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AI-driven non-intrusive occupant monitoring for occupant-centric control: A multi-domain review of thermal, air, and visual environments

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A B S T R A C T

This systematic review evaluates non-intrusive artificial intelligence-based occupant monitoring for Occupant-Centric Control systems, analyzing 82 studies published between 2015 and March 2026 across thermal, indoor air quality, and visual domains. The analysis reveals that deep learning-based computer vision represents the predominant approach, achieving accuracies of 80–100% for physiological parameter estimation under controlled laboratory conditions, and up to 99.3% for occupant detection in field settings. Integrating these technologies into building operations facilitates substantial benefits: energy savings of up to 50% and thermal comfort improvements of 43–73% have been reported in individual experimental studies, though typical field-validated ranges are more modest. Despite these advancements, significant barriers persist, including high implementation costs, privacy concerns, and a persistent scarcity of labeled training data. This paper establishes a comprehensive technical framework for developing responsive, occupant-centric environments that balance human well-being with operational efficiency.

Nomenclature

AI	Artificial Intelligence	CLO	Clothing Insulation
CNN	Convolutional Neural Network	CV	Computer Vision
DCV	Demand-Controlled Ventilation	DL	Deep Learning
DNN	Deep Neural Network	GAN	Generative Adversarial Network
HBI	Human-Building Interaction	HVAC	Heating, Ventilation, and Air Conditioning
IAQ	Indoor Air Quality	IEQ	Indoor Environmental Quality
LLM	Large Language Model	MAE	Mean Absolute Error
mAP	Mean Average Precision	MET	Metabolic Rate
ML	Machine Learning	MPC	Model Predictive Control
NN	Neural Network	NRMSE	Normalized Root Mean Square Error
NRMSD	Normalized Root Mean Square Deviation	OCC	Occupant-Centric Control
PCP	Percentage of Correct Parts	PIR	Passive Infrared
PMV	Predicted Mean Vote	RL	Reinforcement Learning

(*continued on next column*)

(*continued*)

RMSE	Root Mean Squared Error	SHAP	SHapley Additive exPlanations
TIR	Thermal Infrared	TSV	Thermal Sensation Vote
XAI	Explainable AI		

1. Introduction

1.1. Background

Buildings account for approximately 40% of total global energy consumption, with Heating, Ventilation, and Air Conditioning (HVAC) systems responsible for 30–40% of this usage [1]. Consequently, extensive research has been dedicated to enhancing HVAC efficiency and optimizing indoor environmental control [2–5]. Conventional control logic, predominantly governed by static setpoints, often fails to integrate transient environmental variations and personal occupancy profiles. This operational inflexibility leads to significant energy wastage while simultaneously compromising the quality of the indoor

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environment. This rigidity not only leads to significant energy waste but also compromises occupant comfort. Given that individuals spend over 90% of their lives indoors [6], the indoor environment acts as a critical determinant of health, well-being, and productivity. International standards, such as the World Health Organization (WHO) guidelines and the WELL Building Standard, underscore the profound impact of Indoor Environmental Quality (IEQ)—encompassing thermal, air, and visual domains—on human health [7,8]. Thus, building optimization must extend beyond conventional energy-saving objectives to holistically integrate occupant comfort and health. This imperative has driven a paradigm shift toward Occupant-Centric Control (OCC), positioning occupants as the primary agents in building systems operations.

1.1.1. Emergence of occupant-centric control

To overcome the inherent constraints of static building operation, OCC has emerged as a transformative strategy [9–11]. The primary objective of OCC is to dynamically modulate building systems, such as HVAC and lighting, by integrating real-time data on occupant presence, behavior, and environmental preferences [9]. The International Energy Agency (IEA) EBC program defines OCC as an approach that incorporates occupant behavior modeling into building control logic to enable high-precision operations [10]. This transition represents a fundamental shift from rigid, schedule-based management to responsive, human-in-the-loop systems that incorporate real-time occupant feedback into the building's decision-making framework. By identifying actual occupancy and activity patterns, OCC yields several critical benefits: (1) enhanced adaptability to transient environmental needs, (2) personalized comfort tailored to individual physiological and psychological states, and (3) maximized energy efficiency through the elimination of wasteful operations in unoccupied zones. Consequently, OCC is positioning itself as a cornerstone technology for the next generation of sustainable smart buildings.

1.1.2. Transition to AI-driven non-intrusive monitoring for OCC

The effective implementation of OCC systems hinges on the acquisition of accurate and reliable occupant information in real time. Early research primarily relied on intrusive methods, utilizing wearable sensors or direct measurement devices to collect physiological data such as Metabolic Rate (MET) and Clothing Insulation (CLO) [12–16]. However, these approaches often encountered substantial challenges regarding scalability and practical deployment, primarily due to occupant discomfort and privacy concerns associated with physical contact.

To address these limitations, non-intrusive AI-driven monitoring has emerged as a viable solution, leveraging recent advances in Computer Vision (CV) and Deep Learning (DL). Unlike traditional sensors that provide limited binary data (e.g., presence/absence), AI-integrated systems extract high-resolution, semantic information from the occupants and environment [17,18]. This capability enables the interpretation of complex contexts—such as estimating MET via pose analysis or thermal sensation from occupants' facial skin temperature—without physical intrusion. In this review, 'Non-intrusive AI-driven Monitoring' is defined as the holistic process of deriving high-level occupant attributes using AI methodologies. Key approaches include:

- Vision-based physiological estimation: Utilizing DL models to estimate MET, CLO, and skin temperature from RGB or thermal imagery [19,20].
- Behavior and context analysis: Recognizing occupant activities and spatial distributions in real time to optimize zone-level environmental control [21,22].
- Signal-based sensing: Processing radio-frequency signals (e.g., Wi-Fi, Bluetooth) with AI to detect occupancy [23].

These technologies enable a holistic approach to IEQ control, allowing building systems to respond to diverse occupant data—ranging from physiological states to behavioral patterns—thereby advancing the realization of truly smart and human-centric buildings.

1.2. Existing review articles on OCC

As OCC has established itself as a pivotal strategy for enhancing building performance, a multitude of literature has explored its methodologies and applications. To delineate this evolving landscape, a comprehensive search of the SCOPUS and Google Scholar databases was conducted, identifying 15 representative review papers (Table 1).

Most existing reviews have predominantly focused on control strategies, system implementation, and energy-saving potential [24–26]. While some recent studies have touched upon vision-based sensing [26], significant gaps remain in the current literature:

- Insufficient emphasis on the 'Monitoring' pipeline: Prior studies often prioritize control logic over the data acquisition phase. There is a lack of in-depth examination of how raw data is sensed, processed, and transformed into actionable occupant information, which is the foundational step for any OCC system.
- Limited technological scope: Many reviews focus narrowly on specific vision-based systems, failing to integrate emerging non-visual AI methodologies, such as RF-based sensing, which are vital for privacy preservation.
- Lack of cross-domain IEQ integration: Few studies systematically evaluate how acquired information is utilized across the three primary IEQ domains—thermal, air, and visual quality—in a unified manner.

Therefore, this review aims to address these voids by providing a multi-dimensional analysis of non-intrusive AI-driven monitoring technologies, with a specific focus on the robust acquisition of high-fidelity occupant data and its practical integration into integrated IEQ control strategies. Beyond extending the literature coverage to year 2026, this review maps occupant variables to control actions, evaluates sensing modalities across accuracy, privacy, and deployment feasibility, and traces an information-to-control pathway across IEQ domains.

1.3. Review objectives and scope

To bridge the critical research gaps identified in the preceding sections—specifically the lack of attention to the monitoring pipeline and the fragmentation of IEQ domains—this study establishes a comprehensive technical framework for AI-driven non-intrusive occupant monitoring. The primary objective is to evaluate how high-fidelity occupant data, such as MET, CLO, and physiological responses, can be extracted and synthesized to facilitate integrated OCC.

The scope of this review encompasses 82 peer-reviewed studies published between 2015 and 2026, focusing on thermal, air, and visual environmental qualities. While essential for holistic comfort, acoustic quality is excluded at this stage due to the relative scarcity of AI-driven OCC research in that domain. This work serves as a pivotal technical reference for an interdisciplinary audience, including building scientists, AI researchers, and facility engineers, by providing performance benchmarks and addressing socio-technical barriers like privacy and cost-effectiveness. To guide this inquiry, three core research questions are established:

- RQ1 (Acquisition): How do non-intrusive AI-driven monitoring technologies acquire occupant information, and what are their distinct technical characteristics compared to traditional methods?
- RQ2 (Application): How is this extracted information integrated into domain-specific and cross-domain control strategies, and what are the quantifiable benefits in terms of comfort and energy efficiency?
- RQ3 (Future Prospects): What are the critical challenges limiting the current technologies, and what future research directions are required to overcome them?

Table 1
Review articles on OCC (2018–2025).

No. [Ref]	Title	Year	Keywords
1 [24]	A review of occupant-centric building control strategies to reduce building energy use	2018	Building automation, Building energy management, Occupancy
2 [25]	A critical review of field implementations of occupant-centric building controls	2019	Occupant-centric control, Smart building, Occupant behavior, Occupant comfort, Building energy
3 [26]	Design and application of occupant voting systems for collecting occupant feedback on indoor environmental quality of buildings – A review	2020	Occupant voting system, Occupant feedback, Indoor environmental quality, Post-occupancy evaluation, Occupant-centric control, Human in the loop
4 [27]	Is anyone home? A critical review of occupant-centric smart HVAC controls implementations in residential buildings	2021	Occupant-centric controls, Residential buildings, HVAC, Smart homes, Literature review
5 [28]	Review of vision-based occupant information sensing systems for occupant-centric control	2021	Vision-based system, Computer vision, Building control, Occupant information, Thermal comfort, Occupant-centric control
6 [29]	A review of occupant-centric control strategies for adaptive facades	2021	Vision-based system, Computer vision, Building control, Occupant information, Thermal comfort, Occupant-centric control
7 [30]	A data-driven workflow to improve energy efficient operation of commercial buildings: A review with real-world examples	2022	Data-driven, Energy flow, Energy efficiency, Fault detection, Key performance indicators, Metadata, Workflow
8 [31]	From occupants to occupants: A review of the occupant information understanding for building HVAC occupant-centric control	2022	Occupant information, Occupant-centric control, Smart building, HVAC, Energy efficiency
9 [32]	Human-building interaction for indoor environmental control: Evolution of technology and future prospects	2023	Human-building interaction, Topic modeling, BERTopic, Automatic control, Occupant centric control, Human-in-the-loop control
10 [33]	Achieving better indoor air quality with IoT systems for future buildings: Opportunities and challenges	2023	Indoor air quality, Data-driven modeling, Machine learning, Internet of things, Occupant-centric control, Digital twins
11 [34]	Challenges and opportunities of occupant-centric building controls in real-world implementation: A critical review	2024	Occupant-centric control, Comfort, Sensing, Controls, Learning, Energy efficiency, Smart buildings
12 [35]	A review of current research on occupant-centric control for improving comfort and energy efficiency	2024	Occupant-centric control, Occupant behavior, Occupancy, Data-driven models, IoT technology
13 [36]	A review on enhancing energy efficiency and adaptability through system integration for smart buildings	2024	Green building, Intelligent control, Energy-efficient building, Occupant-centric control, Smart building, Machine learning, Sustainable architecture, Renewable energy integration
14 [37]	State of the art review on the HVAC occupant-centric control in different commercial buildings	2024	Occupancy information, Occupant-centric control, HVAC, Commercial building
15 [38]	From needs to control: a review of indicators and sensing technologies for occupant-centric smart lighting systems	2025	Indicator system, Smart lighting system, Occupant-centric control, Sensor, Non-visual effect

1.4. Review structure

The organizational framework is systematically aligned with three research inquiries regarding acquisition, application, and future challenges. Following the methodological criteria outlined in Section 2, Section 3 evaluates the technological landscape of data acquisition (RQ1) by examining how advanced AI architectures transform raw sensor signals into high-level occupant information. Section 4 subsequently analyzes the operational integration of this information into domain-specific control logic to enhance performance and comfort (RQ2). Finally, Sections 5 and 6 provide an in-depth discussion on implementation barriers and emerging computational paradigms to outline future research trajectories (RQ3).

2. Method

This section establishes the systematic protocol used to identify, filter, and analyze the literature relevant to non-intrusive occupant monitoring. To ensure transparency and methodological rigor, a multi-stage refinement process was adopted, focusing on the integration of advanced data acquisition with occupant-centric environmental control strategies. The following subsections outline the search criteria and the technical framework used to categorize the selected studies, forming the foundation for the subsequent technical analysis. Fig. 1 summarizes the overall workflow of this systematic review, comprising (I) research scope definition and data collection through database search and screening, (II) an analytical framework linking occupant information acquisition to OCC implementation across thermal, air, and visual quality domains, and (III) synthesis of key challenges and future research directions.

2.1. Literature search

A systematic search protocol was implemented across Scopus, Google Scholar and IEEE Xplore for the period from January 1, 2015, to March 31, 2026. This timeframe was selected to capture the proliferation of DL and CV applications in the built environment, which saw a significant surge in adoption post-2015 [39].

As detailed in Table 2, the search query was structured around the intersection of three thematic categories: (1) occupant-centric operational frameworks, (2) non-intrusive AI and machine learning (ML) methodologies, and (3) specific indoor environmental domains including thermal, air, and visual quality. While Table 2 summarizes the core keywords fundamental to each category, the actual search strings were expanded by incorporating a comprehensive range of related technical synonyms and domain-specific terminology through the extensive use of the 'OR' Boolean operator. This multi-layered approach ensured a comprehensive retrieval of studies integrating advanced sensing technologies with environmental management logic, providing a robust empirical foundation for the subsequent technical evaluation.

2.2. Study selection criteria

The initial set of studies identified through the systematic search was rigorously screened based on titles, abstracts, and full texts to ensure alignment with the review objectives. The eligibility of each study was determined according to the following inclusion and exclusion criteria:

Inclusion criteria:

- Focus on occupant monitoring: The primary contribution must pertain to the technical frameworks for monitoring occupant information.

