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Revealing the gaps in multi-domain comfort control: A relationship-graph approach based on a systematic review

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ABSTRACT

Multi-domain indoor environmental quality (IEQ) control has emerged as a promising approach for balancing occupant comfort and building energy use (BEU). However, the absence of a clear conceptual structure for defining and evaluating such systems has led to inconsistent formulations and limited comparability across studies. This study examines existing approaches and assesses their alignment with a newly developed conceptual structure for multi-domain control. A systematic review was conducted using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology guided by the CIMO (Context–Intervention–Mechanism–Outcome) logic. An initial identification of 972 studies addressing control strategies across multiple IEQ domains and BEU was identified, from which 125 studies were retained following screening and eligibility assessment.

The analysis shows that only 15 studies explicitly integrate more than one IEQ domain with BEU within a control system formulation. All retained studies incorporate energy use and thermal comfort, while indoor air quality (IAQ) appears in one study, visual comfort in two, and acoustic comfort in none. Across these studies, comfort is frequently reduced to single environmental variables and governed through fixed setpoints, with indoor environmental conditions treated as direct proxies for occupant comfort. A relationship graph is introduced to interpret these patterns and reveals structural limitations, including the omission of cross-domain interactions, the absence of an intermediate IEQ layer linking environmental conditions to perceived comfort, and the selective treatment of contextual drivers due to computational and uncertainty-related constraints. These findings indicate that most existing approaches function as autonomous rather than occupant-centric control systems.

1. Introduction

Buildings account for over 34% of global energy use [1], mostly driven by building technical systems that provide an established level of indoor environmental quality (IEQ) [2]. IEQ considers thermal, visual, acoustic, and air quality conditions, each affecting comfort, health, and satisfaction. Evaluating these domains simultaneously is referred to as multi-domain comfort [3]. Given that people spend approximately 87% of their lives indoors [4], maintaining occupants' multi-domain comfort is essential for their well-being and productivity. Efforts to improve comfort often conflict with energy reduction goals, especially when environmental domains are managed in isolation. As building systems grow more complex, achieving both energy efficiency and high occupant satisfaction requires a deeper understanding of how these factors interact.

In this context, occupant-centric control systems offer a promising pathway. Occupant-centric control refers to an advanced building management approach that combines sensing of IEQ, occupant presence, and occupant–building interactions to enhance operational performance while maintaining occupant comfort [5,6] and it uses occupant information (such as presence/absence, thermal preferences, or activity levels) to meet occupants' requirements—particularly thermal comfort [7]. These systems can reduce building energy consumption while maintaining indoor conditions within the comfort range of occupants in the building [8]. Initially, control logic relied solely on direct occupant interactions with building systems, such as manual thermostat adjustments or window operations. However, occupant-centric control

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Nomenclature

BACS	Building automation and control system
BEU	Building energy use
BMS	Building management system
CIMO	Context-intervention-mechanism-outcome
HVAC	Heating, ventilation, and air conditioning
IAQ	Indoor air quality
IEQ	Indoor environmental quality
MPC	Model predictive control
FOMPC	Fractional-order model predictive control
PMV	Predicted mean vote
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
RL	Reinforcement learning
MORL	Multi-objective reinforcement learning

algorithms require diverse data that capture occupant-related, environmental, and operational aspects of indoor spaces. Key occupant data includes real-time presence, movement patterns, and comfort preferences across IEQ domains, typically gathered through sensors, surveys, or wearable devices. Indoor environmental variables, such as temperature, humidity, CO_2 levels, illuminance, and noise, are also essential to assess conditions in the indoor environment. These variables help determine how indoor conditions align with or deviate from occupant preferences and expectations [9]. In addition, operational data from building systems (e.g., Heating, ventilation, and air conditioning (HVAC) settings, lighting status, and window positions) and system-level energy consumption help link environmental changes to energy use. These operational data are used for evaluating the energy impact of various control actions [10]. Outdoor environmental variables data further support occupant-centric control strategies by enabling the system to anticipate and respond to changing external conditions, which can significantly influence indoor comfort and energy demands [11]. Also, these aspects are not independent; rather, they influence one another in complex ways. For example, indoor temperature can affect occupant behavior, such as window opening, which in turn alters CO_2 concentration and energy consumption [12].

The above-mentioned elements and the cross-domain interactions are critical for considering when designing a control algorithm for buildings. The review of existing review papers that attempted to regulate multiple domains as the base of my study shows that current approaches capture only a portion of the factors that shape indoor conditions. Most studies manage a limited set of aspects, as shown in Table 1, and consider only a subset of the interactions among these elements [20,21].

Table 1
Review of existing review papers on occupant-environment interactions and their relevance to control algorithm input domains.

Study	Occupant behavior factors	Indoor variables	Outdoor variables	Building systems	Energy outcomes
Heydarian et al. [13]	√	√	X	√	√
Chinazzo et al. [14]	√	√	X	√	X
Zhao et al. [15]	√	√	X	√	X
Khovalyg et al. [16]	X	√	√	√	X
Bavaresco et al. [17]	X	√	√	√	√
Torresin et al. [18]	√	√	√	√	X
Schweiker et al. [19]	√	√	X	√	X

In this context and to better understand the relationships among relevant factors, the objectives of this paper are: (i) to synthesize the existing literature on multi-domain control approaches that simultaneously consider more than one IEQ domain and building energy use (BEU); (ii) to derive a conceptual relationship graph from the reviewed literature that structures the interactions among IEQ domains, occupant comfort preferences, building control systems, and energy outcomes; and (iii) to use this synthesized graph as an analytical lens to examine existing control approaches and identify areas that remain underrepresented in current occupant-centric, multi-domain control strategies.

2. Methodology

2.1. Review process

A systematic literature review was conducted in November 2025 to identify studies addressing the relationships among occupants, indoor environmental variables, building systems, and outdoor conditions. The CIMO (Context–Intervention–Mechanism–Outcome) structure was applied to define the search strategy and inclusion criteria. Following the initial retrieval of publications, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique [22] was employed on the index keywords to filter and prioritize papers based on their distinctiveness and relevance to the research objectives.

The keywords applied in the literature search were organized according to the CIMO logic. This categorization enabled a systematic and targeted retrieval process aligned with the research aim. In the Context category, the selected terms refer to various spatial units and building types within the indoor environment, ranging from general terms (e.g., buildings, indoor spaces) to specific spatial units (e.g., rooms, floors, dwellings). The Intervention category includes keywords related to environmental control systems and strategies, encompassing both conventional components (e.g., HVAC systems, lighting control) and advanced technologies (e.g., adaptive systems, automated blinds). The Mechanism category covers the control and feedback methods associated with these interventions. It includes rule-based, model-based, and data-driven approaches, with a focus on occupancy-driven and sensor-based control strategies. The Outcome category comprises terms related to performance evaluation, including energy consumption metrics and occupant-focused measures. These outcomes address IEQ conditions, as well as subjective indicators such as satisfaction, comfort, wellbeing, and physiological or behavioral responses. In practice, the CIMO framework was operationalized by grouping keywords within each CIMO component and combining them using Boolean operators. Specifically, all keywords within a category (e.g., all keywords in Context) were connected using the OR operator, while the four CIMO categories themselves were linked using the AND operator. This ensured that the search results would only include studies that simultaneously addressed all four dimensions: a specific context, a defined intervention, a mechanism of action, and measurable outcomes.

For the identification section of PRISMA, the literature search was conducted using the Scopus database, applying CIMO-based keywords to identify relevant studies. To extend the coverage, additional records were manually retrieved from other academic sources, including Web of Science and Google Scholar. Only peer-reviewed journal articles published in English in the last decade were considered for inclusion. This period was selected because the past decade has seen a substantial increase in research activity matching the CIMO keyword search (Fig. 1), alongside significant technological advances in occupant-centric control, IoT-based sensing, and data-driven or machine learning approaches for building management.

The initial query in Scopus returned 885 articles. These records were exported and organized with associated metadata, including title, authors, publication year, journal, abstract, and indexed keywords. An

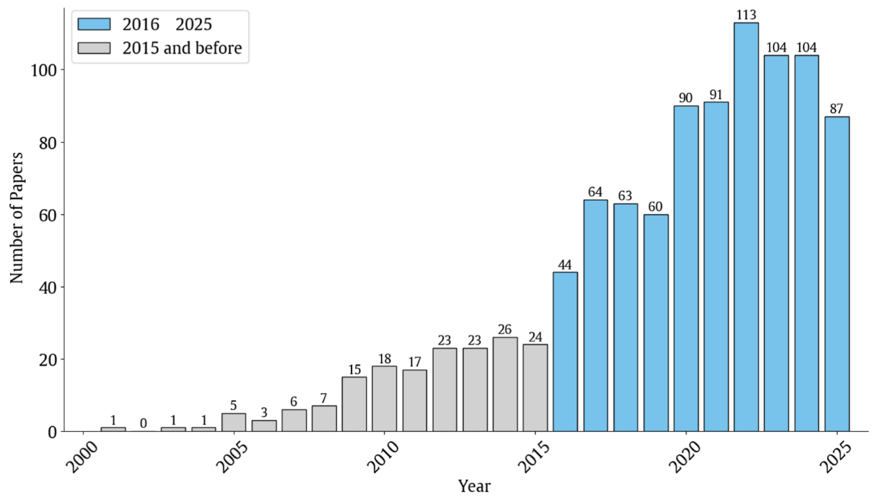

Fig. 1. Number of articles retrieved annually from the CIMO keyword search.

additional 87 articles were manually selected based on relevance to the research topic. These records met the same inclusion criteria and were processed using the same extraction method. The resulting collection of 972 articles formed the dataset for the subsequent filtering and analysis. Duplicate entries were identified and removed using the reference management software Mendeley [23]. This process resulted in the exclusion of 21 duplicate records from the initial set of retrieved articles prior to the screening stage.

To minimize subjectivity and reduce manual effort during the screening stage of the PRISMA procedure, a text similarity-based approach was implemented. The cosine similarity approach was used to quantify the relevance of articles retrieved during the identification phase. This method aligns with previously established applications of automated techniques in systematic reviews, where similarity measures have demonstrated utility in improving reproducibility and selection efficiency [24].

