence on the primary objective.

Multi-domain DT-applications explicitly integrate thermal, indoor air, visual and acoustical variables within shared monitoring or simulation platforms [48–50,52,76]. These studies employ distributed sensor networks, combined dashboards or multi-domain simulations to represent the simultaneity of environmental conditions. In several cases, occupant feedback mechanisms are integrated to capture cross-domain comfort responses [50,51]. Compared to single-domain DTs, multi-domain systems require higher sensor density, more complex data fusion procedures and more articulated calibration strategies. They are frequently implemented in controlled environments or pilot buildings, where experimental conditions can be managed more systematically. Despite these challenges, multi-domain frameworks demonstrate the capacity to identify cross-domain trade-offs that remain invisible in domain-specific implementations.

Rather than constituting a strict dichotomy, single- and multi-domain DTs can be interpreted as points along a continuum of integration. Thermal- and IA-focused DTs represent the most mature and widely deployed configurations, particularly in educational and office buildings. Multi-domain DTs, though fewer, illustrate the potential of integrated IEQ modelling aligned with the broader Healthy Buildings paradigm. The transition toward more comprehensive frameworks therefore involves balancing the operational robustness of single-domain systems with the systemic representativeness of multi-domain approaches.

4.2. Interaction between IEQ-domains and with outdoor environment (OE)

The reviewed studies consistently indicate that indoor environmental domains cannot be treated as independent variables. Thermal, air, visual and acoustical conditions interact dynamically, and these interactions influence both occupant experience and building performance [80,81]. While single-domain DTs often simplify this interdependence, multi-domain implementations explicitly reveal cross-domain coupling mechanisms.

Two primary interaction layers emerge from the literature: (i) interactions between IEQ domains and (ii) interactions between indoor conditions and the outdoor environment (OE).

4.2.1. Interactions between IEQ-domains

Outdoor conditions constitute a second, equally influential layer shaping indoor environmental behaviour. Climatic variables, outdoor pollution and solar radiation act as boundary conditions for most DT-implementations. Thermal behaviour is strongly modulated by outdoor temperature and solar exposure, particularly in simulation-based DTs [54,73,78]. Field studies show that adaptive behaviours such as window opening link indoor thermal and IA conditions directly to outdoor variability [18,56]. IAQ dynamics are similarly influenced by outdoor pollutant levels and wind-driven ventilation patterns. Several studies report that improvements in indoor CO_2 levels through natural ventilation may coincide with increased particulate infiltration in polluted urban contexts [55,57]. This ventilation paradox highlights the need for OE-aware DT-modelling. Solar radiation and façade orientation simultaneously affect daylight distribution, thermal loads and, in naturally ventilated buildings, acoustic exposure [51,70]. These findings reinforce the importance of modelling the building envelope as an active mediator between indoor and outdoor conditions.

4.2.2. DT implications of multi-domain and OE interactions

Across the reviewed literature, IEQ interactions are consistently mediated by shared mechanisms: ventilation, occupancy, envelope performance and façade configuration. When these mechanisms are simplified or isolated within single-domain DTs, prediction accuracy and interpretability may be reduced. In contrast, multi-domain and OE-aware DTs incorporate boundary conditions and cross-domain dependencies within unified analytical frameworks [48,50]. Although these systems require higher data granularity and more articulated calibration strategies, they provide a more coherent representation of indoor environmental dynamics aligned with the Healthy Buildings paradigm. The evidence suggests that IEQ-domains and outdoor drivers form an interconnected system rather than a set of independent variables. DT-applications that explicitly account for these interactions offer a more robust basis for comfort assessment, predictive modelling and environmental control.

4.3. Spatial, temporal and behavioural inhomogeneity in IEQ modelling

A recurring theme across the reviewed studies is the intrinsic inhomogeneity of indoor environmental conditions. IEQ-variables are not uniformly distributed in space or stable over time, nor are they experienced homogeneously by occupants. This spatial, temporal and behavioural variability introduces significant modelling challenges for DT applications.

4.3.1. Spatial variability

Spatial heterogeneity is observed in thermal gradients, airflow patterns, daylight distribution and pollutant concentration fields. CFD-based simulations and multi-sensor deployments demonstrate that temperature and air velocity vary across room zones depending on façade exposure, HVAC-configuration and occupant density [20,34,78]. Similarly, daylight availability and glare risk are unevenly distributed according to orientation, shading and interior layout [51,70]. In field-based DTs, limited sensor density may fail to capture these micro-environmental differences, especially in large or highly occupied spaces (Gnecco et al., 2023; Serroni et al., 2021). Spatial inhomogeneity therefore affects both calibration reliability and the representativeness of comfort indices derived from single-point measurements.