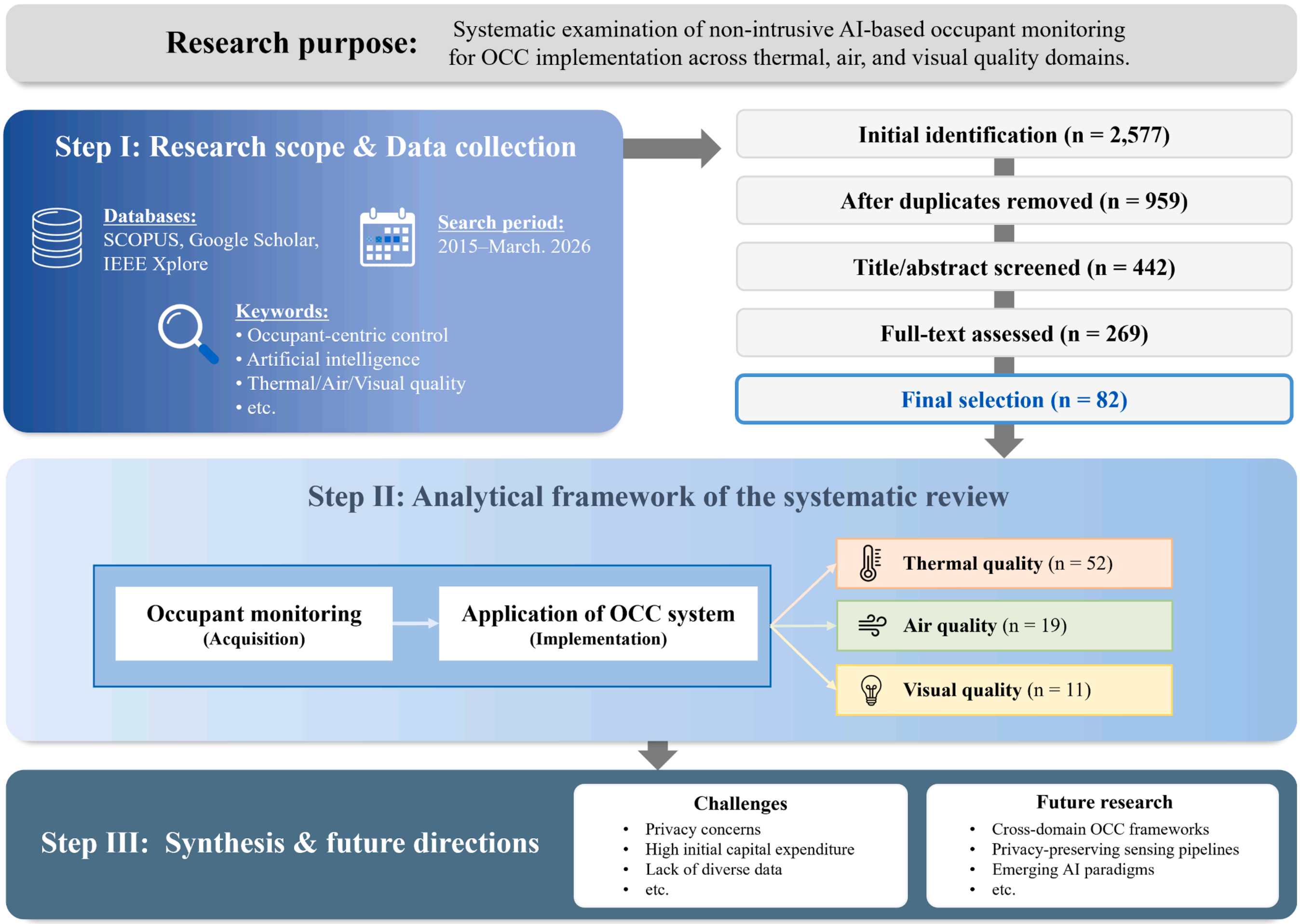

Fig. 1. Overview of the systematic review framework and scope.

Table 2
Boolean search queries for the literature search.

Domain	Search query (TITLE-ABS-KEY)
Common terms	("occupant-centric control" OR "occupant information" OR "occupant monitoring") AND ("indoor environment")
AI terms	AND ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "computer vision" OR "neural network")
Target specific	Thermal: AND ("thermal quality" OR "thermal comfort" OR "HVAC") Air: AND ("air quality" OR "ventilation" OR "CO_2") Visual: AND ("visual quality" OR "lighting" OR "visual comfort")

- AI implementation: Artificial intelligence (AI) or ML methodologies, such as DL and CV, must be utilized in the acquisition of occupant information.
- Non-intrusive methodologies: The sensing technologies must be non-intrusive and indirect, excluding wearable devices or any methods requiring physical contact.
- Application to OCC: The extracted occupant-information must be integrated into, or explicitly intended for, OCC systems to optimize thermal, air, or visual environmental quality.
- Publication type: Only peer-reviewed research articles published in English were considered.

Exclusion criteria:

- Studies that do not meet the inclusion criteria.
- Studies focusing on technologies not directly related to the indoor environment or building operations.
- Non-peer-reviewed publications, such as theses, conference abstracts, or white papers lacking comprehensive experimental validation.

Screening followed an adapted PRISMA 2020 framework, with duplicate removal and full-text exclusion criteria detailed in Fig. 1.

2.3. Data extraction and analysis

To ensure a systematic and consistent synthesis of the selected literature, key information was retrieved based on the following analytical dimensions:

- Occupant parameters: Physiological and behavioral data (e.g., MET, CLO, skin temperature, occupant count, position, activity).
- AI techniques: Specific algorithms and architectures employed (e.g., YOLO, ResNet, OpenPose, Random Forest).
- Sensing modalities: Data sources used for monitoring (e.g., RGB cameras, thermal cameras, Wi-Fi/Bluetooth signals, environmental sensors).
- Evaluation metrics: Quantitative indicators for performance validation (e.g., Accuracy, RMSE, mAP; see Appendix B.)
- OCC implementation: Target environmental variables in IEQ domains (thermal/air/visual/cross-domain) and the specific control strategies employed.

The synthesized data was evaluated through a tripartite analytical framework designed to capture the transition from sensing to intelligence. Initially, the analysis characterizes the technical fidelity of non-intrusive monitoring pipelines, benchmarking acquisition accuracy and sensing characteristics across diverse IEQ domains (Section 3). Subsequently, the operational integration of this information into domain-specific control logic is evaluated to assess its quantifiable impact on human comfort and energy performance (Section 4). Finally, the study examines socio-technical implementation barriers and explores emerging AI frontiers for holistic, human-centric OCC systems.

2.4. Overview of selected studies

Based on the systematic search protocol, 2577 papers were initially identified. Following a rigorous multi-stage screening of titles, abstracts, and full texts against the predefined inclusion and exclusion criteria, 82 papers were selected for in-depth analysis. This corpus comprises 52 studies on thermal quality, 19 on air quality, and 11 on visual quality (see Appendix A for the complete list categorized as T1–T52, A1–A19, and V1–V11). Notably, Cross-domain analysis indicates that most research remains focused on individual IEQ factors; however, three studies have begun to bridge thermal and air quality assessments. These pioneering efforts underscore a transition toward integrated OCC systems, leveraging shared occupant information to achieve synergistic control of multiple environmental variables simultaneously.

Fig. 2 illustrates the quantitative distribution of the selected studies. Fig. 2(a) illustrates the temporal distribution of these studies, highlighting a significant escalation in research output since 2022. This upward trajectory corresponds to the maturation of high-performance DL frameworks, such as YOLO and OpenPose, which have facilitated the deployment of non-intrusive monitoring in indoor environments. Fig. 2(b) depicts the geographical distribution of the research, showing that activity is most prominent in China (36%) and the Republic of Korea (25%). This concentration in East Asia accounts for 61% of the selected studies, indicating a robust research cluster in this region. Fig. 2 shows the prevalence of author keywords across the selected studies. Author-provided keywords were collected from each article and visualized as a word cloud in Python (wordcloud), where word size is proportional to each keyword's frequency in the reviewed corpus. Terms such as "occupant-centric control," "computer vision," "deep learning," and "thermal comfort" appear most frequently. This visual representation confirms the strong alignment of the selected literature with the scope of this review: the convergence of non-intrusive AI technologies and occupant-centric building operations.

It is noteworthy that the number of selected studies varies significantly across domains: 52 studies (63%) focus on thermal quality, whereas only 19 (23%) and 11 (14%) address air and visual quality, respectively. This quantitative disparity, further reflected in the keyword cloud in Fig. 3, highlights a pronounced thematic non-ubiquity in current research efforts. Such a skewed distribution suggests that high research activity in the thermal domain does not necessarily equate to a universal technical maturity across all IEQ factors. Instead, it underscores a fragmented technological landscape where AI-driven monitoring is selectively optimized.

3. AI-driven non-intrusive occupant monitoring

This section provides a structured overview of non-intrusive AI-driven technologies utilized for acquiring occupant information in OCC systems. Unlike traditional methods that rely on intrusive sensors or fixed assumptions, recent studies leverage non-contact sensors and AI methodologies—particularly CV and DL—to extract high-resolution occupant data in real time. As illustrated in Fig. 4, the workflow typically proceeds from raw data collection via non-intrusive sensors to AI-driven feature extraction, and finally to the generation of actionable occupant information. This acquired data is integrated into thermal, air, and visual quality control to simultaneously enhance comfort and energy efficiency. To provide a systematic analysis, this section examines technological trends and key findings across four specific dimensions: (1) data sources and processing methods, (2) specific AI algorithms, (3) quantitative performance metrics, and (4) practical challenges such as computational load and privacy concerns."

3.1. Thermal quality

Recent studies have actively explored non-invasive monitoring of various occupant information without requiring occupant intervention by leveraging CV and sensor technologies. Primary occupant parameters extracted in thermal quality domain include MET, CLO, facial skin temperature, and occupant count. These variables primarily serve as inputs for thermal environment assessment indices, such as the Predicted Mean Vote (PMV), thereby contributing to improved thermal comfort and optimized energy consumption. For occupant monitoring, a range of DL-based CV techniques—including YOLO, ResNet, and OpenPose—have been employed, enabling real-time estimation with accuracies exceeding 80%. Such non-invasive technologies are applicable even in multi-occupant settings and provide a technical foundation for enhancing the accuracy of personalized thermal environment control based on OCC.

Fig. 5 illustrates the overall framework of non-intrusive AI-driven occupant monitoring for thermal environmental control. Complementing this visual overview, Table 3 provides a comprehensive summary of the representative studies reviewed in this section, detailing the input data, AI methodologies, and performance metrics. Based on these technological foundations, this subsection organizes the relevant occupant information into five specific categories. Sections 3.1.1 and 3.1.2 address key personal variables directly used for PMV calculations, such as MET and CLO. Section 3.1.3 examines approaches that estimate MET

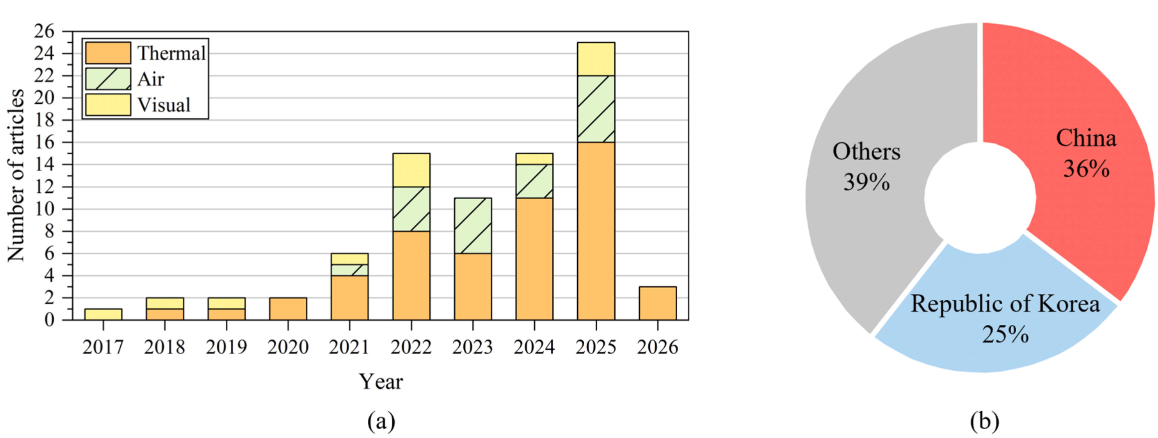

Fig. 2. Spatiotemporal distribution of the selected literature.

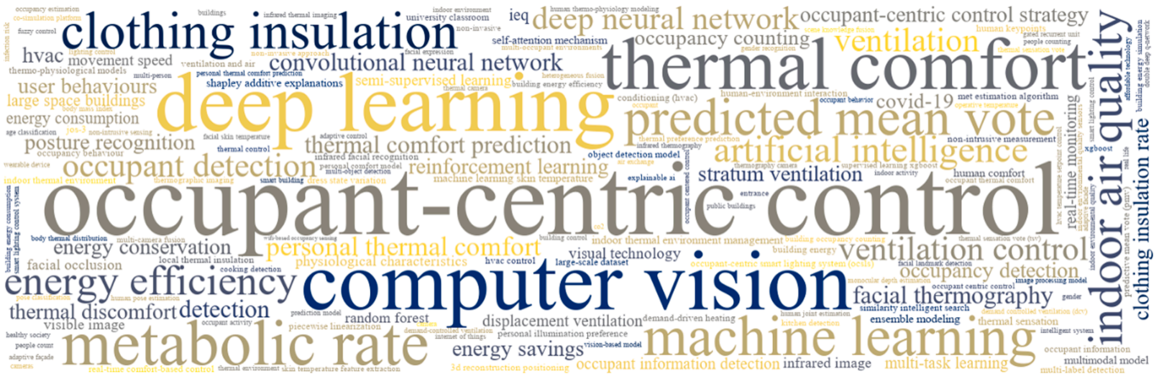

Fig. 3. Keyword cloud illustrating the primary research themes and domain-specific focus in the selected studies.

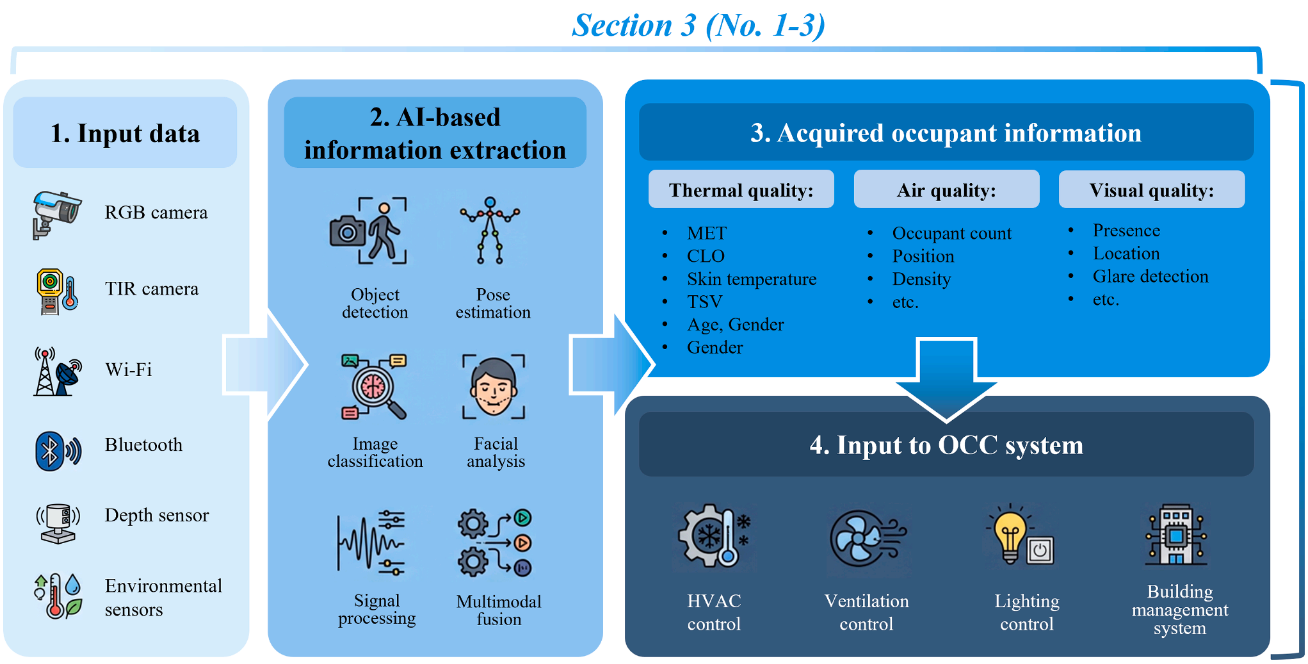

Fig. 4. General framework for non-intrusive AI-driven occupant information acquisition.

and CLO simultaneously. Section 3.1.4 reviews studies on skin surface temperature analysis based on thermal imaging. Finally, Section 3.1.5 covers additional factors, including occupant count, position, and personal attributes.