The screening was applied to the initial set of articles obtained using a CIMO-structured search in the Scopus database. Index keywords served as the textual features for comparison. These keywords were transformed into numerical vectors using Term Frequency–Inverse Document Frequency (TF-IDF), and pairwise cosine similarity scores were calculated to estimate the similarity between documents. The automated screening procedure was implemented using Python 3.11.5 through a custom script, employing the Scikit-learn machine learning library version 1.5.1 for TF-IDF vectorization and cosine similarity computation. This procedure enabled the identification of thematically related publications regardless of exact keyword overlap.

Cosine similarity was used to quantify the textual similarity between publications in the initial dataset. Cosine similarity is widely applied in bibliometric and text-mining studies because it provides a normalized measure of similarity between documents represented as vectorized textual features, enabling systematic comparison of large document collections while reducing subjective interpretation during screening [25,26]. In bibliometric analyses, threshold values used to filter similarity relationships are determined empirically, as their appropriate level depends on the structure and size of the dataset, as well as the objective of the analysis [27,28]. Lower thresholds are often adopted when the goal is to retain broader thematic relationships, particularly in interdisciplinary research landscapes, whereas higher thresholds are used when identifying tightly connected thematic clusters [25].

In this study, a lower cosine similarity threshold was selected to preserve the thematic breadth of the literature while maintaining a manageable screening pool. Specifically, a 10% cosine similarity threshold was applied to identify highly similar publications within the initial dataset. When two papers exceeded this similarity threshold, the paper with the lower citation count was removed in order to reduce redundancy while retaining the more influential record. This threshold was selected to balance inclusion coverage and review workload. Prior studies have shown that similarity-based filtering approaches can substantially reduce the number of records requiring manual screening while maintaining a high recall of relevant studies for subsequent PRISMA eligibility assessment.

Following the application of cosine similarity, 725 articles were excluded during the screening phase due to high textual similarity scores. A total of 226 papers were retained for full-text eligibility assessment. Each of these articles was reviewed to verify consistency with the predefined inclusion criteria. During the eligibility phase, 101 papers were excluded due to their focus on unrelated technical areas. The remaining 125 studies met all inclusion criteria and were incorporated into the systematic review. All the steps of the PRISMA approach are presented in Fig. 2.

2.2. *Construction process of the relationship graph*

This graph was developed to represent the main relationships among IEQ, building energy use, and their effects on the building management system (BMS). Its purpose is to support the conceptual development of occupant-centric control algorithms by visually organizing interactions reported in the literature. The graph was constructed based on a review of 125 studies. When studies identified a directional relationship between two elements—such as an environmental condition influencing occupant behavior or energy demand—that connection was recorded. Each element was represented as a node, with arrows indicating the direction of the relationship. Similar elements were grouped into broader categories: building, occupant, control, and IEQ.

Relationships were included in the graph when they were supported by at least two independent studies to ensure a minimum level of replicability across different contexts. For instance, if two or more studies reported that increased indoor temperature leads to higher occupant dissatisfaction, or that elevated CO_2 levels are associated with adaptive window-opening behavior, these connections were incorporated into the graph. This criterion aimed to reduce the inclusion of isolated findings and to ensure that only relationships repeatedly observed in the literature were represented.

In cases where conflicting results occurred, the relationship was not automatically excluded if multiple independent studies reported a similar interaction. Instead, the connection was retained as an indicative relationship reflecting recurring patterns identified in the literature review. As such, the relationship graph should be interpreted as a conceptual synthesis of commonly reported interactions rather than a

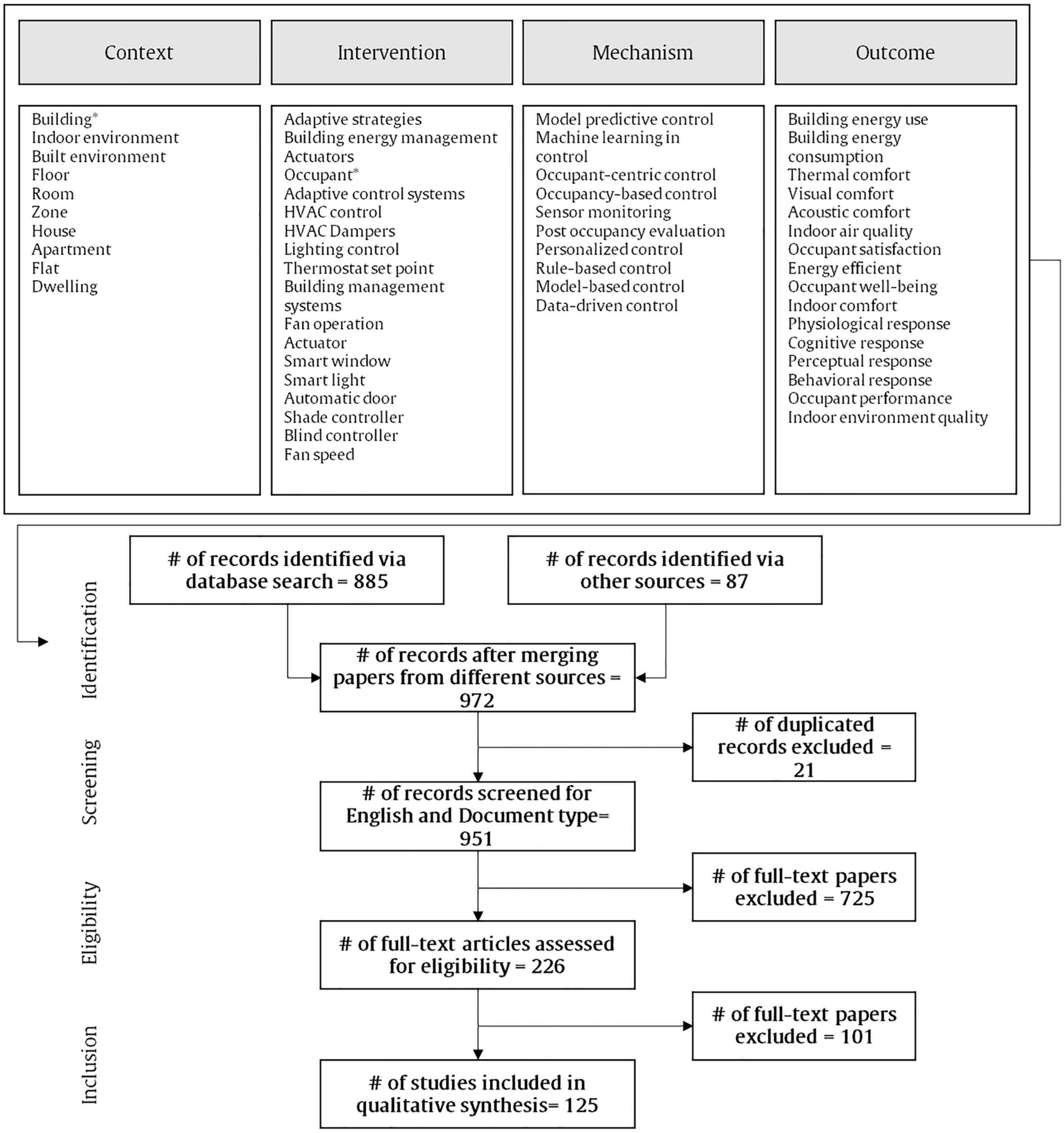

Fig. 2. Prisma and CIMO schemes for this systematic literature review.

deterministic representation of causal mechanisms.

Furthermore, elements acting solely as modifiers, such as building orientation or window-to-wall ratio—factors that influence other variables but are not directly affected in the chain of interaction—were excluded for clarity. Similarly, connections that were weakly supported (e.g., a single study reporting a vague or statistically insignificant trend) or appeared only once in the reviewed literature were also omitted. Although the reviewed studies covered diverse building types, climates, and occupant profiles, the relationship graph represents a synthesis of recurring interaction patterns reported across the literature.

3. Results and discussion

This review is based on an analysis of 125 studies selected through the PRISMA procedure. These studies were examined to identify relationships between the various components that influence control systems in buildings, as well as the elements that are influenced by them. To guide this investigation, a series of targeted classifications was carried out to structure the review and enable comparative analysis across studies. These include building type classification, building operation strategy classification, control strategy typology, methodological approach analysis, and IEQ domain coverage. Each classification was developed to capture recurring patterns and distinguish features relevant to building control research.

3.1. Descriptive statistics and classifications of the reviewed studies

All 125 studies in the inclusion section are reviewed. They addressed IEQ coverage through four main domains: thermal comfort, visual comfort, indoor air quality, and multi-domain comfort. Thermal comfort was the most studied, appearing in 48.2% of the papers. Multi-domain comfort followed closely, representing 42.4% of the studies. However, almost all of these also emphasized thermal comfort, with only one study [29], which focused on acoustic conditions and indoor air quality [29]. Research dedicated solely to visual comfort or indoor air quality was limited, found in just 7.1% and 2.4% of the studies, respectively. No study focused exclusively on acoustic comfort. This uneven distribution reflects a tendency to prioritize thermal conditions, even in studies that claim to address multiple domains. Over time, however, there has been a gradual increase in studies that consider multiple comfort domains, indicating a shift toward more integrated evaluations. The distribution of domain coverage is illustrated in Fig. 3.

Control strategies reported in the reviewed studies fall into three main categories: closed-loop, open-loop, and hybrid systems. Closed-loop systems are the most frequently studied, appearing in 72% of the papers. These systems rely on feedback from indoor or occupant-related variables to adjust building operations in real time. Open-loop systems are used in 16% of the studies and are applied in field investigations. Hybrid control strategies, which incorporate features of both open-loop and closed-loop systems, are the least explored, appearing in only 12% of the studies. Most of the papers discussing hybrid control approaches were review papers, but a few studies (e.g., Shi et al. [30]) proposed concrete implementations.

3.2. Relationship graph of occupants, IEQ, energy, and control

This section presents the key results of the study, which aims to characterize the relationships between IEQ, occupants, buildings, energy performance, and control systems, based on a literature review using the CIMO approach. Fig. 4 illustrates the conceptual diagram resulting from this analysis, showing the interactions between occupants and buildings. A detailed description of the identified relationships and their supporting evidence is provided in the Supplementary Material, while the interactions among IEQ domains and their influence on building energy use are discussed in Section 3.4. Initially, occupants perceive the indoor environmental variables, and after the perception, occupants evaluate the indoor environment. Based on this evaluation, they may choose to adjust indoor conditions by interacting with building systems, such as altering the HVAC setpoint, or by modifying personal factors, such as changing their clothing [31,32], which subsequently influences their perception of the environment [33,34].