4.3.2. Temporal inhomogeneity and time-varying comfort states

Temporal inhomogeneity arises from occupancy dynamics, outdoor weather fluctuations and operational schedules. Indoor temperature, CO_2 levels and illuminance may change significantly over short time intervals due to window opening, HVAC cycling or varying solar radiation [58,73]. High-resolution data streams (1–5 min intervals) capture these fluctuations more effectively than coarse logging intervals [18,76]. However, short monitoring campaigns and seasonal bias remain common limitations in the reviewed literature [22,63]. Temporal inhomogeneity therefore influences both predictive accuracy and cross-context generalisability of DT models.

4.3.3. Behavioural and human preferences variability

Occupant behaviour introduces an additional layer of variability. Adaptive actions such as window opening, thermostat adjustment or blind control modify thermal, IA and visual conditions simultaneously [49,50]. In classroom and office contexts, occupancy density and activity levels further influence heat gains and CO_2 production [40]. Several studies integrate occupant feedback or wearable sensing to capture personalised comfort responses [18,32].

These approaches reveal that identical environmental conditions may generate heterogeneous subjective evaluations, highlighting the limits of uniform comfort thresholds. Moreover, human preferences are not static: individuals may modify comfort expectations over time and across different situations depending on activity patterns, adaptive behaviors and seasonal adaptation, as highlighted by adaptive comfort theory [81,82]. This intra-individual variability further challenges the assumption of stable comfort preferences often embedded in simplified DT-based models.

4.3.4. Implications for sensor placement and measurement strategies

The spatial and temporal variability described above has direct implications for sensor deployment strategies within DT-frameworks. Several reviewed studies highlight that single-point measurements may inadequately represent heterogeneous indoor conditions, particularly in large, naturally ventilated or highly occupied spaces [50,52]. Sensor placement influences the reliability of comfort indices and pollutant assessments, as thermal stratification, airflow patterns and solar exposure generate localized gradients [20,79]. In classrooms and open-plan offices, positioning sensors near façades, occupants or ventilation outlets can yield significantly different readings compared to centrally located nodes. Measurement resolution also interacts with spatial deployment. High-frequency sampling may capture transient peaks in CO_2 or temperature associated with occupancy cycles or behavioural events [18,76], whereas coarse logging intervals may smooth short-term fluctuations and obscure dynamic processes. Multi-sensor networks and distributed configurations are therefore increasingly adopted in multi-domain DT-implementations [48]. However, higher sensor density introduces calibration complexity, data fusion challenges and maintenance constraints. The reviewed literature suggests that sensor placement should be treated as a modelling parameter rather than a purely technical installation choice. Within DT-ecosystems, spatial representativeness and measurement strategy directly affect data-driven inference, simulation calibration and predictive reliability.

4.3.5. Implications for DT-modelling and validation

Spatial, temporal and behavioural inhomogeneity directly affect DT-design and validation. Low sensor density, short monitoring periods or simplified occupancy assumptions may produce models that are locally accurate but structurally fragile when applied to different zones or seasons. Multi-sensor configurations, high-frequency data acquisition and occupant-centred feedback mechanisms mitigate part of this variability [48,50]. Hybrid ML–simulation frameworks also attempt to accommodate temporal and spatial non-linearities [22,34]. Overall, the reviewed evidence indicates that IEQ inhomogeneity is not an exception but a defining characteristic of real buildings. DT implementations that explicitly address spatial resolution, temporal continuity and behavioural diversity demonstrate greater robustness in representing indoor environmental dynamics.

4.3.6. Toward DTs that account for inhomogeneity

The studies indicate a gradual shift toward DT approaches that explicitly incorporate inhomogeneity. Four methodological directions emerge:

1. Sensor-aware BIM integration: enabling precise spatial mapping of measurement nodes [27,48].
2. Graph-based representations: capturing local divergences and spatial adjacencies [50].
3. Zonal or sub-zonal modelling: often enabled by simulation or clustering [37].
4. Wearable-based or occupant-centric feedback: adding personalised granularity to DT validation [18,36].