3.1.1. Metabolic rate (MET)

MET represents the energy expenditure per unit of skin surface area, where 1 MET corresponds to 58.2 W/m^2 [89]. It is a crucial personal variable for PMV calculations [90]; however, relying on fixed standard values limits the ability to capture dynamic activity changes and inter-individual variability. To address this, non-invasive estimation approaches have been developed to quantify MET using video footage without wearable sensors [40–42,44,49,50]. In terms of sensing and data sources, most studies utilize indoor RGB or RGB-D cameras to capture the occupant's full body or upper body. While early research focused on recognizing basic postures (e.g., sitting, standing) using single RGB cameras [40,49,50,54]. Subsequent studies have adopted RGB-D cameras to incorporate depth information for 3D skeleton extraction [41,42]. More recently, multi-view camera setups have been introduced to address occlusion issues in multi-occupant environments [43,91]. Regarding AI methodologies, the extraction of pose information and spatiotemporal features is the dominant approach. The workflow typically involves extracting joint coordinates using pose estimation models like OpenPose, followed by activity classification using Neural Networks (NN) or Deep Neural Networks (DNN) [40,49]. To improve stability, recent frameworks increasingly integrate YOLO-based object detection to distinguish activities with similar pose characteristics [43,91].

Performance validations have generally been conducted in laboratory settings or emulated indoor environments. Activity classification accuracy is commonly reported in the range of 80 to 95%, while real-time MET estimation via non-visual sensors typically achieves an accuracy around 80%, limited by difficulties in resolving subtle activity nuances and individual physiological variability [42,43,49]. Some studies emphasize that applying post-processing logic further stabilizes estimation outcomes for real-time deployment [43]. Despite these advancements, challenges remain. Occlusion caused by furniture or multiple occupants directly degrades pose estimation accuracy [53]. Furthermore, datasets are often limited to specific environments, hindering generalization [54,91], and the use of RGB cameras raises privacy concerns that may restrict long-term monitoring. Nevertheless, MET estimation remains a key enabling technology for personalized OCC.

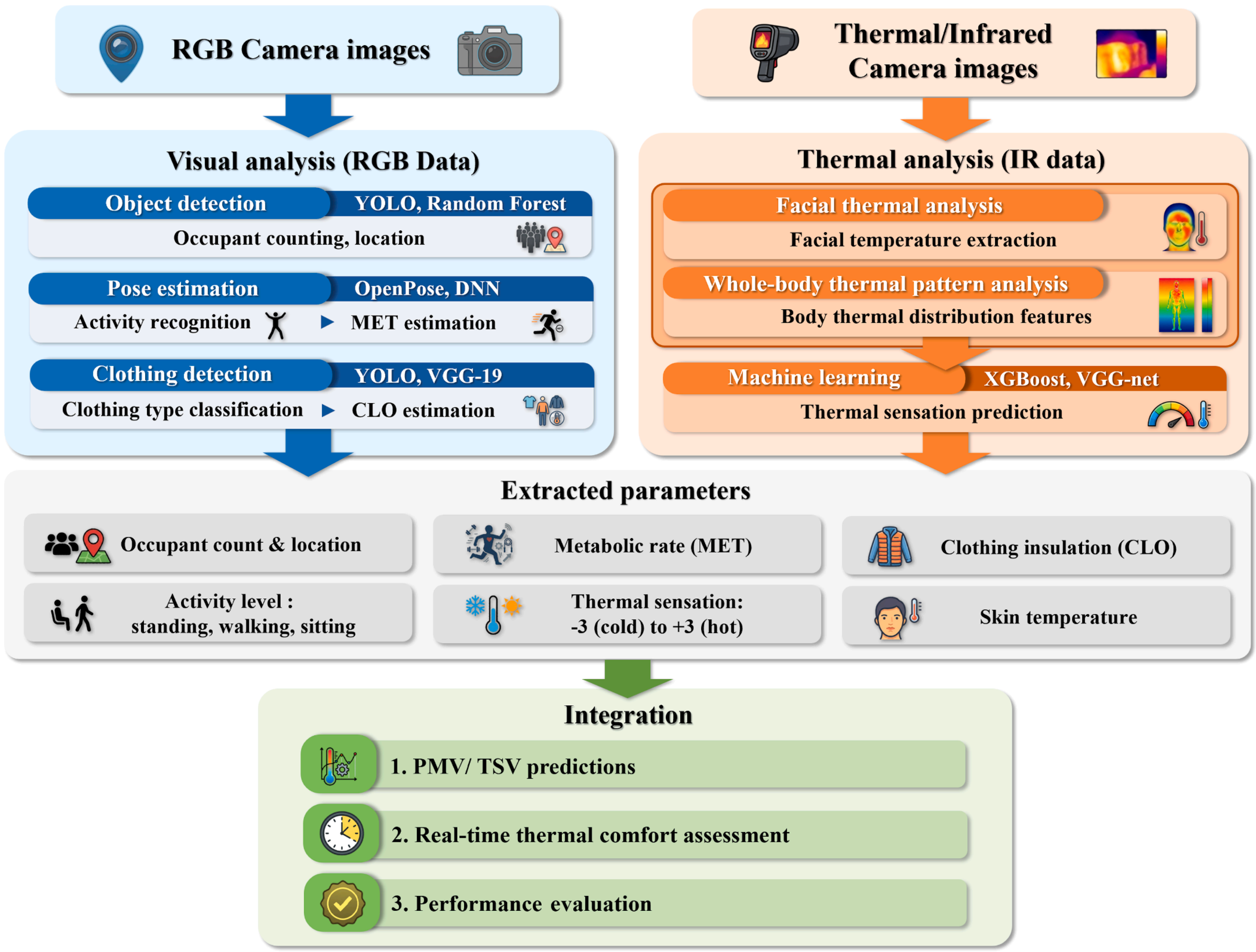

Fig. 5. General pipeline for AI-driven non-intrusive occupant monitoring for thermal environment.

3.1.2. *Clothing insulation (CLO)*

CLO quantifies the thermal resistance of clothing, where 1 clo equals 0.155 m^2·K/W [89]. Similar to MET, CLO is a critical input for PMV models. However, conventional approaches that assume static CLO values fail to account for seasonal or daily variations, resulting in significant discrepancies in thermal comfort assessments. Consequently, recent studies have focused on estimating CLO as a time-varying variable using vision-based technologies. Data acquisition primarily utilizes RGB cameras to extract visual information about occupants' clothing. While many studies analyze frame-based still images [20,45,46,48], some incorporate temporal information from continuous video sequences to track clothing changes [47]. AI methodologies for CLO estimation have evolved along two main streams: classification and combination. The classification-oriented approach uses Convolutional Neural Network (CNN) (e.g., VGG-19, GoogLeNet) to directly categorize insulation levels from images [45,47]. Conversely, the combination-oriented approach employs object detection models (e.g., YOLOv5) to identify individual clothing items and sums their insulation values to derive the total CLO [20,46].

Validation studies across laboratories and real classrooms demonstrate performance levels suitable for real-time applications. CLO estimation accuracy is typically reported at 80% or higher [45], with field-validated estimation errors averaging between 0.03 and 0.04 clo [20,46], indicating sufficient precision for thermal control models. However, limitations include the scarcity of large-scale datasets covering diverse clothing styles and viewpoints, which hinders model generalization. Additionally, privacy issues associated with RGB video and performance degradation due to variations in illumination and occlusion remain significant hurdles [20,45–47]. Nevertheless, converting CLO from a fixed value to a real-time variable enables PMV control systems to respond flexibly to seasonal and individual variations, enhancing control precision.

3.1.3. *Integrated metabolic rate and clothing insulation (MET&CLO)*

MET and CLO are interdependent variables that change simultaneously with occupant behavior. Estimating them independently can lead to cumulative errors in thermal comfort assessment as activity variations are frequently correlated with alterations in clothing configuration, necessitating simultaneous estimation [19,56,57,61–63]. Therefore, simultaneous estimation is increasingly adopted to reduce input uncertainty and better reflect individual variability. To achieve this, non-invasive sensing technologies, particularly RGB and Thermal Infrared (TIR) cameras, are widely utilized to capture occupants' activities and clothing states concurrently [20,56,58]. While RGB-based approaches extract information from image frames or video sequences [58–60], TIR-based methods analyze temperature distributions across skin and clothing regions [56,57]. The predominant AI approach involves a unified pipeline integrating object detection, pose estimation, and multi-task classification. Typically, YOLO-based models identify occupants, OpenPose extracts skeletal keypoints, and multi-label detection frameworks estimate MET and CLO simultaneously from a single frame to enhance computational efficiency and consistency [19,

Table 3
Summary of non-intrusive occupant monitoring technologies for controlling thermal quality.

Occupant information	Ref.	Input data	AI methodology	Study type	Performance
MET	[40]	RGB image	CNN (ResNet), DNN	[Lab] Mockup laboratory in Chung-Ang University	MET estimation accuracy improvement: 74.0% (home), 55.3% (office)
	[41]	RGB-D frames (color + depth)	Custom CNN (ResNet)	[Lab] Yonsei University College of Engineering, Korea	RMSE: 0.23met (self-individual evaluation), RMSE: 0.93met (third-party evaluation)
	[42]	RGB video	3D CNN (video-based activity recognition)	[Simulation + lab] Simulation, MSR Daily Activity 3D Dataset	Action Recognition Accuracy: 96.9% (MSR 3D Dataset)
	[43]	RGB image	CNN (YOLOv5, OpenPose)	[Lab] Mockup laboratory in Chung-Ang University	MET estimation accuracy: 83.0% (real time), 99.0% (15 s mode value)
	[44]	RGB image	CNN (OpenPose)	[Lab] Room 504 of Xi'an University	MET estimation MAE: 0.35met, RMSE: 0.43met
CLO	[45]	RGB image	CNN (VGG-19)	[Lab] Yonsei University College of Engineering, Korea	CLO estimation Accuracy: 86.0%
	[20]	RGB image	CNN (YOLOv5)	[Lab] Mockup laboratory in Chung-Ang University	CLO estimation error: 0.03clo
	[46]	RGB image	CNN (YOLOv5)	[Lab] Mockup laboratory in Chung-Ang University	CLO estimation error: 0.04clo
	[47]	RGB video	CNN (YOLO, GoogLeNet)	[Field] Marmont lecture room at University of Nottingham	CLO estimate accuracy: 94.2%
	[48]	RGB video	Fine-tuned MLLM (Gemini-2.0-flash)	[Field] Diverse indoor and outdoor environments	CLO classification accuracy: 94%
Activity	[49]	RGB image	DNN	[Lab] Mockup laboratory	Activity classification accuracy: 98.9% (home), 88.2% (office)
	[50]	RGB image	DNN	[Lab] Mockup laboratory	Activity-specific PCP: 0.71 −0.92
	[51]	RGB image	CNN (OpenPose)	[Field+Simulation] Harbin Institute of Technology Classroom, Grasshopper Virtual Unit Office	Posture classification accuracy (validation): 96.01%, Posture classification accuracy (actual test): 91.67%
	[52]	RGB image	CNN (Crowd-YOLO)	[Field+Simulation] Qingdao University Gymnasium, EnergyPlus & Python API (Eppy)	Posture classification accuracy: 91.2%
	[53]	RGB image	CNN (YOLOv7), Faster R-CNN	[Field] Marmont lecture room at University of Nottingham	Activity classification F1 Score: 0.77 - 0.94
	[54]	RGB image	CNN (OpenPose)	[Field] Real building	Skeletal Coordinate Displacement (Units): Stationary Baseline: x ≈ 1000, y ≈ 1000 Active Motion Shift: Rightward & Upward Directions
	[55]	RGB video	CNN (Yolov5 CrowdHuman, SlowFast), SVM, RF, XGBoost, ANN, DT	[Lab] Tsinghua University, experimental Chamber	Action Recognition Accuracy mAP: 88.9% (SlowFast)
MET, Activity & CLO	[56]	Thermal images	CNN (OpenPose, Inception v2)	[Field] office environment at Aalborg University, Denmark	Activity & clothes estimation accuracy: 76.9% (90fps), 95.2% (30fps)
	[57]	Thermal images	CNN (YOLOv5, OpenPose)	[Field] typical office environment at Denmark	Activity accuracy: 95.6%, Skin/clothes accuracy: 96.2%
	[58]	RGB image	CNN (YOLO, Simple Pose Network)	[Lab] Yonsei University College of Engineering, Korea	Activity & garment accuracy: 97.0%, MET & CLO accuracy: 100%[a]
	[19]	RGB image	CNN (YOLOv5, OpenPose), DNN	[Lab] Mockup laboratory	MET estimation MAE: 0.031, CLO estimation MAE 0.028
	[59]	RGB video	CNN (YOWO, YOLOv8)	[Field] University building	Activity & clothing accuracy (mAP): 45.0%
	[60]	RGB video	CNN (YOWO, YOLOv7)	[Field] office meeting room environment within the university	Activity detection mAP improvement: +15.8% Clothing detection mAP improvement: +25.0%
	[61]	RGB image	CNN (YOLOv8, YOLOv7-pose), TSSTG, RF	[Field] Office spaces within a university located in Xi'an, China	CLO: 85.5% accuracy (MAE: 0.014 clo), MET: 98.9% accuracy (MAE: 0.029 met)
	[62]	RGB image	CNN (Multi-task SlowFast), Gemini 3 Pro, VLM	[Synthetic] High-fidelity synthetic environment (UE5)	Gemini 3 Pro: MET MAE: 0.31, CLO MAE: 0.021
	[63]	RGB image	CNN (YOLOv8-s), ByteTrack, Sequential Mamba)	[Field] Large public waiting hall (High-density testbed)	MET estimation MAE = 0.20 met (Individual) CLO: 90.0% Top-1 accuracy for clothing material
	[64]	WiFi connection count	ML (Poisson Regression)	[Field] Concordia University Academic Building	Occupancy pattern prediction R^2_D: 0.98 (weekdays), Occupancy pattern prediction R^2_D 0.81 (weekends)
	[65]	WiFi connection count	ML (Multiple Linear Regression)	[Field] Concordia University library	Real-time Occupancy Estimation R^2: 0.96 (weekdays), 0.98(weekends) Day-ahead Occupancy pattern Prediction R^2: 0.92 (weekdays), 0.82(weekends)
	[66]	RGB video	CNN (YOLOX, DeepSORT)	[Field] Tsinghua University FIT building (Room 624) & Baoding National University Science Park	Occupancy estimation accuracy: 99.2%, 98.5%, 94.9% (video 1,2,3)

(continued on next page)

Table 3 (*continued*)