Inside buildings, indoor environmental variables are influenced by contextual factors, such as outdoor environmental conditions [35], building location [36], construction characteristics [37], seasons [38], and time of day [39], as well as by building systems, including shades, fans, and HVAC systems [40]. Building systems can be operated either directly through occupant interaction [41] or via control systems [42]. They play a direct role in determining building energy use by regulating space heating and cooling, ventilation, and lighting, which directly influence energy consumption based on the efficiency of the system and the level of occupant demand [13] and occupants' comfort [43,44]. To optimize the performance of these building systems while addressing occupant comfort and energy efficiency, occupant-centric control strategies that leverage both objective and subjective data have been developed [45].

For adjusting indoor environmental variables in occupant-centric control, both objective and subjective data are required. There are several methods to capture data, including sensors [46], wearable devices [47], and questionnaires [48]. Once processed, these data inform adjustments to building systems according to the goals of the occupant-centric control algorithms. One of the primaries aims of these algorithms is to minimize BEU and maximize occupant comfort [49]. To do this, it is important to account for all four domains of IEQ, as they are interrelated and fundamental in assessing the conditions within an indoor space. IEQ can be assessed subjectively and objectively – the subjective assessment is the result of occupants' qualitative evaluation of indoor environmental variables (i.e., air temperature, relative humidity, illuminance, noise level, and concentration of various substances such as CO_2, volatile organic compounds, particulate matter, etc.), and it shows how occupants are satisfied with them [48,50]. Objective evaluation of IEQ involves measuring those indoor environmental variables and quantitatively analysing them to provide a precise and unbiased assessment of the indoor environment [51].

Fig. 4 serves not only as a synoptic graph of the critical themes in the literature survey but also as a guide to developing integrated multi-domain control systems that give rise to improved comfort and efficiency in buildings. In this study, multi-domain control is defined as a control strategy that simultaneously considers at least two performance dimensions drawn from the four IEQ domains and building energy use.

The evaluation of this system demonstrates the impact of occupants on the indoor environmental variables and how the presence and behavior of these individuals influence various indoor variables. Holistic representation and modeling of those interactions raise prospects for innovative ideas for managing smart buildings and developing user-centered designs.

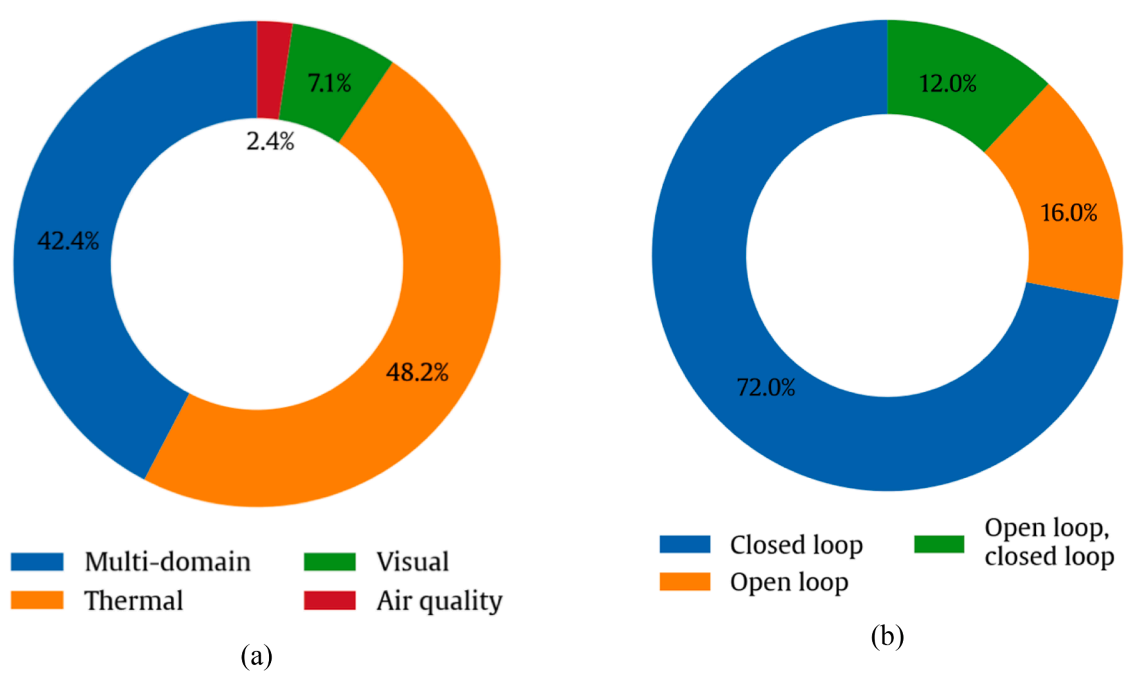

Fig. 3. Summary of classified attributes across the reviewed studies on: (a) IEQ domain coverage; (b) Control strategy type.

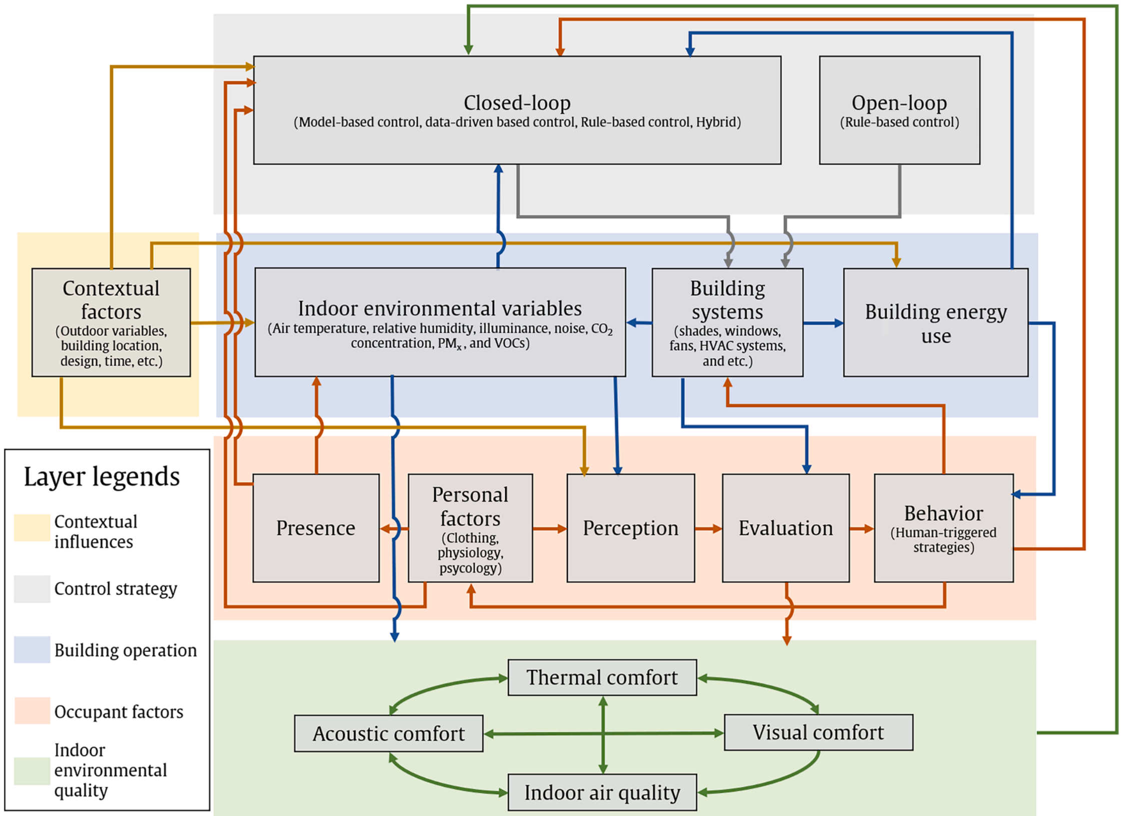

Fig. 4. Relationship graph indicating the relations between occupants, indoor environmental quality, ad building energy use, and control systems.

3.3. *Inputs for building automation and control system*

Building automation and control system relies on three classes of inputs: (i) indoor environmental variables that describe the current state of the space, (ii) information on occupant presence, activity, and behavior, and (iii) contextual and building factors that constrain feasible actions. In the following subsections, all the mentioned categories of input are discussed.

3.3.1. *Indoor environmental variables*

Indoor environmental variables provide essential input to building control systems, enabling automated control of heating, cooling, ventilation, and lighting systems. These variables include temperature, relative humidity, carbon dioxide concentration, and illuminance. The quality and resolution of the input data influence the responsiveness and accuracy of BACS operations. Accurate and continuous monitoring allows BACS platforms to maintain acceptable indoor conditions and respond promptly to changes in the environment.

Carbon dioxide concentration is commonly used to estimate occupancy levels and guide ventilation strategies. When CO_2 levels exceed a predefined threshold, the control system increases air exchange to maintain air quality [52,53]. Similarly, relative humidity must be monitored to avoid discomfort and health-related issues. High humidity levels are associated with microbial growth, while very low humidity can cause irritation and dryness. Maintaining indoor humidity within a defined range requires reliable input data and active control measures [54,55].

Sensor platforms supply the data used by BACS systems. Their performance varies based on cost, calibration, and deployment. Low-cost sensors allow multi-zone monitoring but have limitations in measurement resolution and accuracy. They are often used for initial diagnostics rather than precise control applications [56]. Even when measured variables fall within recommended limits, reported occupant dissatisfaction may persist, indicating that sensor readings alone may not fully represent subjective comfort [57].

To interpret sensor data and determine appropriate actions, BMS platforms apply threshold-based logic or comfort models. Common models include the predicted mean vote (PMV) and adaptive thermal comfort methods, which estimate occupant satisfaction based on indoor conditions [58]. These models rely on standards [59] and predefined comfort limits [60]. However, variability in individual preferences can lead to uncertainty in model-based predictions [57].