These approaches collectively indicate the direction of future Healthy Building DTs: from global, room-averaged models toward fine-grained, occupant-centred, spatially explicit representations of the indoor environment. Beyond measurement considerations, spatial, temporal and behavioural inhomogeneity challenge the implicit assumption of environmental uniformity embedded in many comfort standards and simplified DT implementations. When comfort models rely on averaged values or single-point monitoring, they risk overlooking micro-environmental gradients and personalised responses. The reviewed evidence suggests that Digital Twins intended for adaptive or predictive control must incorporate variability not as noise, but as a structural feature of indoor environmental systems. In this sense, inhomogeneity becomes a defining modelling constraint that shapes data requirements, algorithm selection and validation protocols.

4.4. From monitoring to prediction: the operational evolution of DTs

The reviewed literature reveals a clear operational distinction between monitoring-oriented and prediction-oriented DT-applications. While both configurations rely on sensor networks and data integration pipelines, they differ in temporal orientation, modelling depth and control logic. Monitoring-based DTs are primarily reactive. They collect and visualise environmental parameters in near real-time, supporting awareness, reporting and threshold-based alerts [27,48,56]. These systems are widely implemented in schools and office buildings, where dashboards display temperature, CO_2, illuminance or comfort indices. In many cases, monitoring frameworks are integrated with BIM visualisation environments or building management systems through rule-based logic. Monitoring configurations benefit from relatively simple architectures and lower calibration demands. However, they operate on a feedback-after-event principle: corrective actions are typically triggered once comfort deviations or pollutant peaks are detected. Prediction-oriented DTs extend this logic by incorporating forecasting models, simulation engines or machine-learning algorithms to anticipate environmental evolution [22,47,54]. These systems perform short-term thermal forecasting, IAQ estimation or occupancy-based prediction, enabling anticipatory control strategies such as Model Predictive Control (MPC) or adaptive ventilation scheduling. The transition from monitoring to prediction requires higher data granularity, longer monitoring horizons and more structured calibration procedures. Predictive DTs depend strongly on training datasets, model validation and cross-seasonal robustness [22,63]. When datasets are short or spatially limited, forecasting accuracy may degrade, particularly in buildings characterised by high inhomogeneity (Section 4.3). An emerging configuration integrates physics-based simulation and data-driven models within hybrid architectures [22,34]. In these systems, simulation engines represent building thermodynamics while ML algorithms capture non-linear occupant behaviour or residual dynamics. Such hybrid DTs aim to reconcile model interpretability with adaptive capability.

Across the reviewed studies, monitoring and prediction should not be interpreted as mutually exclusive categories but as successive layers of operational sophistication. Monitoring provides the empirical foundation upon which predictive and control-oriented DTs are constructed. Prediction, in turn, enables anticipatory adaptation, shifting DT-applications from descriptive dashboards toward dynamic decision-support systems. Within the Healthy Buildings paradigm, this evolution reflects a broader transition: from verifying compliance with comfort thresholds to proactively shaping indoor environmental trajectories. The operational maturity of DT-applications therefore depends not only on sensor deployment or computational capacity, but on the ability to integrate temporal modelling, validation and control feedback into coherent workflows.

An additional dimension emerging from the review concerns uncertainty management and scalability. Sensor-based DT-implementations inherently depend on measurement reliability, spatial representativeness and temporal stability. Yet, explicit discussion of uncertainty propagation from sensing to predictive modelling remains limited in most studies. Few contributions quantify how sensor inaccuracy, spatial sparsity or model simplifications influence predictive outcomes. Moreover, scalability beyond controlled living labs or pilot buildings is rarely addressed in depth. Many DT applications are validated within single-building case studies, raising open questions regarding transferability to different building typologies, occupancy profiles and climatic contexts. Addressing uncertainty quantification, standardised validation protocols and multi-building testing frameworks will be essential for advancing DT systems from experimental demonstrators toward robust, generalisable infrastructures for Healthy Buildings research.

Across the reviewed corpus, reporting of calibration procedures, long-term monitoring and independent validation remains inconsistent, particularly in ML-based applications, indicating that technical integration often progresses faster than uncertainty-aware validation and transferability assessment.