Occupant information	Ref.	Input data	AI methodology	Study type	Performance
	[67]	RGB image	CNN (YOLOv5s)	[Lab] Xi'an University of Architecture and Technology (China), Experimental Chamber	Occupant Detection Performance NRMSD: 0.1461
	[68]	WiFi connection count	ML (Random Forest, LightGBM, Stacking Regressor, Blender Regressor)	[Field] University of Dartmouth, University of Detroit Mercy, Dental School, Lawrence Berkeley National Laboratory	Stacking regressor R^2: 0.9972, 0.9540, 0.9482 (static features), 0.9967, 0.956, 0.531 (MOTIF features)
	[69]	Thermal image	CNN (YOLOv5n)	[Field+Simulation] Lawrence Technological University, EnergyPlus	Human classification accuracy: 88.0%, Counting-based precision & recall: 90.0% - 95.0%
	[70]	WiFi CSI	ML (Transfer Kernel Learning, SVM)	[Field] Nanyang Technological University, Singapore	Occupancy Detection Accuracy: 99.1%, Crowd Counting Accuracy: 92.8%
Count & Activity	[71]	WiFi CSI	ML (Density-Based Spatial Clustering of Applications with Noise)	[Field+Lab] National University of Sciences and Technology Test-bed, Real-house	Average Multipath Detection Accuracy: 98.25% Activities of Daily Living Intensity Classification Accuracy: 93% (Mild intensity), 97% (Moderate intensity), 99.0% (Vigorous intensity)
Occupancy Presence	[72]	WiFi CSI	ML (SVM)	[Field] South Korea, Gyeonggi-do, Duplex Apartment Unit	Overall Average Occupancy Accuracy (Real-world): 87.3%
Age & Gender	[73]	RGB + Thermal image	CNN (ResNet50, ResNet101, EfficientNet, Inception v3)	[Field] Subjects' homes and offices	Gender classification accuracy: 95.3% (ResNet50), Age classification exact accuracy: 37.3% (ResNet-50)
	[74]	Thermal image	ML (RF, Bagging, LightGBM, XGBoost, GBM)	[Field] University of Nebraska - Human-centered Integrated Building Operation Lab	GBM: TSV prediction accuracy, F1 Score, precision, recall: 0.89, LGBM: TSV prediction accuracy: 60.0%, F1-score: 57.0% Precision: 56.0%, Recall: 60.0%,
Gender & BMI	[75]	RGB image	CNN (YOLOv8, VGG-Net)	[Field] Wuhan University	Gender/BMI classification accuracy: >80.0%
Age & Gender & Action & Clothing & pose	[76]	RGB + Thermal image	CNN (slowfast, 3D-ResNet, ArcFace RetinaFace, OpenPifPaf, YOLOv7), DNN (MLP, LSTM)	[Lab+Simulation] experimental Chamber, JOS3 Python Open-source Model	Age & gender classification accuracy: 90.7% Action classification accuracy: 93.9% Clothing classification accuracy: 82.4% Pose estimation accuracy: 71.9%
TSV	[77]	Thermal image	Custom CNN, explainable AI (SHAP)	[Lab] experimental chamber	TSV classification accuracy: 96%, F1-score: 95%
	[78]	RGB image, Indoor temperature and relative humidity data	RNN (GRU), ML (Lasso, Gradient Boosting)	[Field] Three residential apartments in the U.S. (Bryan-College Station, Texas and Blacksburg, Virginia)	TSV classification accuracy: 74.1% (GRU), 85.7% (Lasso, GB)
	[79]	RGB + Thermal image	CNN (OpenPose), ML (Random Forest)	[Field+Lab] Outdoor carport, Environmental chamber	TSV classification accuracy: 92–99%
	[80]	Thermal Image, Environmental Data	CNN (Dlib, HRNet), ML (RF, DT, LR, NB, SVM, KNN, DNN, DCF, GBDT, GBM, XGB, BL)	[Lab] University of North Carolina at Charlotte, Test-bed	BL TSV classification accuracy: 0.9044 ±0.0306, DCF TSV classification accuracy: 0.9362 ± 0.0184 (training), BL TSV classification Macro-F1 0.8292 ± 0.0183), DCF TSV classification Macro-F1 0.8069 ± 0.0327 (validation)
	[81]	RGB + Thermal image	CNN (MobileNet-0.5), ML (LightGBM, XGBoost, RF, DT, K-NN, SVM, LR)	[Field] Chongqing University Classroom	LightGBM TSV classification accuracy: 90.04 ± 4.46%
	[82]	Thermal Image	Custom CNN	[Field] Hong Kong Polytechnic University, Office rooms	TSV classification accuracy: 99.51% (3-point TSV), 89.90% (7-point TSV)
	[83]	Thermal Image, Tabular Data	ML (RF, AdaBoost, GBDT, XGBoost, LightGBM), explainable AI (SHAP)	[Lab] Chongqing University experimental Chamber	TSV classification accuracy: 88.2% (XGBoost)
	[84]	RGB + Thermal image, Tabular Data	CNN (Inception-V3, ResNet, VGGNet, MobileNet), ML (RF, SVM, XGBoost, DT, ANN), explainable AI (SHAP)	[Field] Hong Kong Polytechnic University	TSV classification accuracy: 81.48% (ANN + Inception-V3)
	[85]	Thermal Image, Skin Temperature Data, Environmental Data	CNN (OpenPose), ML (SVM, RF, XGBoost, ANN, KNN), explainable AI (SHAP)	[Lab] Tongji University experimental Chamber	TSV classification accuracy: 95.83% (XGBoost)
	[86]	Thermal Image, Environmental Data	CNN (YOLOv11n), Random Forest, Bayesian-optimized RF, Ensemble model	[Field] Office Room	5-class TSV classification accuracy: 83.33% (RF), 95.19% (Bayesian-optimized RF), 96.07% (Ensemble model)
	[87]	Thermal Image	CNN (YOLOv8)	[Field] University of Nottingham Office	TSV prediction MAE: 0.51 (Intra-subject), 0.87 (Cross-subject)
Thermal comfort indices (TSV/TSsat/TPV/TAV)	[88]	RGB + Thermal image, Environmental Data	CNN (YOLOv8 + FaceMesh), ML (Random Forest)	[Lab] Southeast University Office Room	Thermal comfort index accuracy: 68.2–86.7% (TSV, TPV, TSsat, TAV)

Note. A 100% accuracy was achieved by using frequency-based voting and time-weighted averaging to filter image-level classification errors. This result was obtained in a controlled single-environment setting, and its generalizability to broader real-world conditions remains to be validated.

57,58].

Performance evaluations indicate stable estimation capabilities, with simultaneous classification accuracies ranging from 80 to 100% and CLO errors maintained around 0.01–0.04clo [20,56,58,61,62]. Notably, some studies have validated these integrated estimates in real building environments, demonstrating that they can effectively adjust setpoint temperatures to improve thermal comfort [19,57,58,63]. However, simultaneous estimation increases combinatorial complexity and requires sophisticated dataset structures, which can elevate the burden of data annotation and training [59,60]. Furthermore, generalization remains limited as training data are often concentrated in specific seasons or environments with a small number of subjects [20,56,58,61–63]. Future research should focus on ensuring robust detection in crowded environments while preserving privacy. Furthermore, it is essential to extend applicability across diverse building types and advance dynamic MET estimation by incorporating individual characteristics.

3.1.4. Skin temperature

Skin surface temperature is a physiological indicator that directly reflects an occupant's thermal response, capturing variations in externally exposed body regions such as the forehead, cheeks, and hands [79,80,82]. Unlike conventional PMV models that rely on simplified assumptions, skin temperature serves as a direct proxy for subjective Thermal Sensation Vote (TSV), enabling more precise personal comfort assessment. TIR cameras are the primary sensing modality for non-intrusive measurement. To enhance measurement accuracy, recent studies have advanced from simple thermal distribution analysis to sophisticated keypoint-based approaches. For instance, facial landmarks or pose skeletons extracted from RGB cameras are mapped onto TIR images to precisely locate Regions of Interest (ROIs) even under occupant movement [51]. The extracted temperature features are typically processed using tree-based ML models (e.g., Random Forest, XGBoost) to predict TSV [74,81,83,87,88]. More recently, multimodal learning frameworks utilizing hybrid CNN architectures have been proposed to combine thermal images with tabular data (e.g., environmental variables, heart rate), improving robustness against environmental changes [74,83–85]. Furthermore, Explainable AI (XAI) techniques like SHAP are being applied to identify key skin regions contributing to thermal comfort, enhancing model interpretability [77,83,84].

Prediction performance is generally high in controlled laboratory environments such as climate chambers, with facial ROI-based features achieving TSV classification accuracies of approximately 85–95% [74,83], and up to 99% when cheek, nose, and hand temperatures are simultaneously used as model features [79]. However, prediction accuracy significantly drops to around 70% under conditions of facial occlusion, such as wearing masks or glasses, which limits the number of usable ROIs [88]. This issue can be mitigated by incorporating environmental variables, improving model robustness [80]. However, other persistent challenges include the high cost of TIR sensors, privacy concerns regarding facial imagery, and the complexity of ROI extraction in dynamic real-world settings [79,82,83,88]. Future research is needed to develop lightweight feature extraction techniques and expand field validations across diverse environmental conditions to ensure practical applicability.

3.1.5. Other indices

Beyond physiological variables, occupant-related information such as count, position, behavior, and personal attributes (e.g., age, gender, BMI) serves as key indicators for determining operational strategies in occupancy-based and personalized control [51,55,66]. Sensing methodologies utilize both vision-based and non-vision-based approaches. Vision-based methods primarily employ RGB cameras, often combined with depth or thermal sensors, to track stability. The dominant AI framework involves detection-tracking pipelines centered on YOLO-family models, utilizing algorithms like DeepSORT for position tracking [66]. For analyzing fine-grained behaviors and postures, skeleton keypoints extracted via OpenPose are processed using CNNs or time-series models (e.g., LSTM, GRU) [51,76,78]. Conversely, non-vision approaches leverage Wi-Fi signals, including connection logs, client counts, and Wi-Fi CSI, to extract temporal patterns used in regression-based models for predicting key occupancy indicators, such as occupant counts and presence [64,65,68,70–72].

In terms of performance, vision-based behavior classification has achieved approximately 91% accuracy [51,52,66,67], while occupant counting demonstrates low errors with an NRMSD of $\leq$ 0.15 [51,52,66,67]. Gender recognition also shows high reliability (95.3%), whereas age estimation remains a challenge, exhibiting higher error rates and lower precision [73]. Wi-Fi-based models have reported high accuracy for short-term occupancy forecasting, with R^2 values ranging from 0.96 to 0.99 [64,65,68], while CSI-based device-free methods have further achieved up to 93% accuracy in classifying mild-intensity activities of daily living [71], 92.8% crowd counting accuracy [70], and 87.3% room-level occupancy accuracy in multi-zone residential settings [72]. However, vision-based methods suffer from performance degradation under varying lighting and occlusion conditions [51,67]. Full-body detection methods such as YOLO and OpenPose can be vulnerable to inter- and intra-class occlusions in indoor spaces, whereas head detection is often more robust in dense or cluttered scenes [92,93]. Additionally, personal attribute estimation raises privacy and reliability concerns [73]. Similarly, Wi-Fi-based estimation faces uncertainty due to the imperfect correspondence between device counts and actual occupancy [64,65,68], while CSI-based approaches additionally suffer from performance degradation under multipath interference, wall attenuation, temporal channel variation, and cross-room signal interference in multi-zone settings [70–72]. Despite these limitations, integrating these diverse occupant factors remains critical for advancing robust and multi-faceted OCC frameworks. In summary, while vision-based estimation of physiological variables has achieved high accuracy in controlled environments, ensuring robustness against real-world challenges such as occlusion, dynamic lighting, and privacy preservation remains a critical prerequisite for widespread adoption.

3.2. Indoor air quality

Indoor Air Quality (IAQ) is a critical factor directly impacting occupants' health, comfort, and productivity. Conventional ventilation control strategies have notable limitations, as they primarily rely on single indicators such as CO_2 concentration or assume fixed occupancy levels based on predefined schedules. To address these limitations, recent advances in AI technologies have enabled substantial advancement in the real-time detection of occupant information—including occupant presence count, position, density, and activity—optimizing Demand-Controlled Ventilation (DCV) to mitigate over-ventilation and maintain a comfortable indoor environment [94–97]. This section reviews non-intrusive monitoring technologies for occupancy estimation implemented in IAQ controls, focusing on sensing methods, AI models, and performance characteristics. Fig. 6 illustrates the classification framework of occupant information for IAQ control, and Table 4 summarizes the applied technologies and key findings.

Regarding sensing and data processing, occupant count estimation has predominantly relied on video and image data captured by ceiling-mounted RGB cameras [67,95,98,99,105]. To overcome the limitations of single-view camera systems, such as occlusion in crowded areas, several studies have proposed combining multiple RGB cameras installed at different locations or utilizing edge-computing systems for on-site inference [52,100,101]. In terms of AI methodologies,

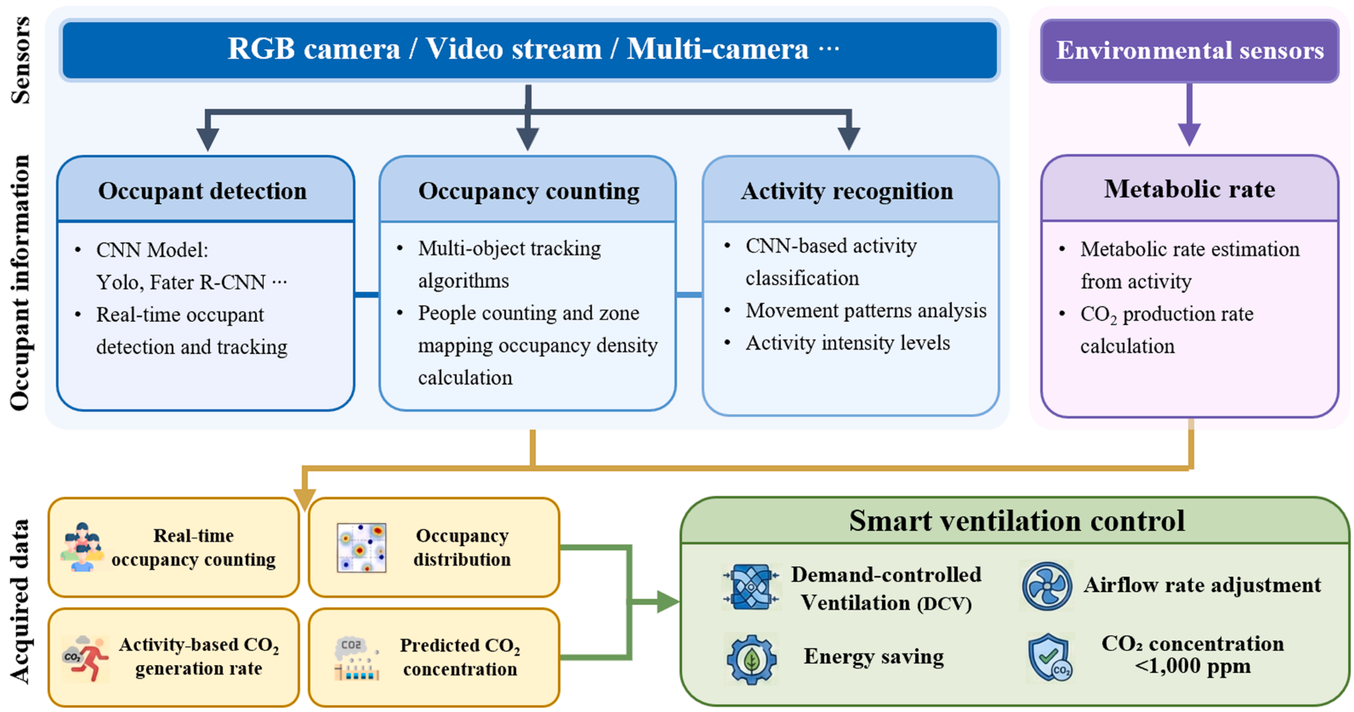

Fig. 6. General pipeline for AI-driven non-intrusive occupant monitoring for IAQ.

Table 4
Summary of non-intrusive occupant monitoring technologies for controlling IAQ.