3.3.2. *Occupant presence, activity, and behavior*

Occupant presence is one of the most influential inputs for building automation and control systems, as it determines when thermal, visual, and ventilation services are actually required. Even in the absence of deliberate actions, occupants influence indoor environmental variables through their mere presence, affecting CO_2 concentrations via respiration [61] and indoor temperature through metabolic heat generation [62]. Presence is commonly inferred through sensing technologies that register either direct human motion or indirect environmental indicators. Studies relying on motion- or schedule-based activation show that aligning system operation with confirmed occupancy reduces unnecessary energy use, as reported by Lee et al. [63] for lighting and by Pang et al. [53] for HVAC control. Presence can be captured using advanced occupancy detection methods, including computer-vision-based systems and AI-assisted sensing techniques that estimate occupant numbers for HVAC forecasting and control [64,65]. Deng et al. [66] applied Bluetooth beacons and lighting sensors to detect room-level occupancy and modulate HVAC services with substantial load reductions, while Salimi et al. [67] employed Wi-Fi signal monitoring to construct dynamic occupancy profiles that outperform fixed schedules. Vision-based detection [60] and environmental inference techniques that use CO_2 concentration patterns [68,69] further extend the range of available sensing modalities when direct motion data are insufficient or unreliable. These approaches highlight the differences between binary presence signals and probabilistic occupancy models, the latter offering time-varying estimates that help controllers anticipate occupancy transitions [67]. Systems that do not incorporate such information often revert to conservative operational assumptions, which degrade energy performance. For example, Ouf et al. [26] find that conservative assumptions about occupancy can account for up to 30% of energy use, whereas occupancy-informed control strategies have been reported to reduce HVAC energy consumption by up to 44% compared to the system without occupancy-aware control [52].

Activity level and space usage provide additional input signals that refine the interpretation of occupancy conditions. Whereas presence identifies whether a space is used, activity data describe the intensity and nature of that use. Activity level determines metabolic rate, a major input need to be considered in control [70]. Choi et al. [60] reviewed vision-based sensing studies showing that occupant activity can be used to infer metabolic rate or heat emission, enabling control strategies (e.g., PMV-based control) to adjust HVAC settings and improve comfort performance.

Behavioral actions form a further category of occupant-related inputs, as they reveal how individuals adjust their environment through interactions with building systems [71]. These interactions include the use of lighting switches, blinds, windows, and thermostats, each of which carries information about comfort preferences and perceived deviations from acceptable indoor conditions across multiple IEQ domains, including thermal, visual, and indoor air quality conditions. For example, window opening may respond to thermal or air quality discomfort, while lighting adjustments reflect visual comfort preferences. Park et al. [72] incorporated manual lighting-switch operations to infer personalized comfort thresholds, using the illuminance levels at which occupants turned the lights on to adapt its definition of 'darkness' and adjust set-points accordingly. A similar statement in Choi et al. [60] noted that occupant adjustments to building services—such as HVAC, lighting, and blinds—represent valuable behavioral information that reflects comfort-related preferences, reporting also that no vision-based studies have yet incorporated these adjustments into control algorithms.

3.3.3. Contextual and building factors

Contextual variables and building systems define the operational boundaries within which control algorithm function. In this study, contextual variables refer to factors that affect indoor environmental conditions but cannot be directly manipulated by the control system during operation. Building systems, however, are not considered contextual variables, as components such as HVAC, lighting, and ventilation systems can be adjusted in real time and therefore serve as controllable elements within the control process. By contrast, variables such as outdoor environmental conditions, season, building location, and structural characteristics remain outside direct operational control and are thus treated as contextual variables. Three categories have been identified from the literature review, with the most relevant for input selection: external boundary conditions, structural properties that govern thermal response, and operational attributes linked to building systems.

External boundary conditions act as exogenous drivers that determine sensible and latent loads on the building envelope and guide the controller in preparing for upcoming gains or losses. Most control schemes incorporate real-time weather measurements [73], while others rely on short-term forecasts to adjust setpoints over a prediction horizon [2]. Forecast-informed operation has been shown to reduce heating and cooling energy when the controller shifts operation toward periods with more favorable outdoor conditions or lower electricity tariffs [74]. In practice, these external drivers enter the control problem as disturbance inputs, and their temporal resolution and forecast horizon influence whether the controller can pre-heat, pre-cool, or reschedule ventilation [75,76]. A short horizon restricts opportunities for load shifting, whereas longer horizons may carry greater uncertainty. Forecast errors can degrade performance, as misclassified weather states may trigger unnecessary conditioning and increase system load [77]. For this reason, several studies incorporate probabilistic forecasts or scenario-based representations to ensure that control actions remain acceptable under different possible weather realizations [78].

Structural characteristics, such as thermal mass [79], envelope composition [80], and window-to-wall ratio [81], act as key contextual inputs to multi-domain control because they determine how quickly indoor conditions respond to actuator changes. High-mass elements absorb and release heat over extended periods, dampening temperature fluctuations, and enabling strategies that shift conditioning to earlier hours [2]. Control algorithms can exploit this storage potential by pre-cooling or pre-heating the building during low-demand periods, with reported reductions in peak loads and daily energy use [82]. To support such strategies, the controller requires inputs that describe the thermal resistance–capacitance relationships of the envelope [83] or low-order models derived from operational data.

Additional building-related operational attributes also shape how multi-domain control is formulated. Building typology [84], system configuration [84], and operational schedules [85] introduce variations in internal gains, distribution losses, equipment responsiveness, and occupancy-driven load patterns. These elements influence state variables, modify disturbance inputs, and impose constraints when system capacity or envelope deterioration limits feasible actuator actions. Their influence on state definitions, disturbance characterisation, and admissible trajectories is discussed in Section 3.5.2.

3.4. Cross-domain interactions between indoor environmental quality and energy use

Cross-domain interactions emerge when adjustments or properties linked to one environmental variable affect multiple comfort outcomes or alter building energy use. These interactions can originate from system operation, occupant behavior, or the physical design of the building. It is noted that a link between two domains may arise from multiple underlying mechanisms; however, for clarity of exposition, a single representative cause is selected for each interaction discussed here, without implying that the described mechanism exhaustively captures all possible pathways of influence. Grouping them into operationally-driven and design-driven interaction mechanisms helps clarify how different sources of change influence indoor conditions and highlights where control strategies may need to account for effects that extend beyond a single domain.

Operationally-driven interactions arise from HVAC, ventilation, and lighting systems; each adjustment intended for one domain reshapes the controller's decision space in others. Humidity control is a clear example: when moisture levels increase, cooling equipment must operate more aggressively, which raises energy use and alters occupants' thermal feedback, meaning that a controller regulating moisture indirectly influences thermal preference signals [86,87]. The same mechanism appears in indoor air quality (IAQ) related responses, where insufficient ventilation allows humidity to support mold growth, prompting additional ventilation demand and altering the conditions the controller must maintain [88]. These interactions extend to lighting systems. Changes in illuminance do not simply affect visual satisfaction; they shift occupants' thermal evaluation, so any lighting adjustment simultaneously modifies the thermal domain that the controller aims to stabilize [38]. In the same way, changes in the shading position affect both visual comfort and HVAC energy consumption [89]. The heat gains introduced by artificial lighting reinforce this link by imposing additional cooling requirements that must be reconciled in the control action [90]. Similarly, in acoustics, when mechanical systems introduce background noise, the controller's attempt to maintain thermal or IAQ conditions can inadvertently reduce acoustic satisfaction, especially in open-plan spaces with long operation periods [46,91]. Window operation illustrates why these cross-domain links must be considered in control design—opening a window improves air movement and reduces cooling demand, yet it also exposes occupants to outdoor noise, altering acoustic satisfaction [46,92,93]; closing it improves acoustics but restricts airflow, forcing the controller to compensate through mechanical ventilation and affecting energy use and IAQ [94,95].

Design-driven interactions are very broad, and although many links between IEQ and BEU exist in practice, only a subset commonly discussed in the literature is included here. These interactions originate from architectural and material choices that shape the baseline conditions a controller must operate within, meaning that design decisions influence how easily multi-domain control objectives can be achieved. Glazing provides a clear example: façades that maximize daylight simultaneously raise cooling demand through solar gains [96] and may transmit additional outdoor noise if acoustic insulation is insufficient [97]. A similar observation appears in ventilation-related designs. Buildings that limit operable openings or prioritize acoustic sealing constrain natural ventilation potential, which can elevate CO_2 concentrations and increase mechanical ventilation requirements, narrowing the range of feasible control actions [94,95]. Material selection can also shape cross-domain performance: elements with high thermal mass moderate indoor temperature swings and can reduce cooling demand [82]. Likewise, materials chosen for acoustic absorption often provide additional thermal insulation, reinforcing the coupling between acoustic quality, thermal comfort, and energy use that the controller must balance [98]. Architectural features that enhance solar gain also affect both thermal comfort and IAQ, as the resulting temperature shifts may promote natural ventilation and alter airflow patterns that later interact with mechanical control decisions [42,99]. Even design elements such as indoor greenery carry multi-domain implications: plants can shape visual comfort through aesthetic and daylight effects, while simultaneously reducing reverberation times, which modifies acoustic conditions that the controller inherits [100].