4.5. Integrated interpretation of indicators, methods and DT-applications

The two alluvial diagrams (Figs. 9 and 10) provide complementary representations of how indicator types, methodological approaches and DT-application categories interact across the analysed literature. Fig. 9 emphasises the flow from indicator typologies toward methodological configurations and DT-application categories, while Fig. 10 highlights the methodological pathways linking indicators to specific computational paradigms. Their combined interpretation highlights three structural patterns that characterise the current state of DT-research for IEQ. Graphs were elaborated using RAWGraphs [83].

Fig. 9 indicates the predominance of dose-related indicators, which generate the most continuous flows toward quantitative approaches and, subsequently, toward text-based programming, visual programming and machine-learning DTs. This configuration reflects a consolidated pipeline centred on environmental sensing (particularly temperature, CO_2, humidity and illuminance) as the main driver for real-time monitoring, comfort estimation and predictive analytics. The focus on exposure variables is reinforced by sensor availability and by the compatibility of these metrics with both established comfort models and data-driven frameworks.

At the same time, the diagram shows a comparatively limited representation of building-related and occupant-related indicators, whose flows appear thinner and more fragmented. Building-level variables, such as geometry, envelope properties or zoning, are frequently employed to contextualise sensor data rather than to support semantically enriched or physics-based reasoning. Occupant-related metrics remain largely confined to hybrid configurations integrating surveys, app-based feedback or wearable sensing (e.g., [18,50]).

Fig. 10 further illustrates how methodological choices act as the central mediating layer between indicator types and DT computational paradigms, highlighting the dominant role of quantitative pipelines. This dominance suggests that many DT implementations continue to prioritise environmental data acquisition, while behavioural and perceptual dimensions are less systematically embedded. Nevertheless, the distributed flows linking hybrid approaches with ML/DL and simulation-based DTs indicate a gradual convergence between environmental and user-centred data.

When interpreted jointly, the two diagrams depict a research landscape still largely structured around sensor-driven monitoring, yet progressively evolving toward multi-domain, predictive and occupant-

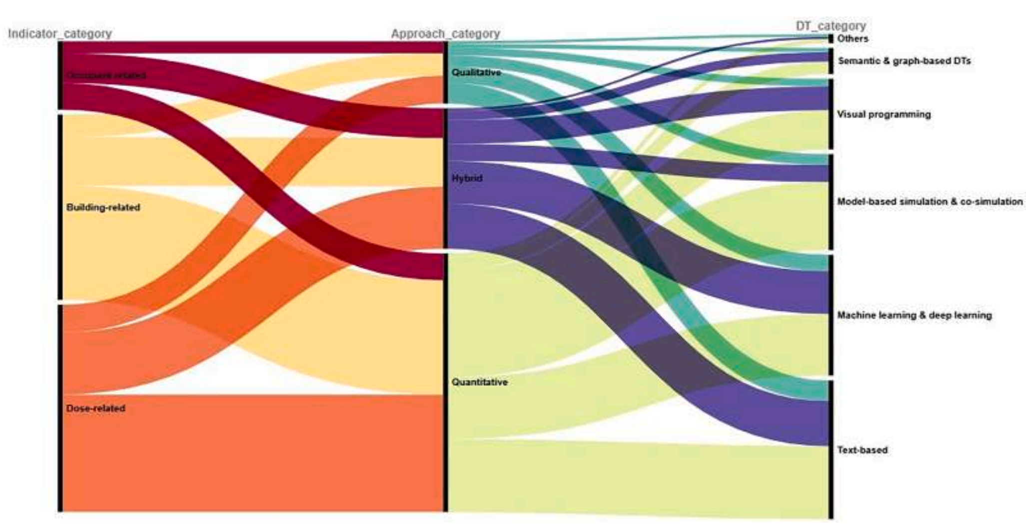


Fig. 9. Alluvial diagram representing connection between Indicators type, Approaches and DT-application categories.