Occupant information	Ref.	Input data	AI methodology	Study type	Occupancy estimation performance
Presence Count	[97]	CO_2 concentration time-series	DL(LSTM), RL(DDQN)	[Field] Australia University Classroom	Averaged accuracy: 72.1%
	[94]	RGB video	CNN (YOLOv4)	[Field] Yonsei University Office	Accuracy: 96.0%
	[98]	RGB video	CNN (Faster R-CNN, Inception V2)	[Simulation] IES VE(BES)	Accuracy: 98.9%
	[99]	RGB video, image	CNN (YOLOv4)	[Field] University Office	RMSE: 0.883 prs. NRMSE: 0.141
	[100]	Occupant count time-series	CNN (YOLOv8)	[Lab] Experimental space	Not mentioned
	[67]	Occupant count time-series	CNN (YOLOv5)	[Lab] Sino-Nordic Research Center Climate chamber	NRMSD: 0.0526
	[101]	RGB video, image	CNN (PPYOLOE)	[Simulation] BES	Accuracy: 98.1–99.3%
	[102]	Occupant count time-series	CNN (Faster R-CNN, Inception V2)	[Field] University of Nottingham office	F1-score: 0.8285–0.9487
	[52]	RGB image	CNN (YOLOv5)	[Simulation] EnergyPlus	Not mentioned
	[103]	Occupant count time-series, Subzone head density map	DL(RAPiD)	[Field] Riga Technical University Classroom	Accuracy: 87.0%
	[104]	Occupant count time-series, CO_2 concentration time-series	SL(ELM)	[Field] Lithuania office	Count prediction R^2(High density): 0.73–0.74 Count prediction R^2(Low density): 0.07–0.56
	[105]	RGB camera	CNN(CSPDarknet53, SPP, PANet)	[Lab+ Simulation] Nanchang University Reading room, EnergyPlus	Accuracy: 99.3%
Position & Density	[95]	bounding boxes	CNN (YOLOv4)	[Field] University Lobby	Accuracy: 92.5%
	[106]	RGB video, image, Subzone head density map	CNN (AS-DA-Net)	[Simulation] FLUENT (CFD)	Accuracy: 89.0%
	[107]	Temperature, humidity time-series	ML (XGBoost)	Control feasibility study	Averaged classification accuracy: 90.0%, Average F1-score: 80.0%
Activity & MET	[96]	RGB video,	ANN_D, ANN_M	[Lab] University Climate chamber	MET prediction accuracy: 91.1%
	[108]	CO_2, $PM_{2.5}$ concentration time-series	RL (DDQN)	[Lab] Dankook University Climate chamber	Not mentioned
	[109]	Window opening state logs	CNN (Faster R-CNN, Inception V2)	[Simulation] IES VE (BES)	Not mentioned
	[110]	RGB image, video	CNN(OpenPose)	[Lab+ Simulation] University Mock-up, living lab(EnergyPlus)	Not mentioned

CNN-based object detection models are the standard [105,110]. The YOLO family has been widely adopted as a representative method for estimating occupant count, position, and density through object detection [67,94,95,100,102,109]. Additionally, alternative frameworks combining Faster R-CNN with Inception V2 have been applied for robust detection [98,102,109]. In crowded environments, approaches leveraging density estimation models specifically designed for head detection, such as PP-YOLOE, AS-DA-Net and RAPiD have been reported to generate density maps for accurate density estimation [101,103,106]. Conversely, non-visual approaches estimate zone-level occupants count, positions and activity level by fusing CO_2, temperature, and humidity sensors data with ML models such as ELM, XGBoost or DDQN [104,107,108]. Beyond basic counting, recent studies further integrate indoor CO_2 sensor data to indirectly estimate emission rates associated with activity levels or incorporate additional sources such as $PM_{2.5}$ concentrations [108,109].

Validation studies have been conducted primarily through field experiments in real buildings, such as university classrooms, offices, and lobbies, with a limited number relying on simulations or climate chambers [67,94,95,100,102,109,110]. Overall, evaluations based on real-building applications constitute the majority, and the reported accuracy of occupant estimation generally ranges from 72.1 to 99.3% [97,98,101,106]. These findings confirm that occupant information serves as a key input for achieving both IAQ-based DCV and subzone-level control. However, recurring challenges include occlusion and crowding in congested areas, performance degradation due to variations in camera placement and lighting conditions, and limited generalizability resulting from short-term experiments in single buildings [96,103]. Vision-based occupancy measurement is sensitive to camera location, mounting configuration, and sensor type, potentially inducing cumulative errors and estimation instability that undermine OCC reliability in real-world applications [111]. Future research should therefore focus on ensuring robust detection in crowded environments while preserving privacy, extending applicability across diverse building types, and advancing dynamic MET estimation by incorporating individual characteristics. Overall, AI-driven IAQ monitoring has successfully transitioned from simple presence detection to sophisticated density and activity-based estimation; however, fusing these visual data with physical CO_2 sensors is essential for ensuring high-precision control in complex environments.

3.3. Visual quality

In visual quality control, incorporating occupant information—collected using advanced sensing technologies such as cameras and specialized detectors—has become a key strategy for achieving both visual comfort and energy efficiency [112,113]. Traditional lighting control systems primarily relied on PIR sensors, which often resulted in occupant discomfort due to limited detection resolution and frequent false triggering [114,115]. To address these issues, recent advancements in ML,DL and CV enable the precise recognition of occupant positions, behaviors, and visual discomfort through non-intrusive methods [116]. This section reviews these technologies, focusing on their sensing modalities, AI models, and performance. Fig. 7 illustrates the generalized

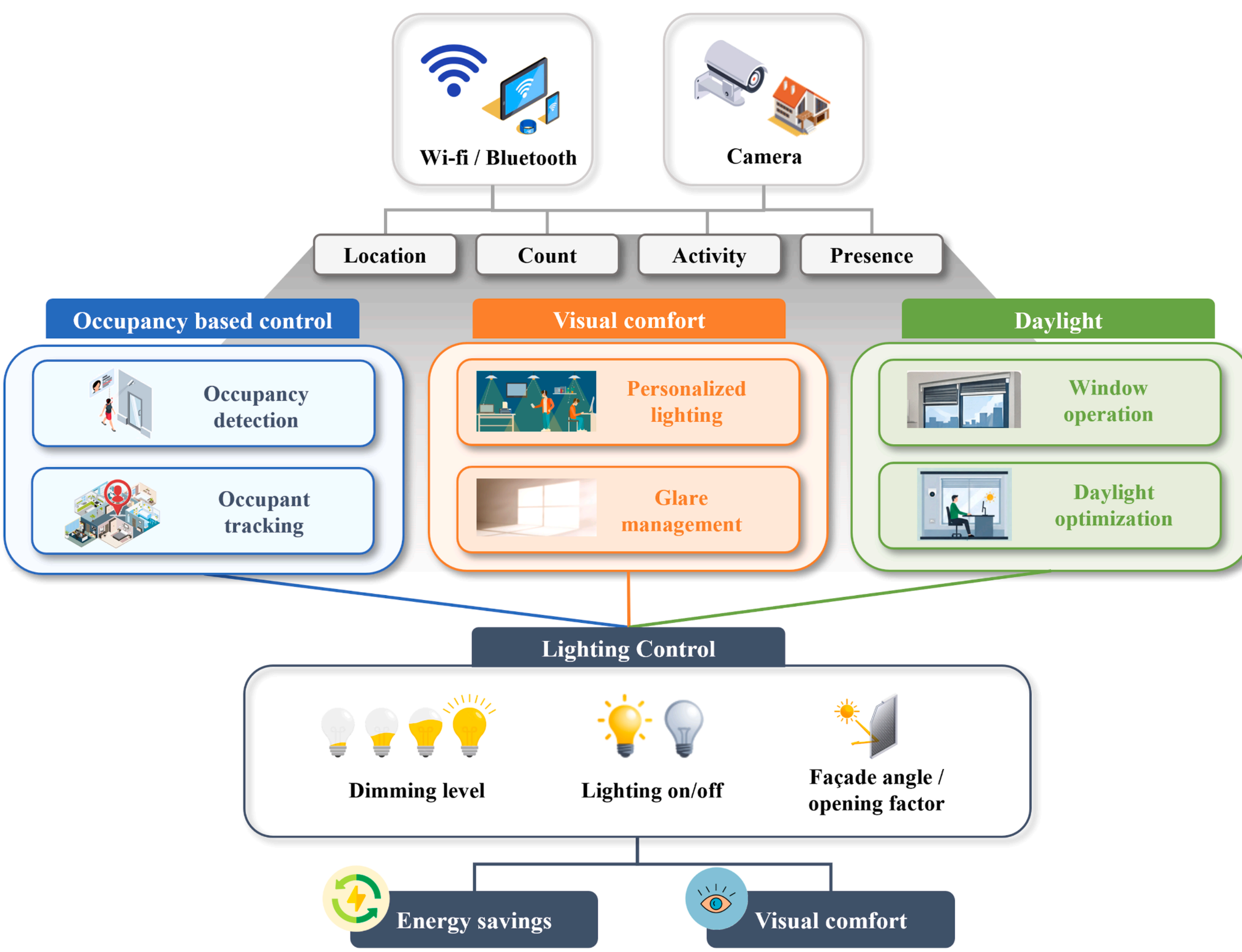

Fig. 7. General framework for non-intrusive occupant information acquisition for visual control.

Table 5
Summary of non-intrusive occupant monitoring technologies for controlling visual quality.

Occupant information	Ref.	Input data	AI methodology	Evaluation environment	Performance
Presence	[116]	PIR Sensor	ML (Recursive (Online) arkov Logistic regression)	Southwest-facing shared office laboratory, Canada	Prediction results were consistent with observed occupant behavior
Presence, Location	[117]	Wi-Fi RSSI time-series	ML (Online Sequential Extreme Learning Machine)	Multi-functional office and laboratory space, CREATE Tower 11th floor, Singapore	Presence Accuracy: 98.9%
Presence	[118]	Bluetooth signal	RL (Markov Decision Process)	Ernest Cockrell Jr. Hall (ECJ) 4th–5th floor, five enclosed private offices A–E, University of Texas at Austin, TX, USA	Presence Accuracy: 85–95% without interference
Presence, Count	[119]	person bounding boxes	CNN (YOLOv5x)	Two offices, 25 m^2 and 100 m^2, Korea	Office A Count NRMSE: 0.0777 Office B Count NRMSE: 0.0918
Presence, Location	[120]	person bounding boxes	CNN (YOLOv4)	Classroom & office, Shandong Normal University, China,	Occupancy detection Accuracy (dynamic state): 94.6% Occupancy detection Accuracy (static state): 98.1%
Activity	[51]	2D key points of the human body	CNN (OpenPose)	Unit office room, 6 × 5 × 4 m, Harbin, China	Pose Recognition Accuracy (in Field): 91.7%.
Location	[121]	person bounding boxes	CNN (YOLOv5)	Graduate student office, 36 m^2, Hunan University, China	Average positioning error: less than 0.30 m
Presence	[122]	Wi-Fi RSSI time-series	CNN	Open-plan office, 9.6 × 8 × 3.2 m, China	Presence Accuracy (in Test set): 90.2% Presence Accuracy (in Field): 69.7%
Location, Occupant Field of View	[123]	HDRI sensor	Computer Vision (COLMAP-OpenMVS)	South-facing office, 3.2 × 4.0 × 3.2 m, West Lafayette, USA,	Position I (1.5 m from the window) DGP: RMSE 0.029, R^2 0.83, Ev: R^2 0.90 Position II (2.5 m from the window) DGP: RMSE 0.013, R^2 0.92, Ev: R^2 0.97
Presence	[124]	human body detection.	CNN (Improved YOLOv5s)	University library, Zhengzhou University of Light Industry, China	Presence Accuracy: 91.4%
Occupant Field of View	[125]	HDRI sensor	**CNN**	South-facing office, 8 × 10 × 3.2 m, West Lafayette, USA,	Preference prediction accuracy: 83–94% (for locations far from the window, 70–75%)

workflow for these systems, while Table 5 summarizes related studies and their outcomes. Given the limited inclusion of eight studies, these findings should be regarded as preliminary.

Regarding sensing and data processing, methodologies can be broadly categorized into wireless signal-based and camera-based approaches. Presence and location data obtained from Wi-Fi and Bluetooth signals have been widely applied to adjust lighting levels, reducing unnecessary operation [117,118]. More recently, camera-based methods have been increasingly explored to capture occupants' locations and activities with greater precision.

These methods predominantly employ bounding-box-based object detection models, such as YOLOv4 and YOLOv5x, to detect occupants [119,120]. Furthermore, to interpret fine-grained movements and behaviors, upper-body keypoints or full skeleton data are extracted using pose estimation models like HRNet and OpenPose [51,121]. In terms of AI algorithms for wireless signals, hybrid models combining CNN with gradient boosting classifiers are utilized to classify occupant states into categories such as enter, stay, and leave [122]. Additionally, the luminance map obtained from a non-intrusively installed HDRI sensor is back-projected onto a 3D interior model constructed through computer vision, and then re-projected into the Field of View (FOV) to predict the luminance distribution actually perceived by the occupant [123].

Performance validations have been conducted in both field studies and simulation environments, with a growing trend toward field-based experiments. Empirical studies utilizing these technologies have reported lighting energy savings ranging from approximately 30 to 90% compared to conventional fixed-schedule control, with some cases showing reductions of up to 97% [118]. However, the reported savings vary substantially depending on building type, control strategy, and experimental conditions. Additionally, several studies have reported model reliability under specific experimental conditions, achieving pose recognition accuracy corresponding to an NRMSE below 0.05 [51]. However, inherent limitations persist. Wi-Fi and Bluetooth-based approaches suffer from signal interference and multipath effects, compromising the consistency of recognition [117,118]. In camera-based approaches, depth estimation errors tend to increase significantly at distances greater than 4 m (up to 1.8 m error), restricting their ability to provide accurate spatial information directly [120]. Across both approaches, issues related to generalization and privacy remain major challenges. Nevertheless, leveraging occupant information—such as presence, location, count, and activity—remains essential for simultaneously achieving energy efficiency and visual comfort. Future research requires the development of advanced models that consider environmental factors, including daylight availability and glare. To conclude, non-intrusive monitoring for visual control is evolving from simple motion detection to behavior analysis. Yet, the complexity of processing high-resolution visual data in real-time continues to pose a trade-off between recognition accuracy and computational speed, necessitating more efficient model architectures.

4. Application of OCC system using non-intrusive AI-driven occupant information

This section analyzes how the non-intrusive AI-driven occupant information acquired in Section 3 is practically integrated into OCC strategies for indoor environmental control. The focus shifts from data acquisition to the implementation of control logic and its effectiveness across three primary domains: thermal, air, and visual quality. Fig. 8 illustrates the classification of these control methods and the distribution of the reviewed studies based on their implementation approach, categorized into simulation-based and experimental validations. As shown in the figure, research activity is currently most prominent in thermal quality and ventilation systems, while studies on lighting and visual control are demonstrating a gradual increase. The following subsections detail the control structures, validation methods, and key findings—such as energy savings and comfort improvements—for each IEQ domain.