The distinction between operationally-driven and design-driven interactions also helps identify which mechanisms can be addressed within a multi-domain control formulation. operationally-driven interactions are adjustable during operation and therefore lie within the scope of building control, and correspond to inputs that can be monitored, predicted, or actuated, allowing the controller to modify environmental conditions in real time. Their influence on IEQ domains means that any control strategy that overlooks these links risks producing suboptimal decisions for multi-domain objectives. Most of the design-driven interactions, by contrast, originate from architectural or material features that are fixed once construction is complete, and they cannot be adjusted by the control system. Their influence is therefore

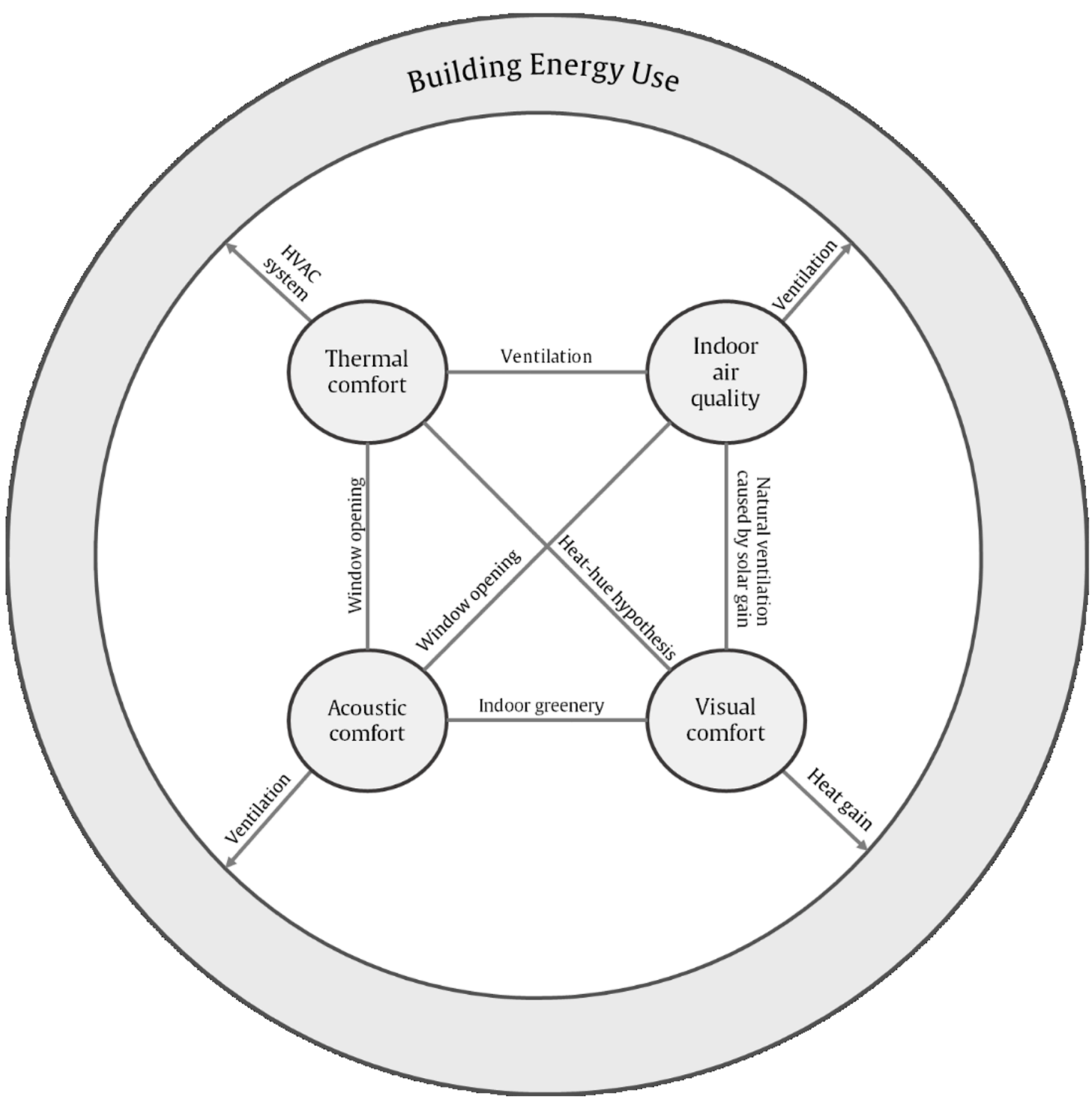

Fig. 5. Interconnection between domains of indoor environmental quality.

embedded indirectly in the control problem. Although these factors are not controllable during operation, they inform the structure of the control formulation, as discussed in Section 3.5.2.

Collectively, these findings are presented in Fig. 5. This underscores that adjustments targeting a single aspect of comfort or performance may initiate changes in others, which can either support or compromise overall system objectives. The multi-domain influence of design-driven interactions and operationally-driven interactions suggests a need for integrated control strategies that account for cross-domain interactions, particularly in energy-efficient and occupant-centric control.

3.5. Review of control system design for buildings

To contextualize how different data, both subjective and objective, are fed into the control algorithms, it is essential to examine the evolution of control system design, considering both logic design and data usage, starting from manual operation and progressing to intelligent occupant-centric algorithms. Over the past few decades, building control systems have undergone significant transformation, driven by the growing demand for energy efficiency, improved occupant comfort, and the availability of low-cost information and communication technologies that support real-time monitoring and control.

Traditional methods for regulating indoor environmental variables—such as temperature, lighting, and air quality—were typically manual, relying on occupant-operated switches that resulted in static control logic, since humans tend to leave active systems to work in certain operational conditions. As technology advanced and concerns over energy use increased, automated approaches emerged. Some of these automated approaches operate without a feedback loop and are classified as open-loop systems. In open-loop control, the system executes predefined actions based on fixed schedules or setpoints, without considering real-time environmental conditions or user feedback [101, 102]. In contrast, in closed-loop control, systems incorporate feedback mechanisms, which can be: mechanical [103] such as bimetallic thermostats, expansion valves, etc., electrical [66] allowing the system to adjust its operation based on sensor data [53], or occupant-driven, enabling more adaptive and efficient control [72]. Occupant feedback aims to regulate conditions based on human perception of comfort that would keep systems active within some conditions, reducing in this way the energy use, instead of having a free-running system [52]. This evolution reflects not only advancements in logic design but also the increasing integration of diverse and rich data sources, including environmental sensors [104], occupant feedback [105], and system-level performance data [52]. The closed-loop controls have different approaches and techniques, which are discussed in the following sections and presented in Fig. 6.

3.5.1. Closed-loop control approaches

Within the category of closed-loop control systems, the design and operational logic vary according to the degree and nature of human interaction. One primary classification distinguishes between human-in-the-loop and human-out-of-the-loop systems. The development of human-out-of-the-loop systems marked a departure from purely manual control. These early autonomous systems introduced operational schedules based on building use patterns, enabling HVAC and lighting systems to follow predefined time-based routines. Khan et al. [106] demonstrated that weather-informed HVAC scheduling can reduce energy consumption by up to 30%. Although these systems did not rely on real-time sensing or interaction, they represented a transitional approach that began incorporating data sources beyond occupant action. The absence of real-time adaptability, however, meant that these systems were unable to respond to changes in occupancy or

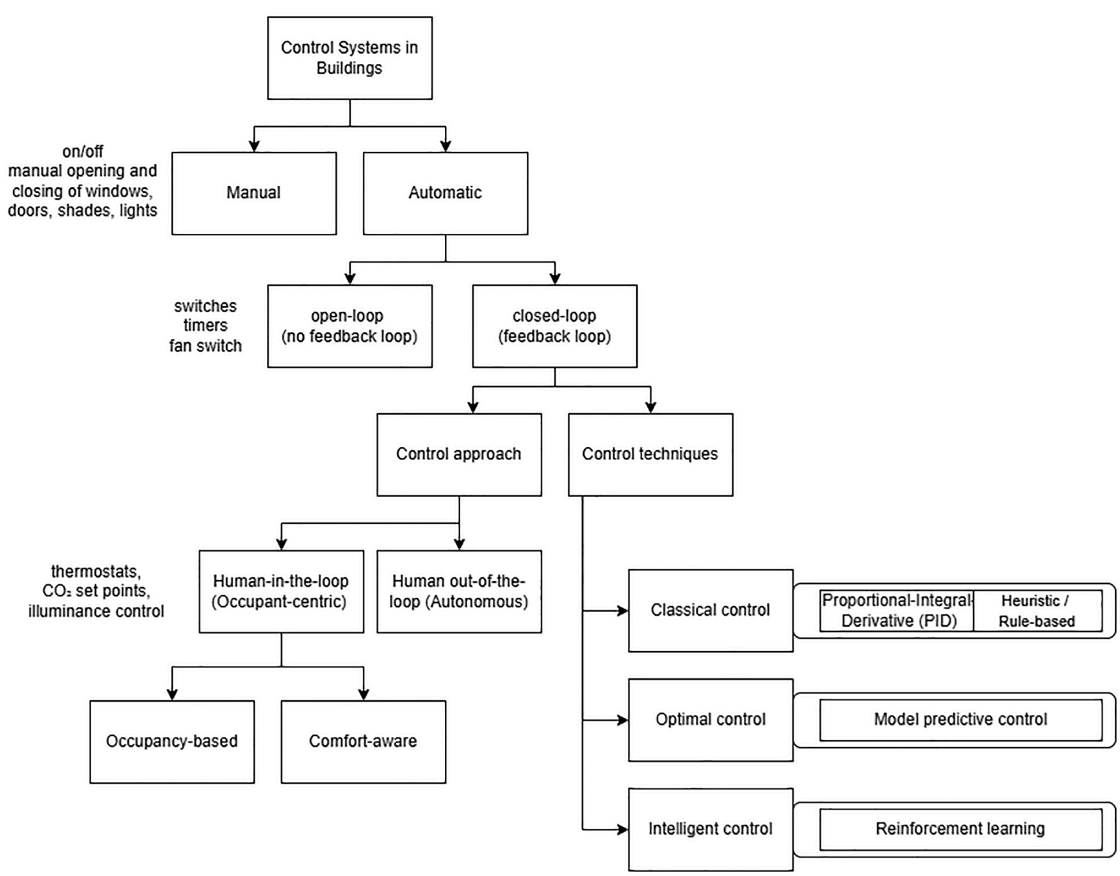

Fig. 6. Classification of control systems for buildings.

environmental conditions. This resulted in scenarios where systems operated during unoccupied periods or failed to respond to unexpected comfort demands [107,108]. Mahdavi [109] conducted a year-long study in 42 office spaces and found that users often neglected to switch off lights even when daylight levels exceeded 1000 lx. The emergence of sensor-based systems addressed these limitations by integrating environmental monitoring to enable real-time adjustments. These systems can autonomously regulate indoor environmental variables based on sensor data related to indoor conditions. Building automation systems represent a more integrated form of this approach, coordinating multiple environmental domains such as thermal, visual, and air quality control through a central platform [110].

