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Current trends and future directions for addressing multi-domain occupant demands in building automation and control systems

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ABSTRACT

Building automation and control systems (BACS) are central to energy performance and occupant comfort in non-residential buildings. Comfort is inherently multi-domain, including thermal, visual, acoustic, and air quality requirements. Multi-domain BACS involves frequent trade-offs across domains when conflicting control actions arise, such as providing glare control versus daylight availability. Yet existing occupant-centric control research treats building services in isolation, and prior multi-domain comfort reviews rarely examine how multi-domain demands are integrated into BACS decision logic across services. We conducted a systematic review of 43 studies to examine how multi-domain occupant demands are represented and operationalized in BACS. Across the evidence base, thermal comfort is universal, while visual and air quality are frequently included. Acoustics is rarely addressed due controllability constraints. Most studies remain unimodal in their demand representation, even when multiple domains are in scope. Integrated BACS implementations are therefore largely built on within-domain formulations. Multimodal demand models that encode cross-domain and combined effects are uncommon and are rarely implemented in integrated BACS. Rule-based strategies dominate multi-domain controllers. Optimization-based and learning-based controllers are also used, but they often rely on fixed weights or reward terms that make trade-offs difficult to interpret. In addition, actuator choice is rarely made explicit when multiple services can achieve the same target state. Future research should benchmark unimodal and multimodal demand formulations under comparable control contexts, extend bottom-up multimodal models beyond thermal and air quality into integrated BACS, especially for façade control, and develop transparent, preference-aware policy designs that make priorities and service actions understandable.

1. Introduction

Building automation and control systems (BACS) are central for achieving energy efficiency, occupant comfort, and operational goals in buildings, with their real-world impact depending on design quality, user interaction, and long-term performance validation [1]. This role is particularly critical in commercial and other non-residential buildings, where energy demand is high and occupancy patterns are diverse [2]. In such contexts, BACS are the primary mechanism for balancing indoor environmental conditions in occupied spaces by coordinating heating, ventilation and air-conditioning (HVAC), lighting, and shading through automated routines designed to optimize performance under varying conditions [3]. In practice, most BACS implement relatively clear strategies for non-occupied periods (e.g., setback, switch-off), but when spaces are occupied, they face additional challenges related to heterogeneous occupant presence, behaviour, and comfort expectations [4].

Most BACS treat occupants as passive recipients, considering IEQ domains individually (unimodal), and when manual control is available, this is often considered a sub-optimal alternative to fully automated ones [4]. This often leads to low occupant acceptance of automated controls in offices [1,5,6], fuelling growing interest in occupant-centric BACS. Occupant-centric approaches seek to learn preferred environmental conditions from actual occupant feedback and behaviours [7]. By integrating the occupant in the control loop, these systems aim to improve occupant comfort and satisfaction by aligning BACS more closely with occupant-specific comfort demands [4,8]. Recent technological advances support this shift. The widespread adoption of sensors, wearable devices, and Internet of Things platforms enables the capture of granular data on personal comfort, indoor climate, and occupancy patterns [9]. In parallel, artificial intelligence and machine learning techniques can interpret large volumes of occupant data, predict individual preferences, and propose adaptive, real-time control strategies that account for

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domain interactions [10–12].

Ensuring occupant comfort is inherently a multi-domain challenge – a balancing act among often different aspects of indoor environmental quality (IEQ), including thermal, visual, acoustic, and air quality [4,13]. Automated facades, for instance, have been shown to actively influence daylight access, glare discomfort, thermal loads and indoor air quality [1,14]. In practice, BACS must navigate trade-offs, as actions improving one factor can negatively affect another [13]. These trade-offs are evident in everyday operation. For instance, lowering a blind to reduce glare can also diminish daylight and solar heat gains. An increase in mechanical ventilation improves air freshness but may also cool the space in winter. Opening a window can impact indoor temperature and introduce noise or air pollutants.

Several reviews address parts of this challenge. A broad mapping of cross-domain perception and behaviour has been provided, exposing weak theoretical foundations and the need for systematic approaches to capture occupant interactions [15]. Others focused on methodological quality, offering criteria and guidelines to strengthen the design and reporting of multi-domain comfort studies [16]. The scalability of comfort models has also been examined, identifying barriers that prevent multi-domain models from being applied in design or operation [17]. Further reviews of empirical evidence on IEQ interactions and overall satisfaction show that domains do not weigh equally [18]. Concentrating on simulation frameworks, research highlights how modelling tools can assess cross-domain interactions but remain limited in capturing occupant-driven trade-offs [19]. Additionally, the role of living laboratories in empirically testing multi-domain comfort under realistic conditions has been emphasized to bridge the gap between laboratory and field studies [20].

When looking beyond multi-domain comfort modelling and focusing on multi-domain operationalisation in control, a challenge emerges. This is illustrated by an exploratory campaign on dynamic façades, where acoustic discomfort caused by the operational noise of automated blinds became a decisive trigger: the noise constrained, and in some cases prevented, blind operation even when glare mitigation was required [21]. A similar occupant-driven trade-off has been reported in which access to view increased occupants' acceptance of higher indoor temperatures, indicating that visual benefits can relax thermal demands under otherwise equivalent conditions [14]. However, recent occupant-centric control (OCC) reviews indicate that most efforts still focus on HVAC and lighting services, separately [22]. Therefore, while existing work advances multi-domain comfort knowledge and OCC research aligns automation more closely with occupants, it still stops short of systematically examining how multi-domain occupant comfort demands are operationalised within BACS control logic across multiple building services.

This review examines the operationalization of multi-domain occupant demands within BACS across multiple building services. We focus on non-residential buildings, primarily offices, because in these buildings BACS are widely used for multiple environmental domains and, in addition, the high variability in occupant demands and schedules poses a persistent challenge for optimal control solutions. We critically examine how multi-domain comfort demands are represented, integrated, and operationalized within BACS in current existing literature. Specifically, we aim to: (i) map the current landscape of multi-domain studies for BACS; (ii) analyse how occupant demands are defined and modelled into the control logic across different building services; and (iii) identify commonalities and gaps in integrating multi-domain occupant comfort demands within BACS.

2. Methodology

A systematic review was conducted to understand how multi-domain occupant comfort demands are represented and integrated into BACS. We define a multi-domain study as one that addresses at least two IEQ domains (thermal, visual, indoor air quality, and acoustics). Since multi-domain considerations can appear either in the occupant comfort demand modelling and/or in the BACS implementation, we collected studies along two main coupled multi-domain characterisations (Fig. 1).