4.1. Thermal quality control

Thermal quality control aims to enhance indoor thermal comfort by estimating occupant characteristics in real time without requiring direct

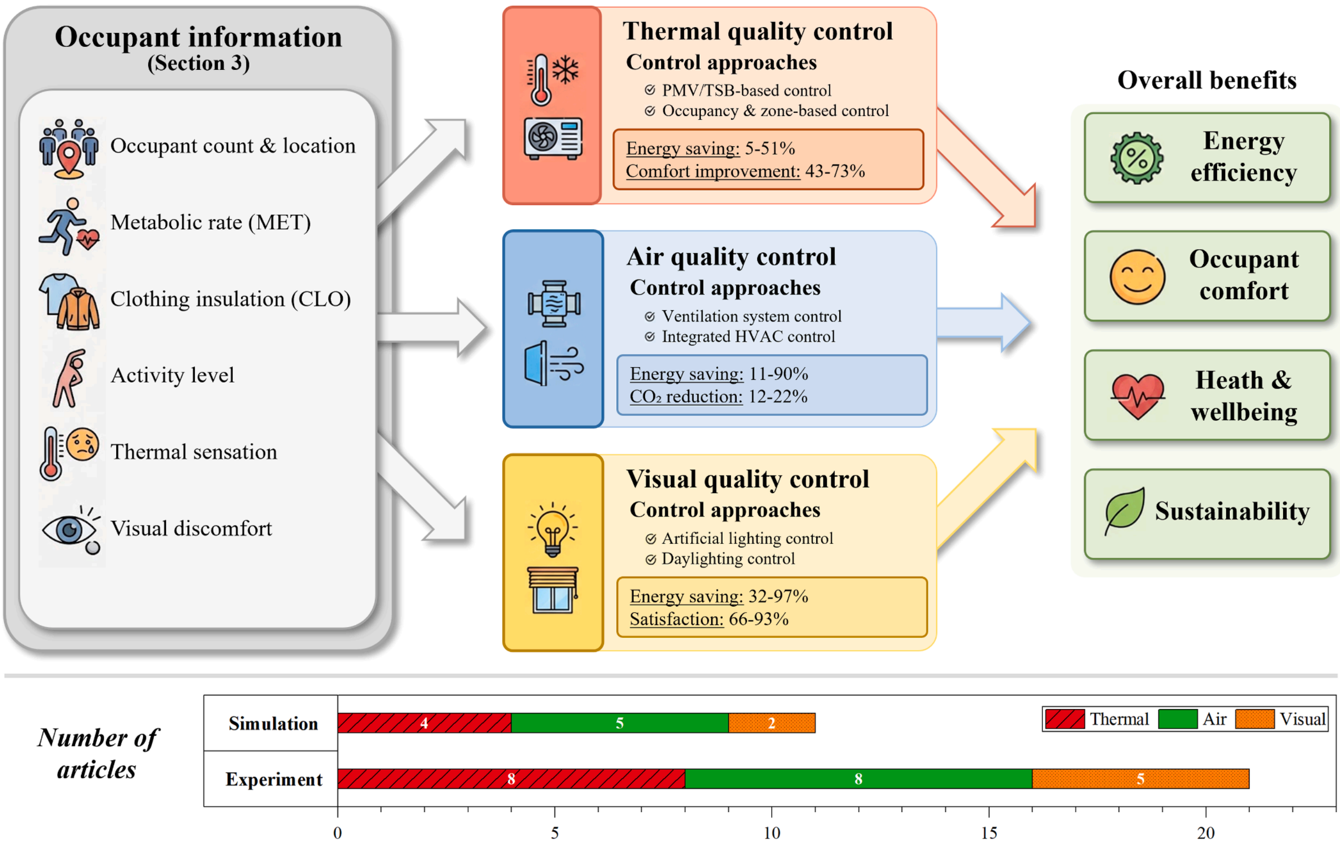

Fig. 8. Implementation approaches and domain-specific distribution of reviewed OCC studies (2018–2025).

intervention. As discussed in Section 3, variables such as MET, CLO, and facial skin temperature are derived using CV and ML techniques. These technologies enable the integration of estimated data into control systems, thereby improving the accuracy of thermal comfort predictions and facilitating occupant-tailored management compared to conventional sensor-based approaches. This subsection reviews OCC studies that apply such information to actual thermal environment control, focusing on their control structures and performance. MET, CLO, and occupant count are immediately actionable for PMV-based control and DCV, whereas TSV and skin temperature require further field validation before real-time integration. Table 6 summarizes the technologies employed in each study alongside the corresponding key performance indicators. The analysis categorizes the studies into two main approaches: (1) PMV/TSV-based control and (2) occupancy- and zone-based control.

4.1.1. PMV/TSV-based control

PMV/TSV-based control adjusts HVAC setpoints or façade opening levels according to occupants' thermal discomfort states or predicted PMV values [20,45,51,58,63,86]. The control logic typically employs rule-based or optimization algorithms based on these predictions, or integrates them into Reinforcement Learning (RL) frameworks as reward functions to update operating conditions [19,46,47,75,91]. Notably, adaptive control strategies that explicitly incorporate real-time personal attributes (MET, CLO) have advanced significantly. These strategies maintain PMV values much closer to thermal neutrality than conventional fixed setpoint control, substantially improving thermal comfort [19,45,47,63,87,91].

From an energy efficiency perspective, most studies have reported significant savings ranging from approximately 5 to 50% [20,46,47]. Nevertheless, these gains are often contingent upon specific operating conditions, as energy performance is highly sensitive to fluctuations in occupant-related variables. Specifically, in scenarios with large variations in MET and CLO, savings can fluctuate or even result in increased consumption [20]. To address these complexities, various advanced methodologies have been implemented. For instance, TRNSYS–MATLAB co-simulations dynamically update setpoints based on real-time PMV feedback [47], while closed-loop control schemes utilize fuzzy inference mechanisms [42]. Furthermore, more recent approaches have leveraged RL-based control utilizing CV inputs has demonstrated improvements of 13.5% in thermal satisfaction and up to 23.9% in thermal neutrality achievement, along with approximately 5% energy reduction in real classroom environments [75].

4.1.2. Occupancy and zoning-based control

Occupancy- and zoning-based control primarily utilizes object detection models to estimate occupant count, position, and behavior in real time, subsequently adjusting indoor temperature setpoints, supply zone partitioning, or HVAC operations [52,67,69]. This strategy aims to mitigate unnecessary cooling and heating loads caused by fluctuations in occupant presence and is configured differently depending on the spatial scale. In studies focusing on relatively small-scale spaces, adjusting indoor temperature setpoints and air supply conditions based on occupant count has resulted in improvements of 43–73% in thermal comfort and 18–48% in thermal acceptability, along with an approximate 8.1% reduction in cooling energy consumption [67]. Conversely, studies conducted in large-space buildings incorporate occupant position information to implement zone-based supply control. Using this approach, indoor temperatures in occupied zones were maintained at approximately 24 °C, while cooling energy consumption was reduced by 51% compared to conventional global control strategies [52].

4.2. Indoor air quality (IAQ) control

The primary objective of occupant-centric IAQ control is to maintain indoor pollutant levels—such as CO_2 and $PM_{2.5}$—within acceptable

Table 6
Summary of selected studies on occupant information-based thermal quality control.

Control target	Ref.	Control logic	Validation type	Environment / Tool	Key Results
HVAC	[42]	PMV-based control	Simulation	Fuzzy Control Logic	PMV RMSE: 0.19 reduction (vs. fixed MET), Temp. RMSE: 1.36 reduction (vs. fixed MET)
	[47]	PMV-based control	Simulation	TRNSYS–MATLAB	PMV: −0.67 to +0.38, Heating energy: 10.7% reduction
	[52]	Occupant information based displacement ventilation	Simulation	EnergyPlus	Energy use: 50.96% reduction
	[69]	Occupant Count, Operative Temperature, Adaptive Setpoint based control	Simulation	EnergyPlus	Energy use: 33.7% reduction
	[45]	PMV-based control	Experiment	Residential testbed (apartment)	Thermal preference (under 0.8 clo): 19% increase, Thermal comfort vote (under 0.8 clo): 0.8point decrease, improved comfort
	[20]	PMV-based control	Experiment	Chamber	Discomfort ratio: 14% reduction, Energy use: 12.6% reduction (vs. fixed setpoint)
	[46]	PMV-based control	Experiment	Chamber	Comfort rate: 28.4% increase (vs. baseline)
	[91]	PMV-based control	Experiment	Chamber	Comfort rate: 28% increase (vs. posed-based model), Energy use: up to 88% reduction (cleaning activity)
	[58]	PMV-based control	Experiment	Chamber	Thermal discomfort (feeling warm): decreased by 19%, Thermal satisfaction: increased by 17%
	[19]	PMV-based control	Experiment	Chamber	Comfort ratio: 13.3% increase (vs. conventional control), Energy use: up to 54% reduction
	[67]	PID principle-based control	Experiment	Chamber	Thermal sensation improvement: 0.57–1.09 Comfort improvement: 43–73% Acceptability improvement: 18–48% Energy use: 8.1% reduction
	[87]	DLPC (Deep Learning-based)	Experiment	Real Office (Meeting room)	Thermal comfort prediction accuracy: 45% increase (vs. PMV model)
	[75]	TSV based control	Experiment	Classroom	Thermal neutrality: 23.9% increase Comfort satisfaction: 13.5% increase Energy use: 5.2% reduction
	[63]	PMV-based control	Experiment	Large-scale Physical Testbed	Comfort ratio within ASHRAE band: 90–92%
	[86]	TSV based control	Experiment	Office room	Thermal stabilization time: 47.4% reduction Energy use: 54.7% reduction
HVAC & Façade	[51]	Façade opening factor, set temperature	Simulation	Grasshopper + EnergyPlus	Not mentioned

ranges to ensure occupants' health and comfort, while simultaneously minimizing energy losses caused by excessive ventilation [52]. To achieve this, control strategies utilize real-time occupant information (e.g., count, spatial distribution, and metabolic activity) to dynamically regulate ventilation rates. This section categorizes existing studies into two categories based on the control target: (1) ventilation system control, which directly regulates mechanical ventilation equipment, and (2) integrated HVAC system control, which adjusts the operating conditions of the overall air-conditioning system. Table 7 summarizes the key characteristics and performance of each approach.

4.2.1. *Ventilation system control*

Studies on ventilation system control predominantly adopt DCV schemes, where ventilation rates are dynamically adjusted based on occupant data rather than fixed schedules [110]. Representative research has demonstrated that using occupant position as an input variable enables CO_2 concentrations to be maintained below 1000 ppm, while achieving an 11.7% reduction in ventilation and heating energy consumption alongside a 12.2% decrease in CO_2 concentrations [95,106]. Similarly, occupant count-based control has reported substantial energy performance improvements, including up to a 90.96% reduction in heat loss compared to natural ventilation, a 7.5% decrease in ventilation energy use compared to the VAV system, and a 35% decrease in ventilation energy consumption compared to schedule-based control [98,99].

Beyond energy savings, recent studies indicate that incorporating occupant activity level information contributes to occupant health outcomes. For instance, activity-based control strategies have reported infection probabilities that were 4.3–6.3% lower than those achieved with conventional occupant-based control [96]. Positive effects have also been observed in particulate matter management, where activity-based control maintained $PM_{2.5}$ concentrations below 25 μg/m^3, and occupant count-based control achieved reductions of approximately 60.5–71.9% in indoor $PM_{2.5}$ concentrations [102,108].

4.2.2. *Integrated HVAC system control*

Integrated HVAC system control aims to simultaneously optimize IAQ and energy performance by adjusting not only ventilation system but also broader system parameters, including supply airflow rates, outdoor air ratio, and operating schedules. Existing studies have demonstrated that such strategies achieve significant improvements in both real-world and simulated environments.

In field experiments conducted in bedrooms and offices, control strategies utilizing occupant count reduced peak indoor CO_2 concentrations by 22% and outdoor air supply by 54%, resulting in energy savings of 17.2–25.2% compared to schedule-based control [52,101]. Additionally, occupant presence-based strategies decreased HVAC operating time by 10.9–30.4% and reduced CO_2 exceedance below 800 ppm by 12.2–17.4% [97]. These findings suggest that occupant-based HVAC control is applicable across diverse space types. Meanwhile, simulation-based studies applying activity-based control increased the proportion of time indoor CO_2 concentrations remained below 1000 ppm from 59.7 to 89.2% [109]. Additionally, position-based control maintained CO_2 concentrations below 700 ppm while achieving energy savings of 2.3–8.1% [67].

Despite these advancements, limitations persist. Most research relies on short-term experiments in single buildings, leading to insufficient validation across seasonal variations [97,100,101,105,107].

Table 7
Summary of selected studies on occupant information-based IAQ control.

Control target	Ref.	Control logic	Validation type	Control Variable	Key Results
Ventilation	[95]	Density-based	Experiment	Ventilation flowrate	Infection probability: reduction from 12.5% → 2% Ventilation energy: 11.7% reduction (vs. fixed ventilation)
	[98]	Count-based	Simulation	Ventilation flowrate	Heat loss: up to 90.96% reduction (vs. natural ventilation), 54.56% (vs. fixed ventilation) Indoor CO_2 concentration: < 1000 ppm
	[99]	Count-based	Experiment	Ventilation flowrate	Ventilation rate: 35% reduction (vs. schedule control) ERV energy use: 40% reduction Heat pump energy use: 27% reduction
	[96]	Metabolism-based	Experiment	Ventilation flowrate	Infection probability: 4.3% reduction (vs. occupant-based control), 4.3–6.3% reduction (vs. MET-based control) Ventilation energy use: 13% reduction (vs. fixed ventilation)
	[94]	Count-based	Experiment	Ventilation system on/off, Ventilation flowrate	CO_2 concentration: ≤ 1000 ppm (in all cases)
	[106]	Density-based	Simulation	Damper Opening degree	CO_2 concentration: 12.2% reduction (vs. DCV) Energy use: 8.8% reduction
	[108]	Activity-based	Experiment	Ventilation system on/off, Air purifier on/off	CO_2 compliance (≤ 1000 ppm) vs. RBC: +0.5%(Case 1), −1.2%(Case 2) $PM_{2.5}$ concentration: < 25μg/m^3 (vs. RBC) Energy use: 14.0–15.3% reduction (vs. RBC)
	[100]	CO_2-based	Experiment	CO_2 setpoint, Ventilation flowrate	CO_2 prediction accuracy: average deviation < 40 ppm
	[102]	Count-based	Experiment	Ventilation flowrate	$PM_{2.5}$ concentration: 60.5% reduction (kitchen), 71.9% reduction (office)
	[103]	CO_2-based	Experiment	Window operations	CO_2 concentration: ≤ 1000 ppm (test period)
	[104]	count-based	Experiment	Ventilation flowrate	CO_2 concentration(vs. VAV): ≤ 1000 ppm Energy reduction(vs. VAV): 7.5%
	[110]	CO_2-based	Experiment	supply airflowrate	CO_2 concentration(Low MET): ≤ 1000 ppm CO_2 concentration(High MET): ≤ 1005 ppm Energy use: 24.74% reduction(vs. RBC)
HVAC (IAQ aspect)	[109]	Presence-based	Simulation	Window operations	CO_2 compliance (≤ 1000 ppm): 59.7% →89.2%
	[67]	Count-based	Experiment	Fresh Air Volume	CO_2 concentration: ≤ 700 ppm (test period) Energy use (vs. CAV): 2.3–8.1% reduction Ventilation rate: 22% reduction (4 occupants), 43% reduction (2 occupants)
	[101]	Count-based	Simulation	FCU fan working level	Energy use: 17.2–25.2% reduction (vs. schedule control)
	[52]	Density-based	Simulation	Fresh Air Volume	Peak CO_2 concentration: 22% reduction (vs. CAV: 1090 ppm)
	[97]	Presence-based	Experiment	Ventilation system on/off	CO_2 exceedance reduction (> 800 ppm): 12.2–17.4% (vs. setpoint control) HVAC system operating time reduction: 10.9–30.4%
	[105]	Count-based	Simulation	Damper Location	Energy use: 52.1% reduction(vs. RBC)

Furthermore, control logic has predominantly focused on CO_2, with limited integration of multivariate control that includes thermal comfort factors and dynamic building characteristics such as inter-zone air mixing and infiltration [98,99].

4.3. Visual quality control

Visual quality control aims to minimize lighting energy consumption while ensuring occupants' visual comfort. Integrating occupant information—such as presence, location, and visual focus—into lighting and façade systems is recognized as an effective strategy for achieving these dual goals. This section reviews application cases of OCC systems utilizing occupant information for artificial lighting and daylight control. Table 8 summarizes the key research findings and achievements.

Control strategies can be categorized into artificial lighting control and façade operation. For artificial lighting, studies have focused on

Table 8
Summary of selected studies on occupant information-based visual quality control.