Human-in-the-loop systems incorporate occupant involvement in the control process, either directly or indirectly, whereas autonomous systems operate without any human interaction during routine functioning. In human-in-the-loop systems, occupants influence environmental conditions through input mechanisms [29,111], feedback [54], or behavioral patterns [72]. Within these systems, the control logic accounts for ongoing occupant influence during system operation. These systems can be classified further into occupancy-based and comfort-aware control. Occupancy-based control uses real-time data on the presence and movement of occupants to regulate the building's active systems. This method improves energy efficiency by aligning system operation with actual space utilization. Kong et al. [112] showed that using occupancy signals to control HVAC operations resulted in weekly energy savings ranging from 17% to 24%, while also maintaining thermal comfort and indoor air quality. Occupancy detection methods fall into two categories: presence detection and head count [53]. Although these systems outperform static scheduling in adapting to space usage, they typically apply uniform settings to all occupants, which can fail to accommodate individual comfort preferences or specific requirements [113].

Comfort-aware control systems integrate environmental sensor data, operational data from building systems, and subjective occupant feedback to guide control decisions. In contrast to occupancy-based designs, comfort-aware systems aim to personalize control outputs based on individual or group preferences; in other terms, a personal comfort system falls under the comfort-aware category [114]. Subjective feedback is collected through interfaces such as mobile applications [115], periodic surveys [116], or wearable devices [117], and this information is used to fine-tune environmental conditions. Multi-domain comfort-aware systems coordinate adjustments across IEQ domains to avoid trade-offs that compromise overall comfort. Research has shown that optimizing one IEQ domain in isolation can have negative effects on others. For instance, thermal comfort is often prioritized in many buildings; neglecting lighting or acoustic comfort can result in substandard indoor environments that compromise occupant wellbeing [118]. By integrating control decisions across multiple IEQ domains, comfort-aware systems aim to preserve occupant wellbeing under varying conditions and are increasingly supported by systems that are trained on historical and real-time data [119] to detect patterns, forecast needs [2], and continuously adjust control outputs [59]. Comfort-aware control does not rely solely on fixed thresholds but adapts to changing conditions and user needs. In doing so, this mode of operation provides a mechanism for balancing comfort objectives with energy efficiency goals. Models incorporating subjective inputs have also been shown to satisfy individual comfort preferences more effectively than traditional static models [120,121].

This range of control strategies—from human-out-of-the-loop to occupant-centric and autonomous systems—illustrates the shift toward increasingly data-driven, user-centric adaptive designs. As control logic becomes more capable of processing diverse inputs, the ability to align system operation with actual usage conditions improves. The integration of occupant behavior, real-time environmental data, and system performance metrics enables new opportunities for improving energy use while supporting occupant satisfaction and wellbeing.

3.5.2. Closed-loop control techniques

The main objective of this analysis is to provide an overview of the closed-loop control techniques in consideration of the multi-domain indoor environmental quality. Closed-loop control in multi-domain IEQ systems is fundamentally shaped by actuator coupling, where a single control action simultaneously influences multiple environmental variables. Across the reviewed studies, ventilation and shading systems consistently emerge as shared actuators whose adjustments affects thermal, air quality, and visual conditions in parallel [91–93]. For example, modifying airflow rates alters both temperature and CO_2 levels [91], while shading position jointly governs solar heat gains and indoor illuminance [92,93]. This interdependence introduces trade-offs, where improving one domain may unintentionally degrade another, with direct implications for both comfort and energy use.

Early multi-domain implementations relied primarily on rule-based and proportional–integral controllers [91,92]. The literature indicates that these reactive strategies struggle to manage coupled IEQ dynamics because their fixed logic cannot anticipate cross-domain effects or respond effectively to stochastic occupancy and environmental disturbances [91]. Reported temperature violation rates of up to 38.33% per day highlight their limited ability to maintain performance in multi-zone environments [91]. Even when combined with proportional–integral feedback, these approaches remain prone to delayed responses and repeated comfort violations under rapidly changing solar or occupancy conditions [92].

This recurring limitation has driven a shift toward predictive control strategies capable of accounting for cross-domain interactions [91,92]. Studies consistently show that effective multi-domain regulation requires anticipating how control actions in ventilation, shading, or lighting propagate across thermal, air quality, and visual conditions [91–93]. Model Predictive Control (MPC) addresses this requirement by embedding predictive models within an optimization framework that explicitly considers these coupled effects [93]. The MPC algorithm diagram is presented in Fig. 7.

The reviewed literature reveals that different modeling approaches within MPC present trade-offs when applied to multi-domain control. Physics-based models, such as RC networks, offer interpretable representations of thermal dynamics but require additional submodels to capture visual or air quality effects, increasing complexity [10,93]. Data-driven models can learn nonlinear cross-domain relationships directly from measurements, enabling joint prediction of variables such as temperature and glare [93], but their performance depends heavily on the availability of representative multi-domain datasets [22]. Hybrid approaches that combine physics-based and data-driven methods are therefore frequently adopted to balance accuracy and computational feasibility, preserving key interactions such as solar gains that affect both temperature and illuminance while remaining suitable for real-time control [93,94].

Within MPC implementations, these predictive models enable the formulation of multi-objective optimization problems where thermal comfort, glare risk, air quality, and energy use are treated as competing operational targets [10,93,95,96]. The objective function formulation is calculated in Eq. (1) [92].

$$J_i = min_{x,u} \sum_{k=0}^{N-1} l_k(x_k, u_k) + l_N(x_N) \tag{1}$$

These individual objectives are combined into a single cost through weighted aggregation using Eq. (2).

$$J_{total} = \sum_{i=1}^{n} \omega_i J_i \tag{2}$$

Here, $x_k$denotes the state of the indoor environment at step k (e.g., temperature, CO_2 concentration, illuminance), u_k represents the control action applied at that step (e.g., heating or cooling power [123], blind position [124], or battery power flow [125]). N is the horizon of MPC, n

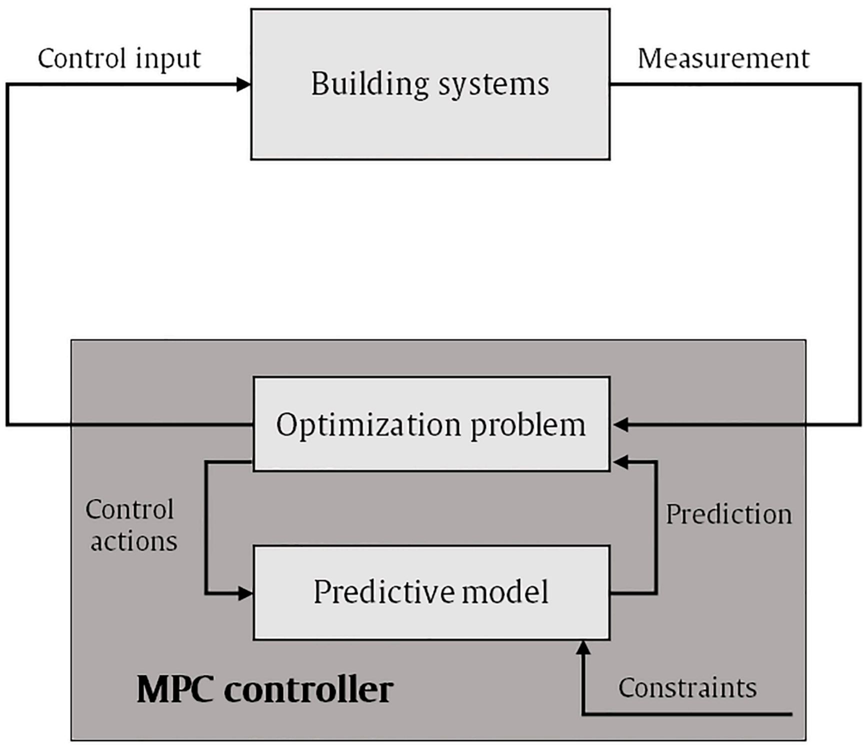

Fig. 7. Multi-domain MPC diagram for building applications, modified from [122].

is the number of objectives in the optimization problem. The stage cost l_k penalizes comfort deviation or energy use, and the terminal cost $l_N(x_N)$ shapes the end-of-horizon condition.

The optimization problem requires predictions of how the indoor environment will evolve under each candidate control sequence. These predictions are generated by the system model, shown in Eq. (3) [124].

$$x_{k+1} = f(x_k, u_k, d_k) \tag{3}$$

which provides the future states used in each objective J_i, and d_k is the disturbances at time k. This relation describes how the indoor environment responds once an action is applied, enabling MPC to evaluate how an action modifies IEQ domains and has coupled effects.

Within multi-domain MPC implementations, constraints define the feasible operating space in which comfort and energy objectives are balanced. Across the reviewed studies, state constraints are most commonly used to enforce acceptable indoor conditions, typically through temperature limits derived from comfort models [9] and CO_2 thresholds linked to ventilation standards [91]. When visual comfort is considered, additional bounds on illuminance or glare indices are introduced [93].

Input constraints, in turn, reflect the physical limits of building systems. Studies consistently impose bounds on HVAC capacity [10], ventilation flow rates [92], and shading movement ranges [93], preventing optimization routines from selecting actions that exceed equipment capabilities. In multi-domain applications, these actuator limits become particularly critical, as shared devices must operate within feasible ranges while influencing several IEQ variables simultaneously.

A recurring characteristic of standard multi-domain MPC formulations is the use of fixed objective weights [9,91], and remains constant throughout the prediction horizon. The literature highlights that this static weighting structure may not fully reflect time-varying comfort sensitivities across domains, where the urgency of thermal, visual, or air-quality deviations can change over time.

To address the issue of having fixed objective weights limitation, recent work introduces adaptive weighting mechanisms such as fractional-order MPC (FOMPC) [98]. By incorporating a time-varying weighting term within the prediction horizon, FOMPC enables differentiated emphasis on immediate versus delayed corrections; the formulation presented in Eq. (4). Reported improvements include gains of approximately 30–40% in tracking performance, along with reduced oscillations and enhanced disturbance rejection [98].

$$J_i = min_{x,u} \sum_{k=0}^{N-1} \omega_k(\gamma, \lambda) \ (l_k(x_k, u_k) + l_N(x_N)) \tag{4}$$

Despite improving flexibility in objective weighting, FOMPC retains key limitations that affect its applicability in multi-domain IEQ control. The parameters governing time-varying weights, ν and λ in $\omega_k(\nu, \lambda)$ parameter, must still be manually tuned [98], preserving designer dependence and limiting autonomy when balancing thermal, visual, and air-quality objectives. More fundamentally, both MPC and FOMPC remain constrained by their reliance on accurate system models. As discussed in Section 3.4, real buildings exhibit coupled and context-dependent responses across domains, making it difficult to develop models that remain reliable under varying operating conditions [91]. This modeling burden reduces predictive accuracy and limits practical deployment in environments where shared actuators simultaneously influence multiple IEQ variables.