First, multi-domain occupant comfort demand modelling can be classified as unimodal or multimodal. Adapted from Chinazzo et al., [16] a study is unimodal when it follows a same-modality formulation, meaning that IEQ factors only inform the corresponding comfort response within the same domain (e.g., thermal comfort predicted from air temperature, or perceived air quality predicted from CO_2). A multimodal study is defined when the comfort demand model explicitly represents interactions across domains through cross-domain and combined effects. Operationally, this requires that predictors from at least two IEQ factors domains enter the occupant demand model as meaningful explanatory variables, enabling cross-domain influence on a domain-specific response or joint multi-domain influence on a non-domain specific response, such as overall comfort.

Second, multi-domain BACS can be classified as integrated, not integrated, or not applied. Integrated BACS refers to control implementations where the same control logic operates multiple building services and/or controls multiple domain objectives and constraints within one decision framework (typically through hierarchical rule-based strategies or multi-objective optimisation-based frameworks). Not integrated refers to control frameworks where services are controlled independently, for example one decision rule for heating and cooling and a separate rule for ventilation, often driven by unimodal occupant comfort models without explicit trade-offs across domains. Ultimately, some studies in this review developed multidomain occupant demand models but do not implement or test them within BACS.

We searched SCOPUS and Web of Science (WoS) using the keywords strategy detailed in Table 1. Our initial search returned 1174 records from SCOPUS and 219 unique records from Web of Science. After screening, 251 studies were found to specifically address occupant demands in BACS, but only 43 (≈20 %) met our criteria for multi-domain integration.

3. Literature review results

3.1. Distribution of studies per time, type of study, and control environment

Fig. 2 illustrates the distribution of studies (2005–05.03.2026) integrating multi-domain occupant demands for BACS. The figure categorizes studies based on monitoring data from laboratories, real buildings, and simulations. The number of studies across real building, laboratory, and simulation settings increased from one in 2005 to 43 at the beginning of 2026. Over the last ten years, a significant increase has occurred, with more than 80% of the studies published during this period. In terms of settings, no clear trends are found for real buildings and simulation studies. Over time, studies shifted to human-centred research considering real occupants' information.

Fig. 3 summarises how monitoring data from laboratories, real buildings, and simulations were used to define occupant demands and whether these demands were tested in BACS. Focusing on studies with monitored data from laboratories or real buildings, only 11 studies (≈25%) implemented and tested multi-domain occupant demands in BACS in real buildings. In contrast, 11 studies evaluated control using a simulated environment with real monitored data, and 7 studies developed occupant demand models without applying them in BACS. Regarding studies considering human participation, 14 studies involve real occupants. Most of these are single-occupant offices, while a smaller subset reports shared offices with 12, 8, 4, or 2 occupants. Overall, the evidence indicates that multi-domain occupant demands are still rarely implemented and validated in multi-domain BACS under real monitored conditions.

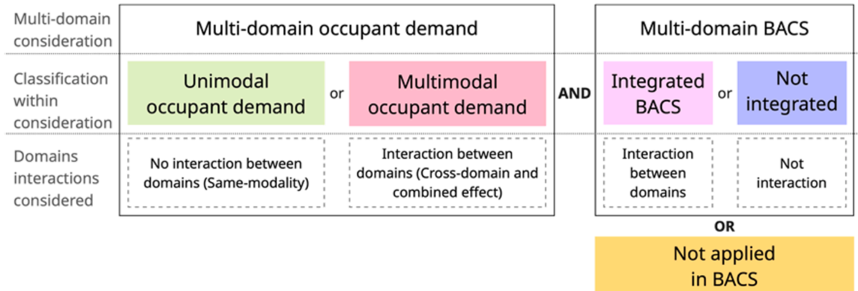

Fig. 1. Classification framework for multi-domain occupant comfort demand representation and integration into BACS. Two coupled characterisations are distinguished: (i) occupant-demand representation (unimodal vs multimodal) and (ii) the level of multi-domain integration in BACS (integrated vs not integrated or not applied). Domain interaction refers to explicit dependencies between domains and is considered present only when it is represented in the occupant demand model (as multimodal demand) and/or in the BACS decision logic (integrated BACS).

Table 1
Summary of keywords used for the systematic search of studies on the occupant integration in BACS (Search date: 06–02–2026).

Search Aspect	Query	Rationale
Occupant and Comfort	TITLE-ABS-KEY((human OR user OR occupant OR individual OR person*) W/1 (comfort OR behaviour OR interaction OR perception OR preferenc* OR requirement* OR acceptance OR sensation OR satisfaction))	Captures studies focusing on occupant in terms of comfort, behaviour, interaction, and perceptions.
Building Environment	TITLE-ABS-KEY((building AND indoor AND environment*))	Limits the search to studies concerned with indoor building environments.
Control And Automation	TITLE-ABS-KEY((control OR automa*))	Ensures the inclusion of studies addressing building control systems and automation, thereby targeting works that integrate control strategies or develop occupant models for those.
Non-Residential	AND NOT TITLE-ABS-KEY (residen* OR home*)	Excludes studies related to residential settings, and home environments.
No review	AND NOT TITLE-ABS-KEY (review)	Excludes review articles
Article and conference papers	AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"cp"))	Restricts results to peer-reviewed articles and conference papers to ensure the inclusion of high-quality, relevant studies.

Note: The search was run as one combined query, where the three 'TITLE-ABS-KEY(…)' blocks relate to 'AND', so a paper had to mention (in its title, abstract, or keywords) (i) occupant-related terms, (ii) building/indoor-environment terms, and (iii) control/automation terms. Within each block, 'OR' lists alternative terms, and '*' is a truncation (e.g., "preferenc*" matches "preference" and "preferences"). The operator 'W/1′ is a proximity rule meaning 'within one word' in either order, so it captures phrases such as "occupant comfort" as well as "occupant thermal comfort". We excluded residential studies using `AND NOT TITLE-ABS-KEY(residen* OR home*)`, and excluded review articles with `AND NOT … (review)`. Finally, we restricted results to journal articles and conference papers using the document type filters (`DOCTYPE="ar"` and `DOCTYPE="cp"`).

3.2. Existing multi-domain integration approaches

Fig. 4 presents a frequency analysis of the indoor environmental quality domains investigated across the 43 studies, highlighting both single and multi-domain coverage. The thermal domain is present in all publications that were selected by the review criteria (n = 43 studies). This is followed by the visual and air quality domains, included in 31 studies. In contrast, the acoustic domain is the least represented, appearing in only four studies.

When examining domain combinations, the most frequent combination is thermal, visual, and air quality domains, appearing in 16 out of 43 studies (approximately 37%). This is followed by the combination of thermal and air quality (n = 12, 27%) and thermal and visual (n = 11, 26%). Only a small subset of studies (n = 3, 7%) adopts a fully integrated approach by explicitly addressing all four domains. This limited consideration may reflect that acoustics is rarely an actively controlled domain in typical BACS, so noise is more often monitored alongside occupants' acoustic preferences (e.g., louder/neutral/quieter) [23,24]. In practice, acoustic performance is typically handled during system design, although operational impacts can arise indirectly through controllable elements, particularly blind movements where motor noise can be disruptive and may constrain use of personal control [21]. Overall, the lack of dedicated actuators for acoustic regulation means that acoustics is more often reported as a contextual nuance than treated as an actively controlled IEQ factor.