Control target	Ref.	Control logic	Validation type	Environment / Tool	Key Results
Dimming level	[117]	Dimming level	Experiment	Office	Lighting energy consumption reduction: 93.1% (vs. static scheduling)
	[121]	Dimming level	Experiment	Office	Lighting energy consumption reduction: 32.8% (vs. baseline)
Lighting on/off	[116]	Lighting on/off	Experiment	Ofiice	Lighting operation time reduction: 30% (309 → 202 h/year, adaptive lighting control)
	[118]	Lighting on/off	Experiment	Office	Lighting energy consumption reduction: 97.1% (vs. the schedule-based baseline)
	[119]	Lighting on/off	Simulation	Co-simulation (MATLAB, EnergyPlus)	Lighting energy consumption reduction: 7.9% (vs. baseline)
	[120]	Lighting on/off	Experiment	Classroom	Lighting energy consumption reduction: 48.6% (vs. static scheduling)
	[122]	Lighting on/off	Experiment	Office	Lighting energy consumption reduction: 78.6% (vs. baseline)
Blind / façade angle, Façade opening factor	[51]	Blind / façade angle, Façade opening factor	Simulation	Grasshopper	Control performance: an error ≤ 0.010 within <60 s
	[123]	Motorized Roller Shades	Experiment	Office	Area Under the Curve (AUC) for Daylight Glare Probability (DGP): 0.81 Illuminance (Ev): 0.89

automating on/off switching or dimming based on occupant presence and position. Early research utilized Wi-Fi signals to transmit position data to a central server for personalized control [117], while more recent methods employ CNN models to classify movement states for rule-based switching [122]. Camera-based approaches leveraging YOLOv5 enable real-time occupant counting for automatic on/off control [119], and advanced methods combine depth estimation with K-means clustering to activate only the luminaires closest to occupant groups [120]. Another notable approach involves optimization frameworks using Illumination Demand Matrices (IDM) and Autoencoders to identify optimal illumination characteristics [121]. Expanding beyond lighting, recent research controls façade opening factors by detecting visual discomfort (e.g., glare) through pose analysis. Using CNNs to classify states like 'dazzled', these systems automatically reduce opening factors to block sunlight while maintaining thermal setpoints [51]. The DGP (Daylight glare probability) is calculated using the re-projected luminance map. If the DGP exceeds 0.35, it is considered glare, prompting the adjustment of motorized roller shades to control the amount of incoming light [123].

Performance evaluations demonstrate substantial benefits in both energy efficiency and comfort. The implementation of an adaptive lighting control algorithm reduced annual lighting operation time by approximately 30% [116]. Research utilizing Wi-Fi signals reported a 93.1% reduction in lighting energy consumption compared to conventional scheduling [117]. Personalized control systems learning occupant interactions achieved up to 97% energy savings while keeping the Uncomfortable Time Ratio (UNC) below 0.04 [118]. Optimization-based frameworks achieved up to 32% energy savings with approximately 86.7% occupant satisfaction [121]. Regarding façade control, the vision-based system classified discomfort status with 91.7% accuracy, successfully integrating occupant feedback into the building's response logic [51].

Despite these advancements, existing studies face limitations due to complex model architectures required to process high-resolution information. This computational burden hinders real-time control speed, reducing the immediate responsiveness required for dynamic visual environments. Future research should focus on enhancing computational efficiency through model lightweighting to improve processing speeds while maintaining high accuracy.

5. Discussion

Building upon the systematic evaluation of non-intrusive AI-driven technologies presented in the preceding sections, this section synthesizes the findings to examine their multi-dimensional contributions to OCC. This section provides a critical appraisal of prevailing technological achievements (Section 5.1) while emphasizing the imperative transition from fragmented, domain-specific paradigms toward holistic, integrated OCC frameworks (Section 5.2). Furthermore, it identifies persistent socio-technical barriers to real-world deployment (Section 5.3), outlines unexplored research gaps (Section 5.4), and explores how emerging AI paradigms—such as Generative AI and Large Language Models (LLMs)—can redefine the future of human-building interaction (HBI) (Section 5.5).

5.1. Overall research trends and key achievements

Over the past few years, non-intrusive AI-driven occupant monitoring has evolved rapidly, driven by synergistic advancement of computing power and AI techniques [126]. A significant paradigm shift is observed from estimating isolated variables toward multi-task learning frameworks that extract high-dimensional occupant attributes simultaneously and in real-time.

Technological progress:

- Dominant AI techniques: While foundational models like YOLO, OpenPose, and ResNet have been instrumental in early MET, CLO, and posture estimation, current research increasingly prioritizes computational efficiency. There is a distinct trend toward adopting lightweight architectures, such as YOLOv8 and MobileNet, or hybrid models that facilitate real-time inference on edge devices.
- Multimodal sensor fusion: The synergistic integration of heterogeneous data sources has significantly reinforced the operational robustness of occupant monitoring. This multi-layered sensing approach effectively mitigates the technical vulnerabilities of individual sensors, ensuring high-fidelity information acquisition. Furthermore, non-visual sensing frameworks, particularly those utilizing Wi-Fi and Bluetooth signal analysis, have established themselves as viable, privacy-centric paradigms. These methodologies provide a robust alternative for occupancy detection, balancing the need for real-time data with the increasing demand for occupant privacy in smart building environments.

Key achievements:

- Enhanced personalized comfort: By integrating real-time physiological datasets—including MET, CLO, and skin temperature—alongside demographic characteristics such as age and gender, these technologies have significantly refined the precision of PMV and TSV prediction. This serves as a robust technical foundation for indoor environments tailored to individual thermal profiles rather than relying on static assumptions.
- Maximized energy efficiency: High-resolution occupancy data, encompassing presence, location, and activity intensity, enables building systems to curtail energy consumption by mitigating redundant HVAC and lighting operations. In particular, spatial zoning strategies informed by actual space utilization patterns facilitate the simultaneous enhancement of energy performance and environmental quality.
- Scalability to real-world multi-occupant Scenarios: Improvements in DL computational efficiency and the adoption of lightweight algorithms have facilitated the practical deployment of AI-driven monitoring into real-time operational loops. This ensures stable performance and rapid inference even within spatially complex, multi-occupant indoor environments.

5.2. Necessity and challenges of integrated OCC

Despite significant advancements in individual monitoring domains, this review identifies a critical research gap: a predominant focus on isolated IEQ domains. Out of the 82 studies analyzed, only 3 addressed integrated control strategies—representing only 4.1% of the entire studies. The vast majority of current research remains constrained by domain-specific, fragmented paradigms that treat thermal, air, and visual qualities as decoupled variables. Current research is largely constrained by fragmented paradigms that decouple thermal, air, and visual qualities, failing to address the interconnected nature of IEQ in smart building operations.

To bridge this gap, a paradigm shift toward integrated OCC frameworks is imperative, as IEQ factors in operational settings exhibit a dynamic interplay of stressors. For instance, daylighting strategies not only impact visual comfort but also introduce significant thermal loads, while ventilation rates concurrently modulate air quality and indoor temperature [127,128]. Such interconnected stimuli synergistically modulate the holistic occupant experience (OX), necessitating a transition from fragmented sensing to multi-objective architectures.

Benefits of integration:

- Synergistic optimization: Integrating thermal, air, and visual quality control in a synergistic manner can yield benefits that are difficult to achieve through isolated control. For instance, elevated MET (Section

3.1) correlate with increased thermal loads and higher CO_2 emission rates (Section 3.2). An integrated control strategy could simultaneously modulate ventilation rates and cooling setpoints based on a single activity input, eliminating the latency inherent in decoupled feedback loops. Furthermore, by understanding these interdependencies, systems can make holistic decisions, such as balancing the desire for natural light with the need to maintain thermal comfort, leading to truly occupant-centric environments.

Challenges of integration:

- Complex multi-objective optimization: Satisfying multiple control objectives (e.g., optimal temperature, CO_2 concentration, illuminance) across various IEQ domains simultaneously, while maximizing energy efficiency poses a complex multi-objective optimization problem. Advanced control strategies, including RL or Model Predictive Control (MPC), will be essential to address these complexities.
- Modeling cross-domain interactions: It is necessary to quantitatively model the influence of occupant information (MET, CLO, visual discomfort, etc.) across diverse IEQ domain on other domains. This involves not only understanding physical interactions but also how different IEQ factors collectively affect an occupant's overall perceived comfort. Key barriers include the absence of unified occupant-state representations, conflicting objectives, and data silos. A staged pathway may begin with occupancy-driven DCV, progress to thermal personalization, then extend to lighting control.

5.3. Practical implications and challenges for real-world implementation

For non-intrusive AI-driven OCC systems to be widely transitioned from laboratory settings nto real world building environments, several socio-technical barriers must be addressed:

- Cost and economic viability: The deployment of high-performance cameras and edge computing infrastructure necessitates significant initial capital expenditure (CAPEX). This presents a significant barrier to widespread adoption, particularly in retrofit scenarios where the total cost of ownership (TCO), encompassing hardware, commissioning, maintenance, recalibration, and IT/security overhead, must be justified against ROI. To ensure economic viability, the development of cost-effective sensing modalities and lightweight AI models capable of operating on low-cost hardware remains essential.
- Privacy and user acceptability: The continuous collection of high-resolution visual data raises critical privacy concerns. To mitigate these risks, technical solutions such as edge computing-based anonymization are essential. In this approach, raw visual data is immediately processed at the sensor level to extract only abstract semantic information—such as skeletal keypoints or heatmaps—-while the original identifiable frames are permanently discarded without being stored or transmitted. Furthermore, federated learning provides a decentralized training paradigm where AI models are optimized locally on edge devices. Only encrypted model gradients, rather than sensitive raw data, are aggregated to a central server, ensuring a "data-stay-local" architecture. Beyond data security, addressing the psychological discomfort of “perceived surveillance” is equally important. Therefore, transparent communication regarding data usage protocols, clear consent mechanisms, and the utilization of privacy-preserving sensing modalities (e.g. thermal, Wi-Fi-based sensors) are vital for long-term user acceptance. Low-resolution depth and thermal infrared cameras offer privacy advantages over RGB cameras, though at the cost of reduced detection accuracy, highlighting a key privacy-accuracy trade-off.
- Robustness against occlusion and distance: Visual sensors often suffer from performance degradation due to physical obstructions (e.g., furniture, partitions, occupants themselves), facial coverings (e.g., masks affecting thermal readings), and depth estimation errors at longer sensing distances (exceeding 4 m). To ensure operational robustness, research must evolve toward multi-camera fusion to provide overlapping views and integrate non-visual sensors (e.g., LiDAR, Wi-Fi) to compensate for blind spots and distance-dependent reliability drops.
- Computational efficiency: Real-time processing of high-resolution video streams and complex DL models necessitates substantial computational resources. advancements in edge computing to reduce latency, alongside rigorous model optimization techniques—specifically quantization, which reduces numerical precision to minimize memory footprint, and pruning, which eliminates redundant parameters to streamline the network architecture—to enable efficient real-time inference on resource-constrained devices [129].
- Modeling subjectivity and dynamic human perception: human perception of comfort and preference is influenced by complex, often unpredictable factors, including emotional state, cultural background, and individual histories of environmental stresses. Current models, relying primarily on physical and environmental indicators, often fail to capture this inherent subjectivity. Transitioning toward Human-in-the-loop systems—where subjective input reinforces the learning process—is essential for capturing the dynamic nature of personal comfort. This integration ensures that the control logic remains responsive to each individual's unique, time-varying preferences.
- Data scarcity and generalizability: Constructing large-scale, high-fidelity datasets that reflect diverse building environments and occupant demographics remains a major challenge, hindering model generalizability. The absence of a unified benchmarking framework further limits the validation of AI models across different settings. Hence, establishing standardized, open-source datasets is imperative to foster a collaborative research ecosystem and provide a common ground for high-precision OCC development. Beyond that, applying domain adaptation — adjusting models trained in a source domain to function effectively in a different target domain — and transfer learning — leveraging pre-existing knowledge from related tasks to accelerate learning on new tasks — is vital for maintaining model robustness across diverse operational settings. These techniques, supplemented by Generative AI-driven data augmentation, enable the rapid deployment of high-fidelity models with minimal local retraining.
- Infrastructural lag: A significant disconnect exists between the rapid evolution of AI and the prolonged replacement cycles of building infrastructure. Bridging this gap requires the development of standardized communication protocols and modular software architectures to facilitate the seamless integration of cutting-edge AI technologies into legacy building management systems.

5.4. Unexplored frontiers and emerging research gaps

While this review provides a comprehensive survey of current non-intrusive AI-driven OCC technologies, several critical domains remain under-researched, presenting opportunities for future exploration.

- Integration of acoustic quality: Acoustic quality, while significant for occupant productivity and stress regulation, was excluded from the primary scope of this study due to the current scarcity of AI-driven OCC research in this field. Research on OCC that identifies occupant vocal activity and noise levels through acoustic sensors and AI-driven acoustic analysis, then actively controls the acoustic environment or integrates with acoustic masking systems, is still in its early stages.
- Psychological and cognitive dimensions: Beyond conventional physical IEQ factors, an occupant’s psychological well-being is governed by pivotal determinants such as spatial aesthetics, layout

design, and the perceived degree of personal control. Current OCC frameworks largely lack the computational capacity to ingest and interpret these non-physical variables. Quantifying cognitive comfort and integrating these multi-dimensional metrics into building control logic is imperative for transitioning from passive environmental conditioning to the realization of truly human-centric, responsive environments.
- Longitudinal performance validation: A predominant methodological gap identified in existing literature is the limited duration of experimental validations. Most field studies analyzed were conducted over short intervals—ranging from hours to days—often in controlled laboratory settings. Consequently, there is a persistent scarcity of longitudinal field studies assessing system stability over seasonal variations and long-term occupant adaptation. Future efforts should prioritize longitudinal field validations across diverse seasons to evaluate system durability and occupant adaptation over years of operation.
- Scalability to carbon-neutral building systems: Research must expand beyond individual building-level energy savings toward larger-scale energy infrastructures. Transitioning from localized control to grid-integrated architectures will enable OCC systems to contribute to broader carbon neutrality goals by optimizing renewable energy synergy and regional grid stability. Multi-objective RL-based control: Future research should explore reward function design balancing conflicting IEQ objectives while incorporating control smoothness penalties to protect device longevity

5.5. Emerging AI paradigms for next-generation OCC

The rapid advancement of AI technologies offers transformative pathways to enhance the operational fidelity of OCCs. Generative AI, LLMs, and Explainable AI (XAI) represent the next frontier in building intelligence, providing innovative solutions for high-fidelity data synthesis, intuitive conversational interaction, and interpretable algorithmic transparency, respectively.

Generative AI (GAI):

- Data augmentation and pre-simulation: To mitigate the chronic deficiency of diverse real-world datasets in building research, Generative Adversarial Networks (GANs) and diffusion models can synthesize high-fidelity data reflecting diverse scenarios (e.g., varying lighting, clothing, activities). This approach, alongside weak supervision and self-supervised learning, enhances model generalizability while reducing reliance on large labeled datasets. For example, synthetic thermal images were generated in recent studies via generative AI for pose estimation [130]. Furthermore, GAI facilitates the creation of high-dimensional Digital Twins, allowing for the pre-validation of complex control strategies in virtual environments prior to physical deployment. This enables robust pre-optimization of integrated control logic under diverse, unseen scenarios.

LLMs:

- Semantic HBI: LLMs enable a paradigm shift from rigid dashboards to natural language interfaces. Occupants can communicate comfort preferences or specific discomforts through intuitive dialogue, which the system then translates into precise control commands [131]. Also, by leveraging their semantic reasoning capabilities, LLMs can analyze unstructured data—such as occupant schedules, weather forecasts, and building manuals—to make context-aware decisions that rule-based systems cannot achieve LLMs have also shown promise for occupancy measurement via few-shot learning [132] and occupant-centric HVAC control evaluation through agent-based modeling [133]. Building on this, Vision-Language Models (VLMs) extend these capabilities by jointly processing visual and textual modalities; for instance, Gemini-based VLMs have been benchmarked for zero-shot concurrent MET and CLO estimation from RGB images [62], demonstrating promise for end-to-end occupant-centric pipelines with minimal domain-specific training.