These limitations have led recent studies to explore model-free reinforcement learning (RL) as an alternative control paradigm [91]. By learning policies directly from observed system transitions, RL avoids the need for explicit multi-domain models and can adapt to nonlinear dynamics, occupancy variability, and cross-domain actuator effects that complicate MPC formulations. This shift reflects a broader finding in the literature. When actuator coupling and stochastic disturbances dominate system behavior, adaptive data-driven policies provide greater robustness to real-world uncertainties compared to model-based optimization [126].

Across the reviewed implementations, RL enables joint control of variables such as setpoints, ventilation rates, and shading positions, allowing the policy to learn how these actions interact across IEQ domains without requiring an explicit coupling model [91]. The RL algorithm diagram is presented in Fig. 8. Reported results indicate reductions in comfort deviations and energy use relative to MPC baselines, suggesting improved alignment with the irregular operational behavior observed in real buildings [91]. However, this flexibility introduces new challenges. Model-free RL typically requires extensive interaction data to converge, leading to longer training phases and raising concerns related to data efficiency during deployment. Brandi et al. [126] reported that the operating cost of RL control with only one month of training is 160% higher than the MPC controller and with two months of training the gap drops to 21%, and in the third month the gap is 3.6%.

Comparative analysis between RL and MPC was conducted within a simulation environment, where MPC demonstrated superior performance across most evaluated cases. In well-modelled building applications, prior studies have reported discomfort reductions of up to 90.8% under MPC control, whereas model-free RL agents did not achieve comparable performance [128] and incurred 3.6% higher operating costs compared to MPC [126]. Even if cross-domain interactions within building systems can be represented through modeling, real-world operation introduces uncertainty. Under uncertain conditions, RL achieved a 6.3% reduction in power consumption, whereas MPC attained a 9.5% reduction [129].

A limitation in RL-based control is that constraint handling is not enforced in the same way as in MPC. The bounds included in the reward function act as soft penalties, which means the agent may still select actions that push the system outside the acceptable range when the penalty is outweighed by another objective. This behavior is undesirable when a domain has strict limits, like CO_2 upper limits that must not be exceeded. To address this, Fung et al. [130] introduces hard-constraint mechanisms during the action-selection stage by incorporating barrier terms that grow rapidly as the agent approaches the boundary. These terms restrict the feasible set of actions and prevent the policy from selecting values that would force the state outside the required range. This addition preserves the flexibility of RL while reinstating the strict bounds characteristic of MPC, and it provides a pathway for applying RL in settings where certain domains admit no deviation from their prescribed limits [130].

A similar issue arises in RL when combining several reward terms, each with its own weight, as shown in Eq. (5). In multi-domain control, assigning these weights is challenging because of high complexity in constructing a numerical and reliable equation that captures how different IEQ domains, jointly with energy use, influence the reward. That is because each domain responds differently to the same actuator action, and their effects do not follow a common scale that can be merged into a single weighted expression. This subjectivity becomes evident when comparing existing RL studies that target multiple domains. Cui et al. [101] distribute the weights across thermal comfort, indoor air quality, and energy use with values of 0.38, 0.30, and 0.32, respectively, forming a balanced structure that treats the three objectives as nearly equal contributors to the reward. Chen et al. [111], on the other hand, assign a weight of 5 to thermal comfort and 5 to energy consumption, producing a scheme that reflects a different interpretation of priority and a different scaling of the reward terms. One way to overcome this is to have the reward system focus on one single domain, and for the rest, enforces its limits through hard constraints. This allows the reward to focus on one selected domain, while the barrier mechanism maintains the remaining variables within their acceptable bounds. This separation avoids forcing the learning algorithm to reconcile variables that do not share a compatible numerical structure and prevents distortions that occur when several heterogeneous objectives are merged into a single weighted sum.

In multi-domain contexts, the literature further shows that RL performance depends strongly on how states, actions, and rewards are structured. State representations that incorporate multiple IEQ domains encourage cross-domain responses, while action definitions combining temperature control, airflow adjustment, and shading movement reflect the shared influence of actuators [91]. Reward formulations typically balance constraint variables, such as temperature or CO_2 limits, against objective metrics like energy use, enabling the controller to trade-offs between comfort and efficiency. A general form for the overall reward is presented in Eq. (5) as R [99,100].

$$R(s_t, a_t) = -\sum_{i=1}^{n} \omega_i R_i(\tau) \tag{5}$$

where ω_i and R_i are the weight and reward assigned for each objective, s_t represents the state, a_t is the control action, and τ is the given trajectory

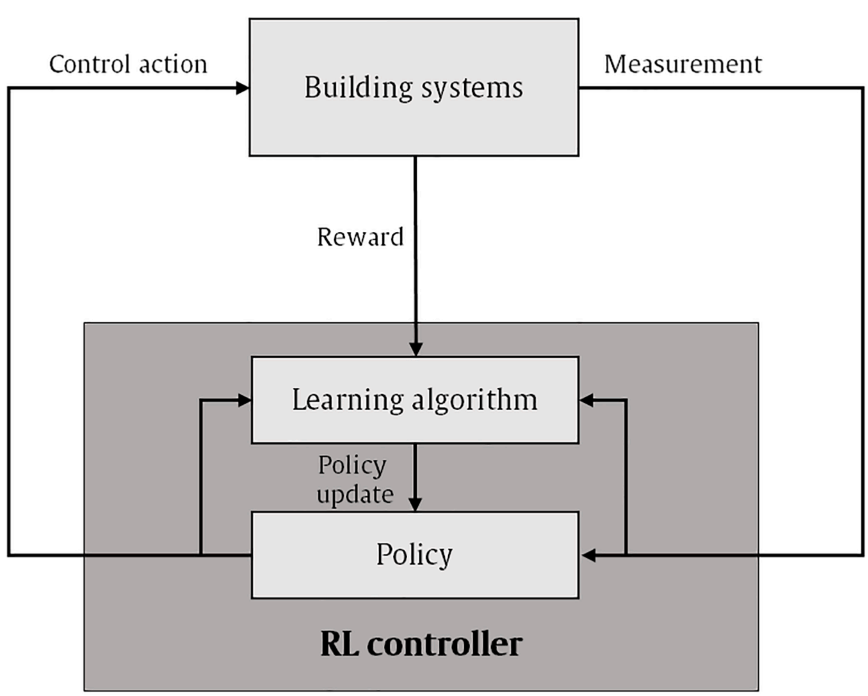

Fig. 8. Multi-domain RL diagram for applications, modified from [127].

$(s_0, a_0, \ldots)$. Through repeated interaction with the environment, the agent adjusts its parameters and learns a policy π_θ that maps each state to an action, as shown in Eq. (6) and maximizes the reward function, which is shown in Eq. (7).

$$a_t = \pi_\theta(s_t) \tag{6}$$

$$R(\tau) = E_{\pi_\theta}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right] \tag{7}$$

The policy serves as the controller once training is complete. In building applications, the policy can be a neural network, a linear model, or any function approximator capable of learning the mapping from multi-domain states to energy- and occupant-centric actions. The discount factor γ determines how much value the agent assigns to future comfort and energy consequences, allowing the controller to anticipate the longer-term implications of the actions.

3.6. Lack of multi-domain control in the literature

The body of work addressing multi-domain control remains narrow. In this review, multi-domain control refers to approaches that explicitly integrate and regulate more than one IEQ domain alongside building energy use within the same control formulation. Based on the systematic review, 23 studies were initially identified as addressing multi-domain control interactions, of which 15 met the PRISMA inclusion criteria and were retained for detailed analysis, as shown in Table 2. Among these, all 15 studies focus on energy use, and within the IEQ domain, the majority of studies focused on thermal comfort, while IAQ was considered in 1 study, visual comfort in 2 studies, and acoustic comfort is not addressed. This uneven domain representation limits the range of cross-domain interactions that can be operationalized, thereby constraining the practical scope of current multi-domain control formulations.

Across the reviewed work, multi-domain formulations are commonly built around MPC or reinforcement-learning schemes, with HVAC systems constituting the primary controlled component, as shown in Table 2. These methods appear consistently, not as a constraint on the field, but as the structure through which authors choose to express the control problem. Their repeated use shapes the way objectives and interactions are framed, even though the underlying domain coverage and comfort definitions remain narrow.

Occupants' multi-domain comfort is often simplified both by limiting the number of considered domains and by reducing how comfort is represented within each domain across the reviewed studies in Table 2. Thermal comfort is reduced to a single variable—indoor air temperature—despite the fact that comfort is shaped by the combined influence of humidity, radiant exchange, air movement, metabolic heat, clothing insulation, and several additional IEQ domains [118]. By narrowing the definition of comfort to air temperature alone, the analyses overlook interactions that can shift perceptual responses, especially in mixed-mode or naturally ventilated environments where multiple domains fluctuate simultaneously. This reduction becomes even more limiting once the definition of acceptable temperature is considered. Most studies adopt fixed temperature limits, spanning 18–28 °C, selected by the authors without reference to the occupants who actually inhabit the space. These limits are treated as universal comfort thresholds. The reliance on static setpoints introduces subjective judgments into the control formulation and creates a mismatch between the assumed and experienced comfort levels. The same reductionist treatment appears in other domains as well, where IAQ is represented solely through CO_2 concentration and visual comfort is restricted to indoor illuminance, leaving out several additional factors that influence perceptual responses in those domains.

According to the relationship graph presented in Fig. 4, this simplification reflects a deeper structural limitation in existing control approaches. The reviewed controllers largely treat indoor environmental variables as direct representations of comfort and use them as control inputs without accounting for how occupants perceive and evaluate these conditions. In doing so, comfort is implicitly assumed to be equivalent to measurable environmental states such as temperature, CO_2 concentration, or illuminance. However, the relationship graph clarifies that comfort does not emerge directly from these variables but from their combined interpretation either through subjective occupant responses or through objective comfort models that translate environmental conditions into perceptual outcomes. By bypassing this intermediate IEQ layer, current controllers neglect interactions both within and across domains, leading to control decisions that respond to physical conditions rather than to experienced comfort. This misalignment explains why many approaches remain unable to support occupant-centric multi-domain regulation despite incorporating multiple environmental measurements.