We characterised the reviewed studies along the domains considered used to model occupant comfort demands, and the set of domains controlled in BACS (Fig. 5). At the occupant demand modelling, the thermal domain is mostly considered. The most frequent domain scope combines thermal, visual, and indoor air quality (n = 15, 35%), followed by thermal with indoor air quality (n = 12, 28%) and thermal with visual (n = 11, 26%). Only one study focuses on the visual domain alone (n = 1, 2%); we considered it because it explicitly operationalises a glare and daylight trade-off in control. Acoustics remains marginal (n = 4, 9%) and appears only in multimodal demand modelling, either combined with thermal and visual (n = 1) or combined with thermal, visual, and indoor air quality (n = 3). Importantly, acoustics is never actively controlled in BACS.

Following the characterisation introduced in the methodology, we further distinguish (i) unimodal and multimodal occupant demand modelling, and (ii) integrated, and not integrated BACS. The majority of follow a unimodal demand modelling (n = 28, 65%), while multimodal approaches that explicitly encode cross-domains or combined effects are less common (n = 15, 35%). Even within the most common multi-domain scope (thermal, visual, and indoor air quality), nearly all studies remain unimodal (14 of 15). This indicates that multiple domains are often present in the study scope, but occupant demands are typically represented through within domain formulations rather than considering interactions within domains.

On the BACS side, studies are split between integrated implementations (n = 16, 37%), not integrated implementations that control multiple services in parallel (n = 18, 42%), and studies that do not apply the demand model in BACS (n = 9, 21%). A key observation is that integrated implementations rely exclusively on unimodal demand modelling: none of the multimodal demand models are operationalised in integrated BACS. Instead, multimodal demand models are either paired with not integrated control (n = 6) or remain offline (n = 8),

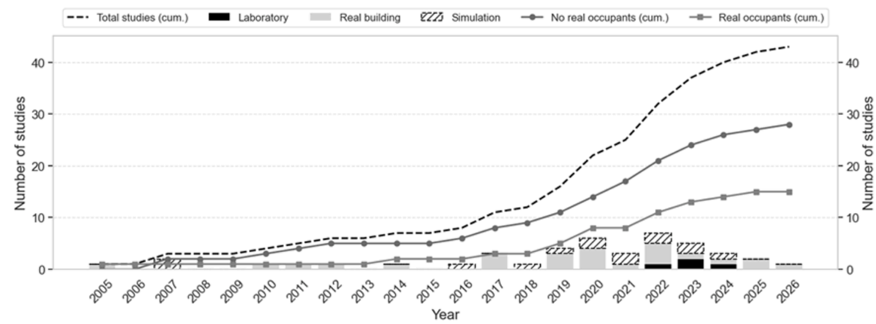

Fig. 2. Number of studies (2005–2024) integrating multi-domain occupant demands, categorized by study setting and real occupant data consideration in bars. Lines represent the cumulative number of studies over the time.

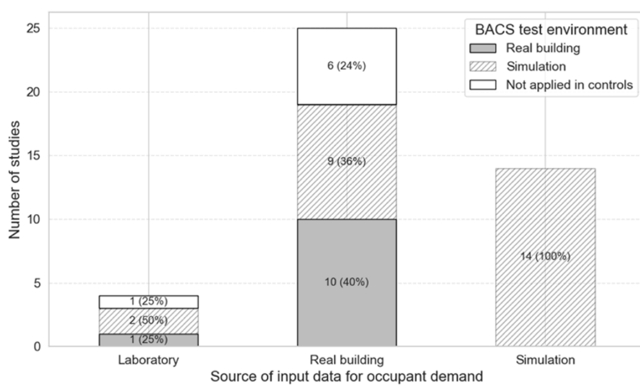

Fig. 3. Distribution of studies by source of input data for occupant demand modelling per control environment test. Studies that do not test occupant demand in controls only work on the development of bottom-up comfort models such as personal comfort models.

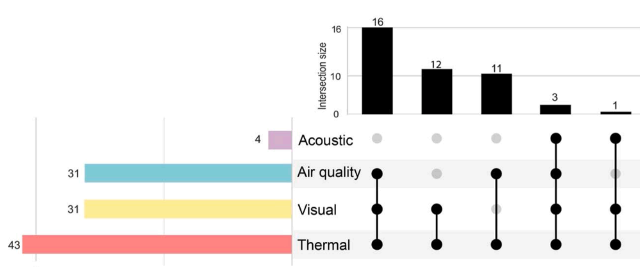

Fig. 4. Distribution of studies across thermal, visual, acoustic, and air quality domains. Horizontal bars show how often each domain is considered, while vertical bars stand for the frequency of different domain combinations in multi-domain studies.

highlighting a gap between modelling domain interaction effects and deploying them within integrated control logic.

Four recurring combinations emerge from multi-domain mapping. First, (Fig. 5 label a) unimodal demand modelling with integrated BACS (n = 16) is the most frequent combination. Here, domain interactions occur at the BACS level even though occupant demands are modelled within each domain. Integrated implementations most often coordinate thermal and visual control actions, and a substantial subset extends coordination to include indoor air quality. A representative example is an integrated controller that coordinates shading and heating setpoints using separate within domain comfort formulations, for instance glare and solar gains criteria driving façade actions alongside HVAC control for indoor temperature.

Second (Fig. 5, label b), unimodal demand modelling with not integrated BACS (n = 12) captures studies where multiple services are controlled in parallel, with each service driven by its own within-domain comfort demand or threshold. The most common controlled domain scope combines thermal and indoor air quality, followed by thermal, visual, and indoor air quality, and then thermal and visual. A typical example is a system where ventilation is triggered by a CO_2 threshold while heating and cooling follows an independent temperature rule set, without coordination between the two decisions.

Third (Fig. 5, label c), multimodal demand modelling with not integrated BACS (n = 6) is less common. Here, cross-domain or combined-effects are represented in the occupant demand model, yet control remains service specific rather than coordinated across domains. A representative example is cross-domain comfort models for thermal preference that includes CO_2 as a predictor with air temperature, while the implemented control only control the HVAC air temperature setpoint.

Fourth, (Fig. 5 label d) multimodal demand modelling not applied in BACS (n = 9) is the dominant pathway for multimodal studies, indicating that occupant demand models accounting for domains interactions are developed and evaluated offline but rarely implemented within BACS. A typical example is a unified multi-domain preference or segmentation model that jointly uses thermal, visual, acoustic, and indoor air quality variables to infer occupant types or preferences but is only validated as a predictive model without being translated into control actions.