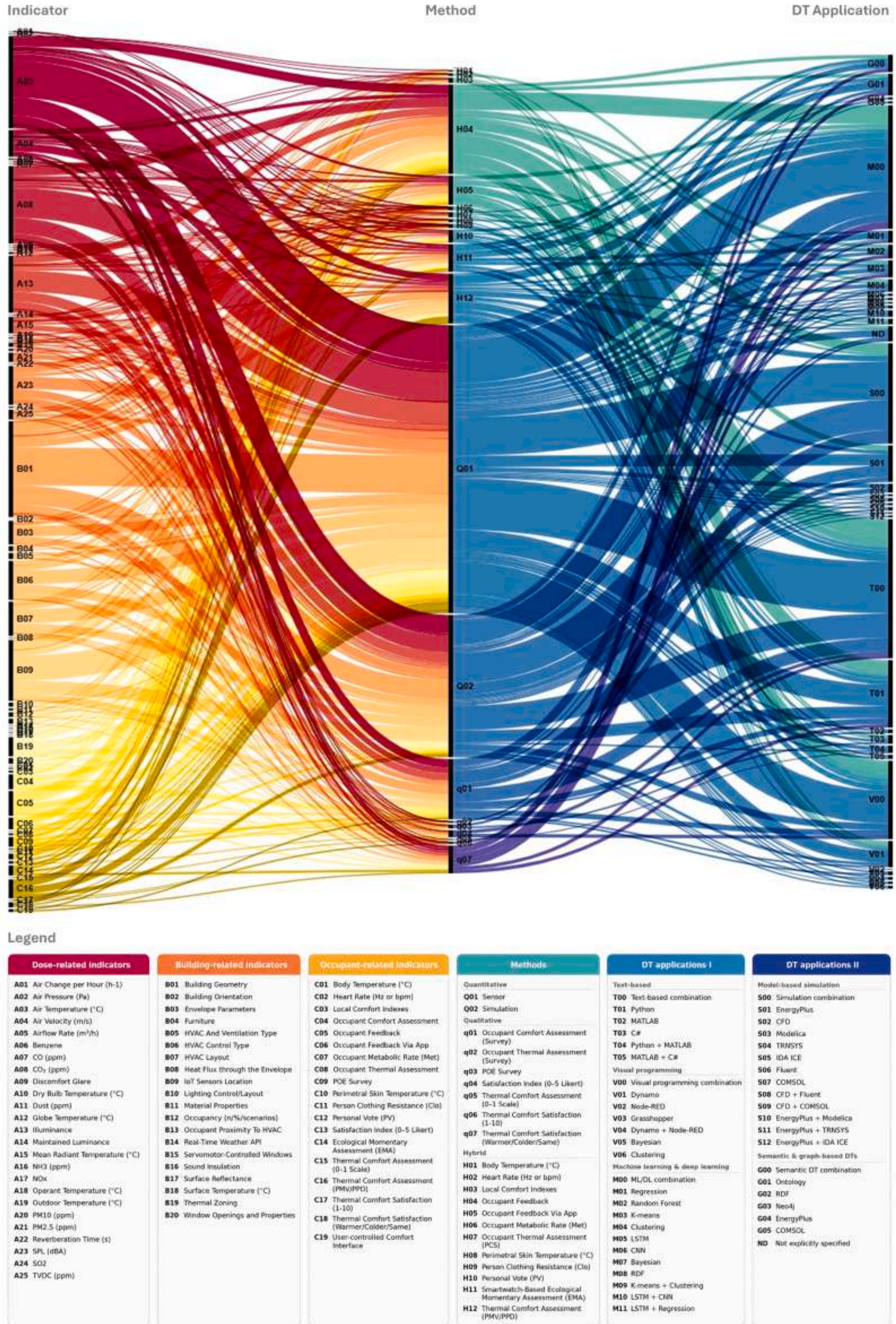


Fig. 10. Alluvial diagrams representing connection between Indicators, Methods and DT-application [18,50].

aware DTs. They also reveal persistent fragmentation between environmental sensing, semantic modelling and user feedback. The comparatively weaker integration of building-related and occupant-related indicators suggests that current DT-applications remain more aligned with exposure monitoring than with fully integrated, health-oriented representations of indoor environmental systems.

4.6. *Computational paradigms and DT operational objectives*

Beyond revealing dominant indicator–method–paradigm relationships, the reviewed literature suggests that different computational paradigms tend to support distinct DT operational objectives. Although overlaps frequently occur and hybrid architectures are increasingly common, several recurrent associations emerge.

Text-based programming environments are primarily employed to support data acquisition, processing, interoperability and real-time monitoring functions. Their flexibility makes them particularly suitable for integrating heterogeneous data sources, implementing custom analytics and managing BIM–IoT communication pipelines.

Visual programming and low-code environments are commonly adopted for data visualisation, stakeholder interaction and operational decision support. Their graphical nature facilitates the interpretation of environmental information and supports rapid prototyping of DT workflows, particularly during design and facility management activities.