The issue becomes more pronounced when considering contextual factors. Building typology, envelope properties, occupancy schedules, internal loads, and climatic conditions shape the evolution of the IEQ domains and influence energy use. These variables can shift disturbances, modify constraints, or change how effective the actuators are.

However, as illustrated by the relationship graph, existing control approaches rarely account for the broader contextual factors that influence indoor environmental variables and control performance. Instead, as summarized in Table 2, studies typically incorporate only a limited subset of contextual parameters. For example, Theint et al. [131] addressed building energy use and thermal comfort within their control formulation, yet solar radiation was not included as an input variable despite its influence on both thermal perception and energy demand through its effect on heat gains and indoor conditions. This reflects a common modeling simplification where contextual drivers with indirect influence are omitted.

Including the full range of contextual parameters in a control formulation is not feasible, since the problem size and computational demand grow quickly and prevent real-time implementation [142]. In addition, several contextual factors introduce inherent uncertainty, such as weather-related variables. As a result, control strategies must be robust and remain tolerant to uncertainty [142].

The patterns observed across the literature point in a consistent direction. The formulations presented in these studies reflect the assumptions of the modeler far more than the preferences of the occupants affected by the control actions. Comfort boundaries, domain choices, and contextual treatments are set in advance and remain unchanged, even though real occupants respond to conditions that shift throughout the day and across seasons. This fixed, author-driven formulation places the focus on system operation rather than occupant preference. As a result, according to the control categorization presented in Fig. 6, the control approaches developed in these studies cannot be considered occupant-centric, despite being presented as multi-domain. They can be categorized as autonomous or human-out-of-the-loop.

4. Limitations

Despite the structured screening and synthesis procedure adopted in this study, several limitations should be acknowledged when interpreting the results.

First, the automated screening relied on TF–IDF vectorization and cosine similarity of index keywords to identify highly similar publications and reduce redundant records. Because this procedure depends on the terminology used in indexed keywords, relevant studies that use different vocabulary may receive lower similarity scores and remain undetected as related records. In addition, the selection of the top 10% cosine similarity threshold represents a methodological choice that could marginally influence which studies were retained for full-text review. Although alternative thresholds may lead to minor variations in the included papers, such variations are unlikely to substantially alter the high-level structural patterns and dominant relationships identified

Table 2
Overview of existing multi-domain control studies.

Paper	Control approach	Domains covered	Controlled system	Acceptable ranges of objective	Occupant comfort inclusion	Contextual factors
[131]	MPC	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature (Thermal comfort): 24–28 °C • Variable refrigerant flow (VRF) peak power constraint: 0.27–2.68 kW (10–100% of peak)	Manually picked comfort bound	• Outdoor air temperature • Room characteristics • Electricity pricing
[130]	RL	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature (Thermal comfort): 18–21 °C (occupied) and 15–30 °C (unoccupied)	Manually picked comfort bound	• Outdoor air temperature • System configuration • Seasonal conditions
[132]	MPC	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature: 20.5–28 °C	Only presence	• Outdoor air temperature • Solar radiation
[133]	RL	• Thermal comfort • Building energy use	• HVAC system • Electrochromic Windows	• Indoor air temperature (Thermal comfort): 22–24 °C during 6:00–19:00 (weekdays) and 20–26 °C during all other hours	Manually picked comfort bound	• Outdoor air temperature • Occupancy schedule
[123]	MPC	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature (Thermal comfort): 21–24 °C (occupied) and 15–30 °C (unoccupied) • Max Heat pump electrical power: $\leq$ 4.5 kW	Pre-defined comfort bound	• Outdoor air temperature • Solar radiation • Occupancy schedule • Energy pricing • Building thermal characteristics
[134]	RL	• Thermal comfort • Indoor air quality • Building energy use	• HVAC system	• Indoor air temperature (Thermal comfort): 21–23 °C (Test 1) and 18–24 °C (Test 2) • CO2 concentration (Indoor air quality): $<$ 800 ppm (Test1) $<$ 1000 ppm (Test 2)	Comfort bound is picked from the literature review	• Outdoor air temperature • Solar radiation • Outdoor CO2 concentration • Internal loads • Building physical properties
[124]	MPC	• Thermal comfort • Visual comfort • Building energy use	• HVAC system • Solar shading system	• Indoor air temperature (Thermal comfort): 20 °C $\leq$ T $<$ 28 °C • Daylight glare probability (Visual comfort): $\leq$0.25	Manually picked comfort bound	• Climate variables • Building physical properties
[135]	MPC	• Visual comfort • Energy use	• Artificial lighting system	• light-dependent resistors voltage (Visual comfort): <5 V		• Physical characteristics of lamps
[125]	MPC	• Thermal comfort • Building energy use • CO_2 emissions	• HVAC system • Battery energy storage system	• Indoor air temperature: 19–22 °C	Only presence	• Climate variables • Occupancy schedule • Electricity pricing
[136]	MPC	• Thermal comfort • Visual comfort • Building energy use	• Thermally activated building system • Solar shading system	• Indoor air temperature (Thermal comfort): 20–22 °C • Illuminance (Visual comfort): $\leq$ 500 lx	Picked the air temperature bound from the published standard	• Climate variables • Occupancy schedule
[137]	MPC	• Thermal comfort • Building energy use	• HVAC system (only airflow rate)	• Indoor air temperature: 19–23 °C	Only presence	• Outdoor air temperature • Solar radiation • Internal loads
[138]	MPC	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature: 19–23 °C	Only presence	• Outdoor air temperature • Outdoor relative humidity • Solar radiation • Energy pricing
[139]	RL-MPC	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature	Picked the air temperature bound from the published standard	• Outdoor air temperature • Energy pricing • Solar radiation • Occupancy schedule
[140]	RL-MPC	• Thermal comfort • Building energy use	• HVAC system	• Indoor air temperature (22 $\pm$ temperature tolerance band °C)	Manually picked comfort bound	• Outdoor air temperature • Energy pricing • Energy generation

(continued on next page)

Table 2 (*continued*)

Paper	Control approach	Domains covered	Controlled system	Acceptable ranges of objective	Occupant comfort inclusion	Contextual factors
[141]	MPC	• Battery Degradation cost • Thermal comfort • Indoor air quality • Building energy use	• HVAC system	• Indoor air temperature (23–27 °C) • Relative humidity (40–60%)	Manually picked comfort bound	• Outdoor air temperature • Outdoor relative humidity • Outdoor pollution

in the synthesis. Consequently, the final pool of reviewed papers may partly reflect the dominant terminology in the database, introducing a potential algorithmic selection bias.

Second, the relationship graph was constructed exclusively from relationships explicitly reported in the reviewed studies that satisfied the PRISMA inclusion criteria. If a relationship exists in practice but is rarely examined or not clearly reported in the literature, or discussed in studies outside the final inclusion pool, it will not appear in the graph. Therefore, the resulting structure reflects the current reporting patterns in the literature rather than the full set of potentially plausible interactions among occupants, indoor environmental variables, and building systems.

Third, a minimum requirement of two independent studies was applied before including a relationship in the graph. This improves the reliability of the synthesized relationships but may exclude novel or emerging interactions that have been investigated in only a single study.

Fourth, the reviewed studies originate from different climates, building types, operational conditions, and occupant populations. Because environmental responses and occupant behavior vary across these contexts, the relationships identified in the graph should be interpreted as general interaction patterns rather than universally applicable causal mechanisms.

Finally, the proposed graph represents a conceptual synthesis of reported relationships rather than a quantitative causal model. It does not estimate the strength, magnitude, or statistical significance of the interactions. The graph should therefore be interpreted as a conceptual guide for understanding relationships relevant to occupant-centric control design, rather than as a predictive model capable of generating numerical control rules.

5. Conclusions and future work

This study synthesizes the literature on occupant-centric multi-domain control systems through the development of a conceptual relationship graph derived from a systematic literature review. The graph structures the relationships among IEQ domains, occupant comfort preferences, building control systems, and building energy use, providing a high-level representation of the interactions reported across the reviewed studies. As a conceptual framework, the graph serves as a reference structure against which existing control approaches can be mapped and analysed. By comparing the components and relationships considered in individual studies with those represented in the graph, it becomes possible to identify which aspects are commonly addressed and which remain underrepresented or omitted. In this way, the graph supports the evaluation of occupant-centric control approaches in relation to occupants' perceived comfort, multi-domain IEQ considerations, and energy-related objectives.

The findings of the systematic literature review show a clear imbalance across IEQ domains. Thermal comfort dominates the literature, accounting for 48.2% of single-domain studies and appearing in multi-domain investigations. A similar dominance of the thermal domain is observed in studies that integrate occupant-centric control with building energy use. Only fifteen studies explicitly addressed this type of control, and within this subset, IAQ was included in only one study, visual comfort in two studies, and acoustic comfort was not considered. Among the control methods applied in these studies, reinforcement learning (RL) and model predictive control (MPC) are the most common. MPC performs well in well-defined environments, whereas RL demonstrates stronger adaptability under uncertain conditions.

Beyond the imbalance study across IEQ domains, several recurring limitations emerge when occupant-centric multi-domain control studies are examined against the derived relationship graph. Environmental variables are often treated as direct proxies for comfort, while occupants' subjective evaluations and established comfort models are absent. Additional limitations include the omission of cross-domain interactions between IEQ domains and the exclusion of contextual factors that influence control objectives. These patterns suggest that many existing systems operate as autonomous environmental control strategies rather than genuinely occupant-centric multi-domain solutions. This paper and the proposed relationship graph provide a conceptual reference for analysing and comparing occupant-centric control approaches discussed in the literature, and can support the analysis and future development of occupant-centric control approaches.

CRediT authorship contribution statement

Mohammad Salehi: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Panayiotis Papadopoulos:** Conceptualization, Methodology, Project administration, Validation, Writing – review & editing. **Ioanna Kyprianou:** Methodology, Supervision, Writing – review & editing. **Salvatore Carlucci:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mohammad Salehi reports financial support was provided by The Cyprus Institute. If there are other authors, they 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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.buildenv.2026.114885.

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