The main result of this mapping is a clear separation between where multi-domain complexity is represented and where it is applied in BACS. In most cases, studies either coordinate multiple services using unimodal demand definitions, or develop multimodal demand models without translating them into control. This indicates that the current bottleneck is not only modelling multi-domain occupant demands but operationalising them within integrated BACS.

3.3. Definition of occupant demands for BACS

Two main approaches of describing occupant demands are found in current research: (i) top-down approaches (n = 23), which define occupant demands based on expert design or generalized assumptions about comfort, typically drawn from international standards (e.g., ASHRAE Standard 55, EN 16,798–1) or conventional comfort models such as the Predictive Mean Vote (PMV), Predicted Percentage of Dissatisfied (PPD), or Daylight Glare Index (DGI), representing a general occupant without accounting for individual variance in demands; (ii) bottom-up approaches (n = 20), which infer occupant demands from occupant subjective feedback (e.g., thermal or visual preferences), physiological information, and/or observed behaviours (e.g., thermostat setpoint overrides or manual control of lighting or shading systems). After this information is gathered, some studies directly integrate occupant behaviour into the control policy, whereas others use it to develop data-driven occupant comfort models that define the demands

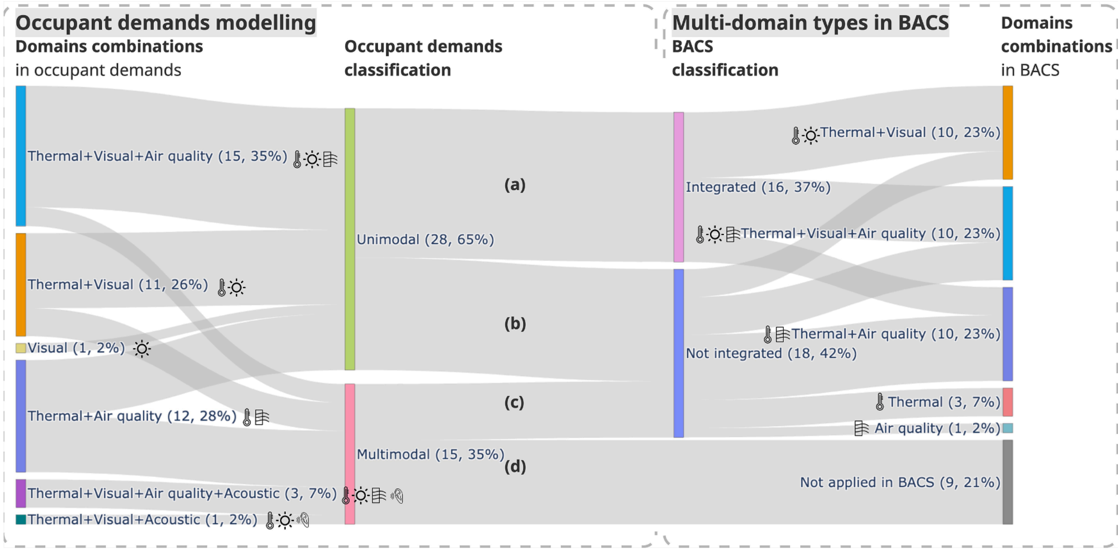

Fig. 5. Sankey diagram representing how multi-domain studies are distributed across (left to right): (i) the domain combinations used in occupant demand modelling, (ii) whether occupant demands are classified as unimodal or multimodal, (iii) the level of BACS integration (integrated, not integrated, or not applied in BACS), and (iv) the domain combinations controlled in BACS. Flow width is proportional to the number of studies, and percentages are reported relative to the full review sample (n = 43). The four labels (a–d) indicate the recurring configurations discussed in the text: (a) unimodal demand modelling with integrated BACS, (b) unimodal demand modelling with not integrated BACS, (c) multimodal demand modelling with not integrated BACS, and (d) multimodal demand modelling not applied in BACS.

for control, either at the individual or group level.

Fig. 6 shows the monitored information used to define occupant demands into four groups: indoor environmental quality variables, personal parameters, occupant behaviour variables, and occupant feedback. Indoor environmental quality dominates across the whole sample and is used almost equally in bottom-up (n = 80, 48% of the group) and top-down studies (n = 85, 52%), because both types of approaches need a physical description of the indoor environmental states to define comfort targets or constraints. Beyond environmental quality monitoring, other monitoring aspects diverge sharply. Bottom-up approaches are designed to capture inter-occupant variability and to support inference of demands from observed data, which explains why they account for almost all personal parameters (25 of 28, 89% of the group), most occupant behaviour variables (28 of 35, 80%), and nearly all occupant feedback variables (25 of 26, 96%). In practice, this includes physiological variables (e.g., clothing, skin temperature, heart rate, age), occupant behaviour with building services such as, and occupant feedback (e.g., thermal preference and sensation votes, visual and acoustic preferences). In contrast, top-down approaches are primarily built to operationalise standard formulations, so they rely on indoor environmental quality variables and only incorporate a limited subset of personal parameters already embedded in classical models (for example clothing and metabolic rate in PMV) plus a small set of occupant behaviour information, most notably occupancy status to support schedules.

3.3.1. Top-down comfort models

Top-down comfort models (n = 23) for defining occupant demands in BACS fall into three categories: (i) *threshold-based*, (ii) *model-based*, and (iii) *hybrid*. Threshold-based demand studies (n = 15) use static setpoints for IEQ parameters, most commonly air temperature and illuminance, sometimes applied to relative humidity, CO_2, or ventilation rate. Because these thresholds are implemented independently and remain fixed, the approach is simple to deploy but inherently unable to reflect changing individual occupant preferences [25–30]. Model-based demand studies (n = 3) estimate comfort using models, most commonly PMV for the thermal domain, or by defining reward functions that integrate variables such as temperature and air quality (e.g., air quality index (AQI)) to train reinforcement-learning agents, rather than relying on pre-defined thresholds. Some studies combining models make use of the PMV and Predicted Glare Sensation Vote (PGSV) [31], and DGP alongside PMV [32]. Hybrid demands (n = 5) integrates comfort models with variable thresholds depending on the IEQ domain. For example, PMV as a thermal comfort model, and CO_2 and illuminance levels as air quality and visual comfort demands to the control logic [33]. Overall, we observe that most studies applying model-based or models in hybrid demands approaches remain predominantly driven by thermal comfort models, while air quality is still treated through threshold-based IEQ parameters (Fig. 7). More broadly, this type of demand formulation is unimodal since it does not include the interactions between comfort domains. Consequently, every domain is treated separately at the occupant demand level.