Machine-learning and deep-learning approaches are predominantly associated with predictive objectives, including forecasting, anomaly detection, comfort classification and adaptive control. These paradigms enable DTs to move beyond descriptive monitoring towards anticipatory and data-driven decision-making.

Model-based simulation frameworks are mainly employed to evaluate future scenarios, test design alternatives and support predictive control strategies. Their strength lies in representing physical building behaviour and enabling what-if analyses under varying operational conditions.

Semantic and graph-based DTs are primarily oriented towards interoperability, knowledge representation and reasoning. By structuring relationships between building components, sensors, occupants and environmental conditions, these approaches facilitate information integration across heterogeneous systems and support more advanced forms of contextual decision support.

Taken together, these findings suggest that computational paradigms should not be viewed as alternative implementations of the same DT concept, but rather as complementary approaches addressing different operational needs. Future DT architectures for Healthy Buildings will likely rely on increasingly hybrid configurations capable of combining monitoring, prediction, simulation, semantic reasoning and occupant-centred adaptation within unified digital ecosystems.

Consequently, the suitability of a given computational paradigm depends not only on data availability or technological maturity, but also on the specific operational objective pursued by the DT.

Beyond the computational paradigms currently observed in the literature, emerging developments in artificial intelligence are likely to play an increasingly important role in the evolution of DT-applications for Healthy Buildings. While most current implementations remain centred on monitoring, data integration and predictive analytics, future DT architectures may progressively incorporate more advanced reasoning and decision-support capabilities.

In particular, the convergence of machine learning, semantic knowledge representations and graph-based modelling may enable DTs to move beyond pattern recognition towards contextual understanding of building–occupant–environment interactions. Such capabilities could support the interpretation of heterogeneous IEQ data, the identification of complex causal relationships and the generation of adaptive recommendations tailored to specific environmental and occupant conditions.

Recent advances in large language models, knowledge graphs and AI-assisted reasoning further suggest the possibility of more interactive DT ecosystems capable of supporting facility managers and occupants through natural-language querying, automated diagnostics and explainable decision-support processes. Although these developments remain largely exploratory within the reviewed literature, they indicate a potential transition from data-centric DTs towards more cognitive and knowledge-driven digital environments.

Future research should therefore investigate how AI-based reasoning, semantic interoperability and hybrid simulation–learning architectures can be integrated within DT frameworks to support more adaptive, transparent and health-oriented management strategies for indoor environments.

4.7. Comfort-driven DTs versus health-oriented DTs

The preceding analysis highlights a structural distinction within current DT applications for IEQ: the predominance of comfort-oriented modelling over explicitly health-oriented frameworks. Most reviewed studies focus on thermal comfort optimisation, IAQ-monitoring or energy-comfort trade-offs, relying on exposure-related indicators such as temperature, CO_2 concentration, humidity and illuminance. These variables are measurable through widely available sensors and are directly compatible with established comfort standards and predictive control algorithms. As shown in the alluvial analyses (Section 4.5), such dose-related indicators form the backbone of quantitative and predictive DT-pipelines.

In contrast, health-oriented representations require broader conceptual integration. While IAQ-metrics such as particulate matter or VOC concentrations relate directly to health risk assessment, many DT implementations stop at threshold-based monitoring rather than incorporating exposure duration, cumulative effects or vulnerability-sensitive modelling. Similarly, behavioural and physiological dimensions, captured through surveys, wearable sensing or ecological momentary assessment, remain largely confined to hybrid and experimental studies [18,50]. The distinction between comfort and health is not merely semantic. Comfort models typically aim to minimise short-term dissatisfaction under assumed steady-state conditions, whereas health-oriented approaches must account for temporal exposure patterns, occupant diversity and long-term risk accumulation. This shift implies different modelling requirements: extended monitoring horizons, integration of occupant-specific data, and coupling between environmental metrics and epidemiological or physiological frameworks. While a limited number of studies explore predictive control strategies or short-term exposure estimation, explicit modelling of cumulative exposure duration, dose–response relationships or long-term health risk metrics remains rare. Most DT-implementations focus on instantaneous threshold exceedance (e.g., CO_2 concentration or thermal comfort bands) rather than time-integrated exposure indicators. This highlights a structural gap between environmental monitoring and health-oriented modelling within current DT-architectures.