Explainable AI (XAI):

- Transparency and trustworthiness XAI enhances system trustworthiness by providing the underlying rationale for automated building responses [134]. For example, an XAI module can explicitly inform an occupant that "the artificial lighting dimming level was lowered because the system detected a high probability of glare," effectively justifying autonomous actions and improving user acceptance.
- Model diagnostics and iterative refinement: XAI facilitates the rigorous diagnosis of predictive errors by visualizing the contribution of input variables to specific control decision. Central to this diagnostic process is the application of SHAP (SHapley Additive exPlanations) — a game-theoretic framework that assigns each input feature a collaborative contribution value toward the final model output. As demonstrated in several studies reviewed in this paper [83–85] SHAP enables researchers to quantify the sensitivity of comfort models to localized physiological indicators. For instance, by determining the dominant influence of specific regions, such as cheek or hand temperatures, on the Thermal Sensation Vote (TSV), researchers can strategically refine sensor placement and eliminate redundant model features. This level of interpretability ensures the development of high-fidelity OCC models that are both computationally efficient and biologically accurate.

6. Conclusion

This study provides a systematic survey of AI-driven non-intrusive occupant monitoring for OCCs by establishing a methodical review framework that integrates factors across three distinct IEQ domains – thermal, air, and visual – with technical factors encompassing both acquisition of occupant information and control implementation.

The analysis confirms that AI methodologies—specifically DL and CV—have successfully replaced intrusive wearable sensors with high-fidelity remote sensing pipelines. By leveraging architectures such as YOLO, ResNet, and OpenPose, contemporary systems can now extract high-resolution semantic data, including MET, CLO, and facial skin temperature, in real-time. This technological evolution signifies that the "monitoring pipeline" has matured from simple binary presence detection to the complex quantification of physiological and behavioral states, establishing a robust technical foundation for OCCs.

The integration of non-intrusive AI monitoring into building control loops has yielded substantial, quantifiable benefits across the three primary IEQ domains:

- **Thermal quality:** Vision-based estimation of physiological parameters has achieved accuracies ranging from 80 to 100%, facilitating a 43 to 73% improvement in thermal comfort metrics and energy savings of up to 50% through personalized PMV-based control.
- **Indoor Air quality:** Advanced occupancy counting and density mapping algorithms have enabled DCV strategies to reduce energy consumption by 11 to 90% while consistently maintaining CO_2 concentrations below 1000 ppm.
- **Visual quality:** The deployment of camera and signal-based tracking for lighting and shading control has demonstrated energy reduction

potential between 32 and 47%, while simultaneously mitigating visual discomfort such as glare.

These findings validate that AI-driven OCC serves as a dual-purpose mechanism, harmonizing the historically conflicting objectives of energy efficiency and occupant well-being.

Despite these advancements, the transition from laboratory validation to widespread real-world deployment faces significant socio-technical barriers. The analysis identifies privacy concerns regarding high-resolution visual surveillance as a primary impediment to user acceptance. While technical solutions such as edge computing and federated learning offer pathways for data anonymization, the psychological aspect of "perceived surveillance" remains unresolved. Economically, the high initial capital expenditure (CAPEX) for sensing infrastructure and the computational latency associated with processing high-dimensional data hinder scalability, particularly in retrofit scenarios. Furthermore, a persistent scarcity of diverse, labeled training datasets limits the generalizability of current AI models, necessitating domain adaptation techniques to ensure robustness across varied building typologies.

Future research should prioritize the transition from domain-specific monitoring to holistic, cross-domain OCC frameworks that simultaneously manage thermal, air, visual, and acoustic environments while accounting for complex cross-domain interdependencies. To ensure real-world scalability, it is imperative to advance privacy-preserving sensing pipelines—such as edge-based anonymization and federated learning—alongside lightweight AI architectures that maintain high-fidelity performance on resource-constrained hardware. Furthermore, the proactive integration of emerging AI paradigms, including Generative AI for data augmentation, LLMs for intuitive HBI, and XAI for algorithmic transparency, will be pivotal in enhancing model generalizability and user trust. Finally, longitudinal field validations across diverse building typologies are essential to confirm the socio-economic viability and long-term stability of these systems within the broader context of carbon-neutral energy infrastructures.

In conclusion, AI-driven non-intrusive OCC is not merely a sensor upgrade represents a transformative leap in the built environment, evolving buildings from passive shelters into cognitive organisms that perceive, interpret, and adapt to the occupants. By harmonizing energy efficiency with human health and comfort, this technology will serve as the cornerstone of future smart cities. Ultimately, by synthesizing the technological landscape across diverse IEQ domains, this study establishes a practical foundation for advancing high-precision, occupant-centric building operations.

Declaration of generative AI use

During the preparation of this work, the author(s) used **Moonlight** to facilitate the literature review workflow by generating draft summaries/explanations to speed up reading and cross-checking of relevant studies. All data extraction, verification of reported valu, synthesis, and final manuscript writing were performed by the author(s). After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Ji Young Yun: Writing – original draft, Validation, Formal analysis, Conceptualization. **Jin Woo Moon:** Writing – original draft, Supervision, Project administration. **Kang Woo Bae:** Writing – original draft, Validation, Formal analysis. **Jun Kyu Kim:** Writing – original draft, Resources, Investigation. **Hae Won Lee:** Writing – original draft, Resources, Investigation. **Hye In Kim:** Writing – original draft, Resources, Investigation, Conceptualization. **Jae Ho Sung:** Writing – original draft, Resources, Investigation. **Michael Kim:** Writing – review & editing, Supervision, Project administration, Methodology.

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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Appendix A. List of Reviewed Articles

No.	Title	Year
T1 [70]	Device-free occupancy detection and crowd counting in smart buildings with WiFi-enabled IoT	2018
T2 [40]	Development of occupant pose classification model using deep neural network for personalized thermal conditioning	2019
T3 [49]	Accuracy analysis of DNN-based pose-categorization model and activity-decision algorithm	2020
T4 [41]	Metabolic Rate Estimation Method Using Image Deep Learning	2020
T5 [45]	Vision-based estimation of clothing insulation for building control	2021
T6 [50]	Development of a Deep Neural Network Model for Estimating Joint Location of Occupant Indoor Activities for Providing Thermal Comfort	2021
T7 [42]	Vision-based dynamic thermal comfort control using fuzzy logic and deep learning	2021
T8 [64]	A framework to identify key occupancy indicators for optimizing building operation using WiFi connection count data	2021
T9 [65]	Using WiFi connection counts and camera-based occupancy counts to estimate and predict building occupancy	2022
T10 [56]	Automatic estimation of clothing insulation rate and metabolic rate for dynamic thermal comfort assessment	2022
T11 [66]	A fusion framework for vision-based indoor occupancy estimation	2022
T12 [73]	Non-intrusive comfort sensing: Detecting age and gender from infrared images for personal thermal comfort	2022
T13 [20]	Effects of thermal comfort-driven control based on real-time clothing insulation estimated using an image-processing model	2022
T14 [51]	An occupant-centric adaptive façade based on real-time and contactless glare and thermal discomfort estimation using deep learning algorithm	2022
T15 [57]	Clothing insulation rate and metabolic rate estimation for individual thermal comfort assessment in real life	2022
T16 [58]	Deep-vision-based metabolic rate and clothing insulation estimation for occupant-centric control	2022
T17 [76]	Toward contactless human thermal monitoring: a framework for machine learning-based human thermo-physiology modeling augmented with computer vision	2023
T18 [46]	Seasonal effects of thermal comfort control considering real-time clothing insulation with vision-based model	2023
T19 [77]	Vision-based personal thermal comfort prediction based on half-body thermal distribution	2023
T20 [79]	Smart detection of indoor occupant thermal state via infrared thermography, computer vision, and machine learning	2023
T21 [67]	A novel occupant-centric stratum ventilation system using computer vision: Occupant detection, thermal comfort, air quality, and energy savings	2023
T22 [78]	Personal thermal comfort modeling based on facial expression	2023
T23 [75]	User-centric approach to optimizing thermal comfort in university classrooms: Utilizing computer vision and Q-XGboost reinforcement learning	2024
T24 [71]	WiSOM: WiFi-enabled self-adaptive system for monitoring the occupancy in smart buildings	2024

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T25 [43]	Performance evaluation of an occupant metabolic rate estimation algorithm using activity classification and object detection models	2024
T26 [59]	Vision-based multi-label detection framework for capturing occupant action and clothing information using large-scale dataset	2024
T27 [47]	Real-time clothing insulation level classification based on model transfer learning and computer vision for PMV-based heating system optimization through piecewise linearization	2024
T28 [80]	Non-intrusive personal thermal comfort modeling: A machine learning approach using infrared face recognition	2024
T29 [81]	Thermal comfort prediction in multi-occupant spaces based on facial temperature and human attributes identification	2024
T30 [82]	Non-invasive vision-based personal comfort model using thermographic images and deep learning	2024
T31 [19]	Impact of thermal control by real-time PMV using estimated occupants personal factors of metabolic rate and clothing insulation	2024
T32 [83]	Prediction of occupant thermal state via infrared thermography and explainable AI	2024
T33 [68]	Occupancy prediction: A comparative study of static and MOTIF time series features using WiFi Syslog data	2024
T34 [74]	Non-intrusive infrared facial thermography for personal thermal sensation prediction models: A field study	2025
T35 [91]	Development and performance evaluation of an indoor thermal environment control algorithm incorporating MET estimation model with object detection	2025
T36 [52]	Occupant information computer vision sensing-based displacement ventilation in large space building for improving indoor environment and energy efficiency	2025
T37 [60]	Occupant activities and clothes detection based on semi-supervised learning for occupant-centric thermal control	2025
T38 [88]	Vision-based personal thermal comfort modeling under facial occlusion scenarios	2025
T39 [84]	Integrating infrared facial thermal imaging and tabular data for multimodal prediction of occupants' thermal sensation	2025
T40 [85]	Using SHAP and Machine Learning for Dynamic Thermal Comfort Estimation during temperature ramp conditions with infrared camera	2025
T41 [44]	A visual prediction method for individual metabolic rate by integrating movement speed and physiological characteristics	2025
T42 [53]	Evaluating single-shot and two-stage vision-based detection of occupancy	2025
T43 [54]	Human-Centered Behavioral Analysis of Window Operation Using AI-Based Skeletal Recognition	2025
T44 [61]	Dynamic detection models for clothing insulation and metabolic rate based on computer vision	2025
T45 [72]	Implementing Wi-Fi CSI-based room-level occupancy Estimation: an experimental study in multi-zone residential environments	2025
T46 [55]	Real-time prediction of individual thermal state based on video understanding	2025
T47 [69]	Streamlining occupant-centric HVAC operations through multi-modal infrared array sensing technology	2025
T48 [86]	Towards personalized HVAC: A non-contact human thermal sensation monitoring and regulation system	2025
T49 [87]	Novel dynamic thermal comfort prediction in buildings with single-shot vision-based deep learning method and low-cost thermographic imaging	2025
T50 [62]	Benchmarking zero-shot vision-language models against supervised learning for concurrent metabolic rate and clothing insulation estimation	2026
T51 [63]	AI-driven thermal comfort management in public waiting halls: Passive sensing and adaptive HVAC control	2026
T52 [48]	Thermal image-driven clothing insulation estimation using a fine-tuned multimodal large language model	2026
A1 [95]	Occupant-density-detection based energy efficient ventilation system Prevention of infection transmission	2021
A2 [94]	Collection and Utilization of Indoor Environmental Quality Information Using Affordable Image Sensing Technology	2022
A3 [98]	Deep learning and computer vision based occupancy CO_2 level prediction for DCV	2022
A4 [99]	Deep vision-based occupancy counting: Experimental performance evaluation and implementation of ventilation control	2022
A5 [96]	Metabolism-based ventilation monitoring and control method for COVID-19 risk mitigation in gymnasiums and alike places	2022
A6 [67]	A novel occupant-centric stratum ventilation system using computer vision: Occupant detection, thermal comfort, air quality, and energy savings	2023
A7 [106]	Computer-vision-assisted subzone-level demand-controlled ventilation with fast occupancy adaptation for large open spaces towards balanced IAQ and energy performance	2023
A8 [108]	The Performance of Reinforcement Learning for Indoor Climate Control Devices according to the Level of Outdoor Air Particulate Matters	2023
A9 [100]	Building ventilation optimization through occupant-centered computer vision analysis	2023
A10 [109]	An occupant-centric control strategy for indoor thermal comfort, air quality and energy management	2023
A11 [101]	High-accuracy occupancy counting at crowded entrances for smart buildings	2024
A12 [102]	DeepVision based detection for energy-efficiency and indoor air quality enhancement in highly polluted spaces	2024
A13 [107]	Exploring occupant detection model generalizability for residential buildings using supervised learning with IEQ sensors	2024
A14 [52]	Occupant information computer vision sensing-based displacement ventilation in large space building for improving indoor environment and energy efficiency	2025
A15 [103]	Natural ventilation automatic operating system based on real-time room IAQ measurements coupled with a human location detection system	2025
A16 [104]	Occupancy-Based Predictive AI-Driven Ventilation Control for Energy Savings in Office Buildings	2025
A17 [97]	Occupancy-driven HVAC control optimization via LSTM and deep reinforcement learning for enhanced indoor air quality, thermal comfort and energy efficiency	2025
A18 [105]	Optimizing HVAC performance through occupancy-based control: A machine learning approach for energy efficiency and comfort	2025
A19 [110]	Real-time ventilation control for indoor CO_2 management using occupant information	2025
V1 [116]	Development and implementation of an adaptive lighting and blinds control algorithm	2017
V2 [117]	WinLight: A WiFi-based occupancy-driven lighting control system for smart building	2018
V3 [118]	LightLearn: An adaptive and occupant centered controller for lighting based on reinforcement learning	2019
V4 [119]	Application of vision-based occupancy counting method using deep learning and performance analysis	2021
V5 [120]	Smart lighting control system based on fusion of monocular depth estimation and multi-object detection	2022
V6 [51]	An occupant-centric adaptive façade based on real-time and contactless glare and thermal discomfort estimation using deep learning algorithm	2022
V7 [123]	Performance evaluation of non-intrusive luminance mapping towards human-centered daylighting control	2022
V8 [122]	Occupant-based control of lighting system for multi-person office rooms based on WiFi probe technology	2024
V9 [121]	Fine-grained modeling and optimal control methods via video-based positioning for multi-occupant smart lighting systems	2025
V10 [124]	Design of library intelligent lighting system based on deep learning	2025
V11 [125]	Toward AI-assisted, human-centered daylighting operation: Non-invasive daylighting preference evaluation using deep learning	2025

Appendix B. Performance metrics used in this review

Metric	Full Name	Type	Unit	Interpretation
Accuracy	-	Classification	%	The proportion of correct predictions among all predictions
F1-score	-	Classification	0–1	The harmonic mean of precision and recall
MAE	Mean Absolute Error	Regression	same as target unit	The mean absolute difference between predicted and measured values
Macro-F1	Macro averaged F1 Score	Regression	0–1	The F1-score averaged across all classes with equal weighting
mAP	Mean Average Precision	Detection	0–1	The average of precision-recall curves computed across all classes
NRMSD	Normalized Root Mean Square Deviation	Regression	0–1	A normalized metric representing the relative magnitude of prediction errors based on mean squared deviation
NRMSE	Normalized Root Mean Square Error	Regression	0–1	A normalized metric of RMSE scaled by the data range
PCP	Percentage of Correct Parts	Detection	0–1	The proportion of correctly estimated keypoints in pose estimation tasks
Precision	-	Detection	%	The proportion of true positive predictions among all positive predictions
R^2	Coefficient of Determination	Regression	0–1	The proportion of variance in the data explained by the model
Recall	-	Detection	%	The proportion of actual positives correctly identified
RMSE	Root Mean Squared Error	Regression	same as target unit	The square root of the mean of squared prediction errors

Data availability

Data will be made available on request.

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