3.3.2. Bottom-up comfort models

This subsection reviews the 20 studies that develop bottom-up comfort models. These approaches either use direct occupant input within the control logic or learn data-driven comfort models to represent occupant demands at the individual level (personal comfort models) or at the group of shared-space level (e.g., occupants sharing rooms or offices). The results therefore focus on (i) whose demands are represented for control (individual vs group/shared space) and (ii) how those demands are represented, distinguishing unimodal versus multimodal formulations based on the model inputs and outputs used for inference and control.

3.3.2.1. Occupant representation. As shown in Fig. 8, these studies are divided into three groups depending on the representation strategy: (i) individual (n = 10), (ii) group-or room-level models (n = 7), and (iii) studies that develop several models that incorporate both individual and group preferences (n = 3).

Individual models leverage the work of personal comfort models (n = 10). Examples include deep-learning forecasts of personal glare and thermal discomfort [34], individual productivity predictors across IEQ domains [35,36], and personalised shading, lighting, or window-operation models [37]. Some studies classify personal thermal sensation or work engagement [38,39], while others infer preferred

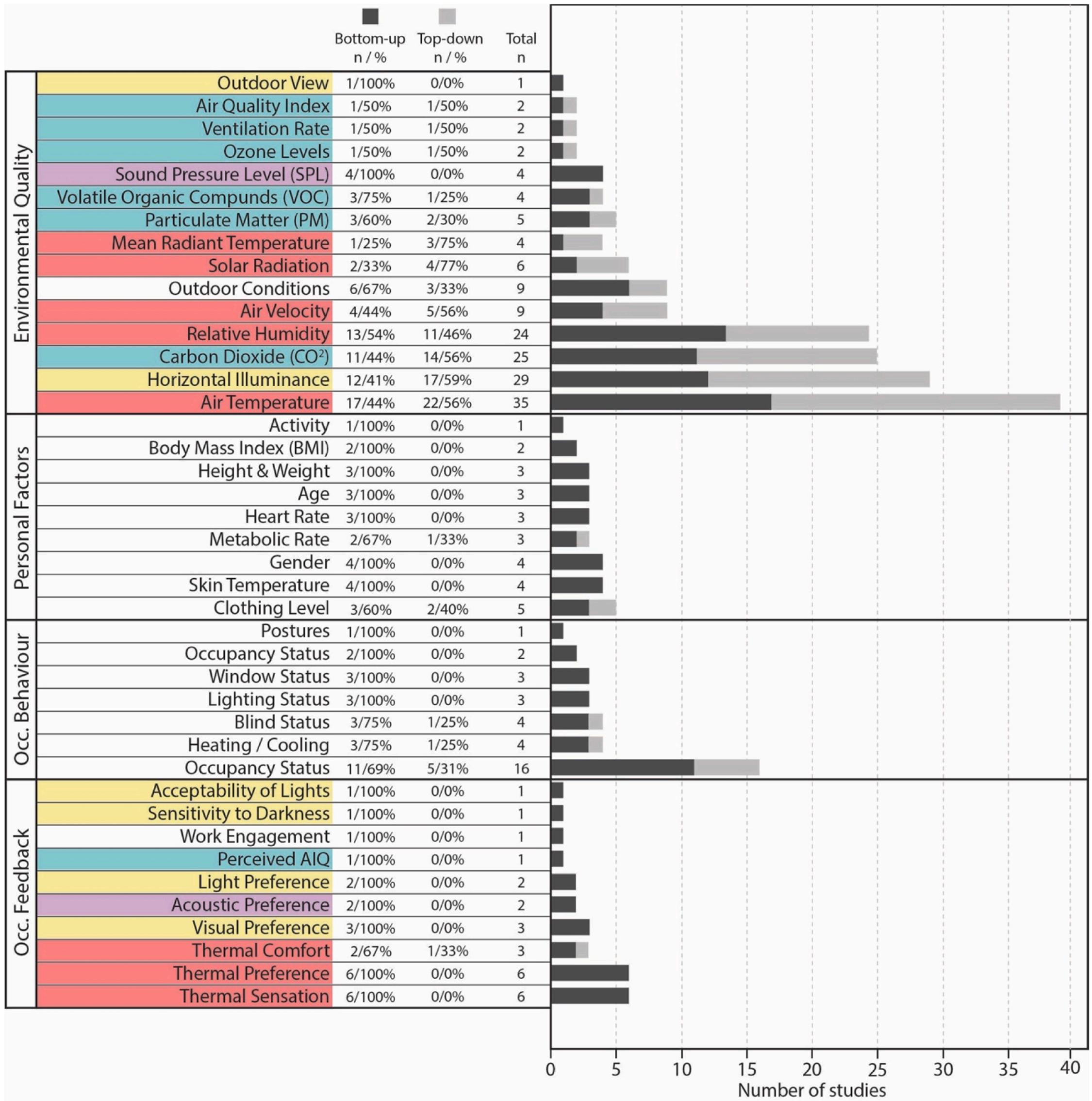

Fig. 6. Distribution of monitoring variables used to define occupant demands, clustered per variable type (IEQ, personal parameters, occupant behaviour and occupant feedback). In dark grey: bottom-up approaches. In light grey: top-down approaches. Colour-code for domain-specific variables: orange for thermal, yellow for visual, blue for air quality, and purple for acoustic.

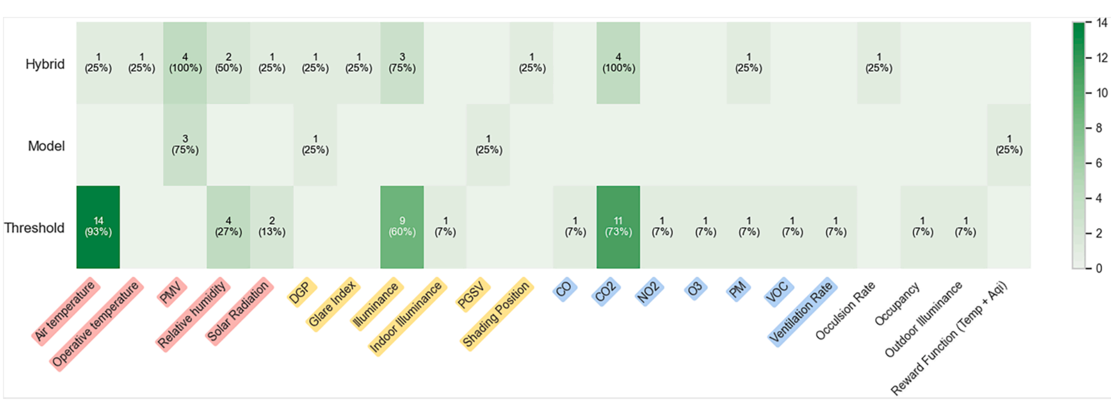

Fig. 7. Heatmap of top-down occupant-demands studies (n = 23), showing the count and percentage of papers within each approach type (threshold, model, hybrid). Rows correspond to the three approach categories; columns list variables and models. Annotations give the raw count and percentage of that approach's total. Colour-code for domain-specific variables: orange for thermal, yellow for visual, and blue for air quality.

temperatures through fuzzy logic [40] or physiological modelling [41].