From an IEQ-perspective, uncertainty is particularly relevant when environmental variables are interpreted against regulatory or comfort thresholds. For instance, minor deviations in CO_2 measurement accuracy may influence ventilation control decisions, while temperature or humidity sensor offsets can affect comfort band classification. Despite this, only a limited number of studies explicitly discuss how measurement uncertainty may propagate into control logic or predictive outputs. Strengthening this link between sensing reliability and decision thresholds represents a critical step toward more resilient DT-implementations. The reviewed literature suggests that current DT-applications are more mature in comfort optimisation than in health-oriented modelling. Multi-domain and hybrid architectures demonstrate the potential to bridge this gap, particularly when environmental sensing is combined with behavioural and semantic layers. However, fully health-centred DT-frameworks remain comparatively limited in scope and validation depth.

Rather than replacing comfort modelling, health-oriented DTs expand its interpretative horizon. Moving from comfort-driven optimisation toward integrated health-aware digital ecosystems requires incorporating exposure dynamics, user heterogeneity and cross-domain interactions within unified modelling environments. In this sense, the transition from comfort to health reflects not a change of objective, but an increase in representational complexity.

5. Conclusion

This review provides an integrated and structured analysis of how indicators, sensing infrastructures and computational paradigms are currently implemented in DT-applications for Healthy Buildings. By examining 62 studies through a combined methodological and computational lens, the analysis clarifies the dominant patterns shaping contemporary DT development.

Across the reviewed literature, dose-related environmental indicators form the backbone of most DT-workflows. Variables such as temperature, CO_2 concentration, relative humidity and illuminance are widely monitored and seamlessly integrated into quantitative pipelines, enabling real-time observation, dashboard visualisation and predictive analytics. This configuration reflects both technological availability and the established role of exposure metrics in comfort modelling and IEQ assessment. However, such reliance often produces representations of indoor environments that simplify spatial heterogeneity, behavioural adaptation and long-term exposure dynamics.

Building-related indicators, such as envelope characteristics, zoning logic, HVAC-configuration and spatial semantics, are integrated more selectively. While these variables are essential for contextualising sensor data and supporting physics-based or semantically enriched reasoning, they frequently serve as background parameters rather than active modelling drivers. Similarly, occupant-related indicators, including subjective comfort votes, app-based feedback and wearable physiological measurements, appear predominantly in hybrid and experimental configurations. As a result, many current DT-implementations continue to infer user experience indirectly through environmental proxies rather than modelling behavioural and perceptual dimensions explicitly.

From a methodological standpoint, quantitative approaches remain predominant, whereas qualitative and hybrid strategies are less systematically embedded. Advances in machine learning, simulation-based modelling and semantic frameworks have expanded analytical capabilities, enabling forecasting, optimisation and structured interoperability. Nevertheless, these approaches often encounter challenges related to dataset continuity, calibration robustness, spatial representativeness and cross-building transferability.

The joint interpretation of indicators, methods and computational paradigms suggests that the field is transitioning from sensor-driven monitoring toward predictive, spatially explicit and progressively occupant-aware DTs. Yet, current implementations remain largely environment-centred and comfort-oriented. Expanding toward health-informed DT-ecosystems requires stronger integration of building semantics, multi-source occupant data and hybrid modelling architectures that combine physics-based reasoning with data-driven inference within interoperable frameworks.

Advancing DT-applications for IEQ will require more standardised validation protocols, interoperable sensing–modelling frameworks, uncertainty-aware predictive workflows and shared benchmarking datasets to improve reproducibility, scalability and transferability across building contexts.

Ultimately, advancing DT-applications for Healthy Buildings requires bridging environmental accuracy, spatial granularity, behavioural variability and human preferences within integrated modelling environments. The findings of this review suggest that future DT-development should be guided by the alignment between computational paradigms and specific operational objectives rather than by technology-driven implementations alone. While monitoring-oriented applications may rely on lightweight BIM–IoT architectures, predictive, adaptive and health-oriented DTs increasingly require hybrid configurations integrating simulation, machine learning, semantic knowledge representations and occupant-related information. In this perspective, DTs are evolving from monitoring tools towards interoperable, explainable and health-aware digital ecosystems capable of supporting adaptive environmental management and occupant-centred decision-making [81].

CRediT authorship contribution statement

Alessandro D'Amico: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Edoardo Currà:** Funding acquisition, Project administration, Supervision, Writing – review & editing. **Philomena M. Bluyssen:** Methodology, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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