Inferring individual preferences in shared spaces is a challenge, most of

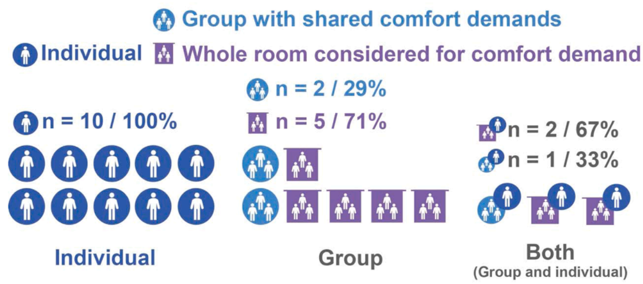

Fig. 8. Distribution of bottom-up studies (n = 20) according to how occupant demand is represented in control models: at the individual level, group level, or both. Within group and 'both' representations, the circle symbol denotes group-level models with shared comfort demands, and the square symbol denotes room/zone-level models where the whole room is treated as the unit of comfort demand. Percentages and counts indicate the proportion of studies using each approach.

them rely on active identification of occupants such as digital-IDs to link comfort feedback to specific individuals. Two studies infer occupant identity passively, using occupancy detection and video detection rather than explicit user IDs. In single-office spaces they simply rely on occupancy detection and prediction.

Group or room-level models (n = 7) treat shared spaces as the unit of analysis and are commonly used when individual identification is not feasible or when occupancy in each zone change frequently. These include room-level thermal satisfaction predictors [42], and statistical models of shared window or door use [43]. Others learn collective patterns through association-based analyses of group behaviours [44], or identification of two kind of occupants based on their sensitivities [45]. Another study infers room-level temperature preference bands from aggregated thermostat overrides and enforces them together with CO_2 levels as hard constraints while optimizing HVAC setpoints and ventilation [46]. However, they are not compared with such a baseline as done in other studies with single-domain focus [47].

There are three studies investigating the combination of comfort models at both personal and room levels simultaneously [48]. Two pursue a two-model strategy [48], where personal comfort models are compared with room level comfort models to derive optimal control setpoints based on wearable information and identification. The remaining study adapts its modelling approach to the type of space. In shared rooms, it combines individual thermal preference votes with CO_2 levels using a neural network to generate control actions, whereas in single occupant offices it relies solely on personal comfort models identified through occupancy detection [49]. To conclude, we observe that the challenge of inferring individual preferences in shared spaces is addressed primarily through digital identification, most enabled by wearable devices.

3.3.2.2. Modelling approaches and domain representation. In bottom-up occupant-demand modelling, unimodal studies are predominantly applied to the thermal domain. Many uses machine-learning classifiers to map thermal votes into categories such as "prefer cooler" or "prefer warmer" based on indoor air temperature [24,38]. Some studies extend this classification framework to window opening prediction or computer vision-based posture analysis for comfort and discomfort states [34,50]. Similarly, statistical modelling studies utilize logistic regression to predict specific comfort probabilities or ventilation behaviours, whereas others employ fuzzy logic to compute preferred temperatures [35,36]. Distinct from predictive modelling, some studies embed occupant input directly into the control policy, for example by translating thermostat overrides into control updates through association-based rules rather than learning an explicit model [44,51].

In multimodal studies, both inputs and outputs become more complex because the occupant-demand model explicitly includes predictors from multiple IEQ domains. The most common pattern is thermal demand models with indoor air quality predictors, typically CO_2, to represent cross-domain or combined effects. In this direction, hierarchical Bayesian and related statistical frameworks have reported improved prediction of thermal satisfaction when CO_2 is included alongside temperature compared with temperature only models [42]. Machine-learning studies similarly combine thermal and indoor air quality predictors in neural networks to infer preferred setpoints [49]. Other approaches combine thermal and IAQ inputs to output setpoints for both heating and ventilation [24,48]. One study learns temperature preference bands from thermostat setpoint overrides using an incremental Naive Bayes classifier and then enforces these bounds, together with CO_2 levels as hard constraints in an MPC that optimizes HVAC setpoints and ventilation. On the statistical side, researchers have employed multinomial logistic regression within semantic digital twins to integrate thermal, visual, acoustic, and CO_2 parameters for occupant segmentation [23]. Conversely, other regression-based models first classify occupants as sensitive or tolerant and subsequently weight IEQ parameters differently [45]. Only one study develops separate classifiers for thermal and visual comfort: the thermal model uses only temperature and humidity inputs, whereas the visual model draws on both thermal (temperature, humidity) and visual (illuminance, glare) variables to capture combined effects for multi-domain model prediction [38]. Only one incorporates a set of 45 factors, spanning thermal, visual, acoustic, and IAQ domains, into one multinomial model that simultaneously classifies multi-domain occupant preference responses as output [24], and only one study incorporates physiological information for thermal comfort modelling while maintaining constant indoor air quality thresholds [41]. Overall, the multimodal bottom-up models identified in this review are largely enabled by statistical and machine-learning approaches, in contrast to top-down formulations that typically treat comfort domains in isolation (Fig. 9).

3.4. BACS strategies

3.4.1. Control logic and policy design for BACS

Among the 43 studies reviewed, 32 incorporate occupant demands into BACS (in a real building and or simulation). The remaining 9 studies modelled multi-domain occupant demands for BACS but did not implement them in control, neither in a simulation environment nor in a real building, leaving implementation for future work. Two types of control logic strategies were identified: (i) heuristics (rule-based) and (ii) optimization-based approaches. In our sample, a total of 15 studies used heuristic approaches relying on predefined rules set based on

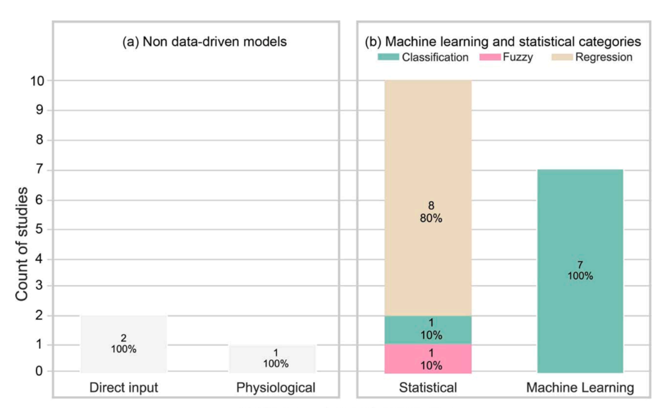

Fig. 9. Distribution of modelling approaches used in bottom-up demand modelling for BACS. Two overarching categories are distinguished: (a) non data-driven models, which include analytical models of physiological response and direct-input formulations embedded in control logic; and (b) data-driven models, being machine-learning (n = 7) and statistical methods (n = 10).

expert knowledge. The remaining 19 studies formulated a mathematical framework as optimization in the control logic. Also, all the reviewed studies focused on zone-level rather than system-level controls.

We identified the controlled building services across the reviewed BACS implementations, as summarised in Fig. 10. Importantly, the co-occurrence of multiple services does not necessarily imply that they are coordinated through an integrated multi-domain decision logic; in several studies, services are still governed by independent rules or separate controllers. Heating and cooling remain the dominant controlled service (n = 29). Within this set, 15 studies also control lighting (52%) and 17 also control ventilation (59%), while fewer include blinds (n = 7, 24%) or windows (n = 4, 14%). Lighting control appears in 18 studies and most often co-occurs with heating and cooling (n = 15, 83%), followed by ventilation (n = 8, 44%) and blinds (n = 8, 44%). Ventilation control appears in 18 studies and is almost always paired with heating and cooling (n = 17, 94%), whereas co-control with blinds is rare (n = 1, 6%). Blinds control is reported in 10 studies; when blinds are controlled, lighting control is typically present (n = 8, 80%) and heating and cooling is also common (n = 7, 70%), reflecting the frequent coupling of façade and lighting actions with thermal objectives. Window control remains the least frequent (n = 5), but when present it usually co-occurs with heating and cooling (n = 4, 80%) and sometimes with lighting (n = 3, 60%), with smaller overlap with blinds and ventilation (both n = 2, 40%).

3.4.2. *Heuristic (rule-based) approaches*

Based on the coordination level among domains and services, the reviewed studies are classified into three categories: single building service control with multimodal demand models (Fig. 11a), decentralized multi building service control (Fig. 11b), and centralized multi building service control (Fig. 11b). Table 2 classifies the 15 rule–based controllers we reviewed by the IEQ domains they control and whether the rules allow explicit integration of those domains.

A large subset of heuristic studies implements not integrated BACS using rule-based logic. Within this set, we distinguish two categories: single building service control (n = 7) and decentralized multi building service control (n = 3). In single building service control, the control action targets only one service, most often heating and cooling, even though the occupant demand model can be multimodal and combine predictors from multiple domains (for example, thermal demand models that use both temperature and CO_2 as explanatory variables, but

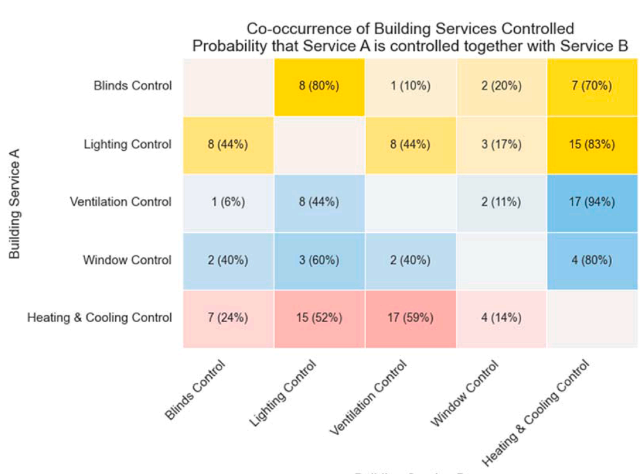

Fig. 10. Co-occurrence matrix of building services controlled together. The rows (Y-axis) list each "base" service and the columns (X-axis) list the "co-controlled" service. Each cell is annotated as "n (p %)", where n is the number of studies controlling both services and p % is n divided by the total studies controlling the row-service (Y-axis). The greyscale indicates the same percentage values.

translate the output only into HVAC setpoint updates) [40,51]. Single-service control studies also exist in the visual domain, for instance lighting dimming rules [52]. In decentralized multi building service control, multiple services are controlled, but each service follows its own independent rule set, typically defined through unimodal demand representations and domain-specific thresholds. In [51], only HVAC is actively controlled, while CO_2, relative humidity, and horizontal illuminance are treated as independent setpoint constraints in the simulation scenarios definition rather than considering interaction between domains and building services. Similarly, mechanical ventilation is often used to maintain CO_2 below a fixed threshold while a separate rule independently enforces thermal bounds for heating and cooling [27,53, 54]. Overall, multimodal demand modelling appears mainly in single building service control, whereas decentralized multi building service control is predominantly governed by unimodal demands.

Rule-based studies that implement centralized multi building service control (n = 5) are considered integrated BACS. In these studies, explicit multi-domain trade-offs are handled within a single rule hierarchy that coordinates multiple services through ordered "if–then" decisions, where one comfort goal is prioritised over the others. This ordered prioritisation was identified in five of the fifteen rule-based studies. First, glare is treated as a hard priority in façade-oriented controllers: blinds are lowered as soon as a glare index threshold (DGI or DGP) is exceeded, and only afterwards do the rules evaluate daylight targets or thermal conditions, which can increase cooling demand when solar gains are reduced through shading [26,32,52]. Second, indoor air quality is prioritised over thermal and daylight targets in one façade controller, where CO_2 is kept below 1000 ppm in the double-skin cavity before stabilising cavity temperature, and only then are blinds modulated for daylight [25]. Third, within the visual domain, some controllers prioritise daylight availability before electric lighting, for example controlling daylight target with electrochromic glazing and then increasing luminaire output if daylight is insufficient, which can reduce lighting energy but does not adapt if thermal penalties dominate [55]. Across these centralized rule hierarchies, the priority order and thresholds are fixed. None of the reviewed studies reports rules that re-rank objectives or adapt thresholds in response to changing occupancy, seasonal context, or dynamic energy prices. The implementations also span different façade technologies, including internal roller shades [32], internal venetian blinds [52], double skin façade with integrated venetian blinds [25], suggesting that the same priority-based logic is applied across hardware types rather than being tailored through adaptive decision rules.

3.4.3. *Optimization-based approaches*

Optimization-based controllers explicitly formulate mathematical frameworks that represent trade-offs between energy performance and/or occupant comfort, subject to indoor environmental quality constraints. These formulations are used to find the optimal state of the indoor environment and derive a policy, i.e., a sequence of control actions, to achieve that state. In this review we classify the 19 optimization studies into three types (Table 3): multi-objective frameworks that jointly optimize comfort and energy metrics alongside constraints (Fig. 12a), single-objective frameworks that minimise energy or cost while treating comfort as constraints (Fig. 12b), and comfort-only approaches that minimise discomfort or occupant actions without constraints (Fig. 12c).

Multi-objective optimisation with constraints studies (MO+C, n = 7) are coded as integrated BACS because they embed multiple domain objectives and constraints within a single optimisation framework, so trade-offs across domains are resolved inside one decision problem. In terms of occupant demand modelling, four of the seven MO+C studies rely on top-down demand definitions, which are coded as unimodal because they use PMV and or fixed IEQ thresholds as domain-specific targets rather than modelling cross-domain interactions [33,36,58,59]. The remaining three incorporate bottom-up demand by bringing

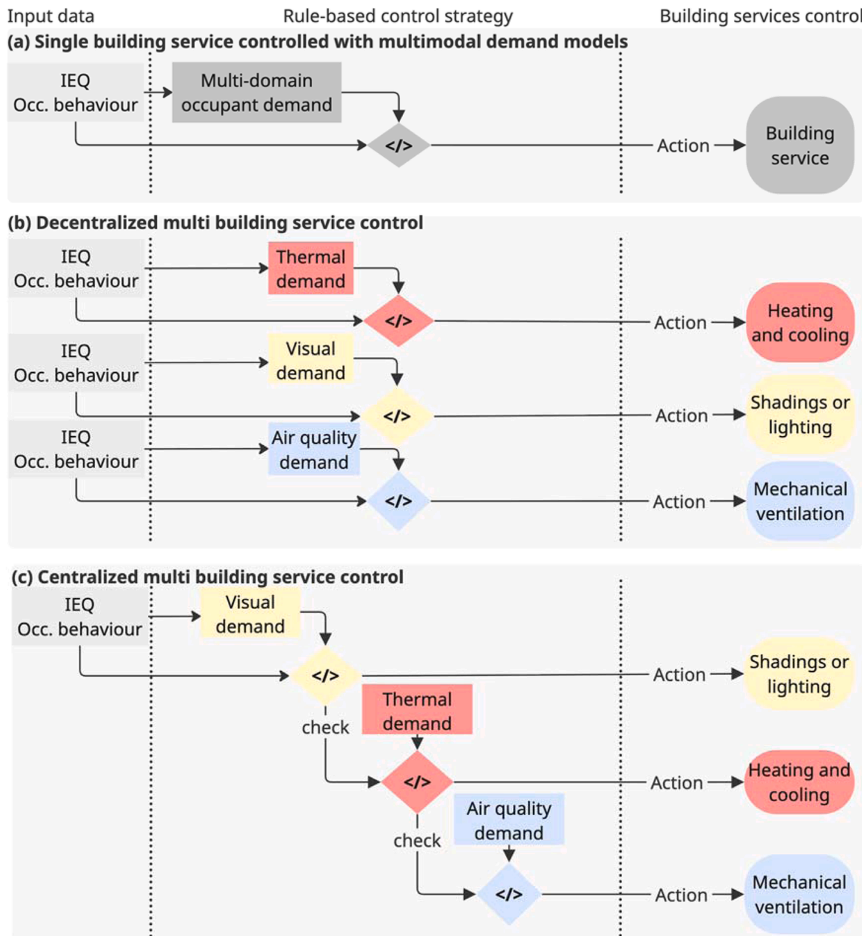

Fig. 11. Representation of the three types of rule-based strategies found in the literature. (a) One building service control with multi-domain demand models. (b) Decentralized multi-domain control without interaction. (c) Centralized multi-domain control.

occupant behaviour or feedback into the objective function, for example by penalising thermostat and lighting overrides alongside energy use [45], or by combining energy costs with preference models learned from longitudinal feedback (e.g., thermal and airflow preference regressions) [35], including formulations that explicitly account for occupant override setpoints within the comfort terms [29].

In single-objective optimisation with constraints (SO+C, n = 9), most studies are coded as not integrated BACS (6 of 9). These formulations optimise a single energy or comfort objective while using IEQ constraints (temperature, illuminance, CO2, humidity, sometimes PM), so multiple domains are considered but just as constraints rather than in an integrated manner. Examples include energy use intensity minimisation with temperature and illuminance bounds [60], HVAC operating-cost minimisation with PMV and perceived IAQ bounds [41], and power minimisation subject to combined IEQ constraints such as CO2, daylight factor or illuminance, air temperature, and plug loads [61]; similarly, several HVAC controllers enforce thermal and IAQ variables as hard constraints without integrating decisions across building services [62]. In contrast, three SO+C studies are coded as integrated because they co-handle multiple IEQ constraints within one optimisation that coordinates decisions affecting more than one domain: a joint HVAC and lighting formulation enforcing thermal and visual comfort limits (PMV and PGSV) [31], an integrated formulation that enforces combined temperature, CO_2, and illuminance constraints while optimising thermal comfort (through PMV) [30], and a power minimisation formulation that jointly manages temperature, relative humidity, CO2, and illuminance under a single optimisation [63].

Finally, only three studies optimise only optimise comfort objectives (SO, n = 3), without energy objectives and without comfort constraints. In these cases, any multimodal structure is primarily expressed in the occupant demand model rather than in integrated BACS decision-making. Examples include minimising thermal discomfort using occupant feedback as the optimisation target [48], minimising window-opening actions based on a bottom-up model of ventilation behaviour that uses both thermal and IAQ predictors [43], or a reinforcement-learning window controller that penalizes thermal discomfort (relative to temperature thresholds) and IAQ discomfort via outdoor AQI when the window is open, without an explicit energy objective and without hard IEQ constraints [64].

Despite the apparent sophistication of these mathematical formulations, multi-domain trade-offs are often handled through simple scalarization. Most studies collapse multiple IEQ factors into a single objective using a weighted sum. RL-based controllers follow the same logic: they optimise one scalar reward that jointly penalizes PMV, CO_2 (or related IAQ indicators), and sometimes energy use. In both cases, the relative importance of domains is fixed a priori by the chosen weights. As a result, it is difficult to infer how the controller resolves conflicts between domains in operation, which limits the interpretability of the reported optimization-based BACS performance.

3.4.4. Performance evaluation of multi-domain occupant demands in BACS

An analysis of 32 studies applying multi-domain occupant demands in BACS indicates a fragmented landscape. While some studies use multi-domain occupant demands equally in both control logic and evaluation metrics [32,35,45,49,56,59,64], others assess comfort with occupant overrides or feedback as KPIs while using thresholds or

Table 2
Description of the rule-based control logic, domains controlled, and whether the logic explicitly coordinates interactions between domains or treats them as independent.

Refs.	Domains controlled	Coordination	Description and decision hierarchy
[49]	Thermal	Single building service control	HVAC setpoints derived from a thermal model (with IAQ inputs) applied directly; no coordination with other services.
[40]	Thermal	Single building service control	Personalized thermal comfort model updates HVAC setpoints; only the thermal domain is controlled.
[56]	Visual	Single building service control	Blinds and dimmable luminaires coordinated to meet visual comfort targets; no thermal or IAQ control.
[53]	Thermal, IAQ	Single building service control	Single HVAC controller uses occupancy, temperature, and ventilation demand to adjust supply air; other services not involved.
[28]	Thermal, IAQ	Single building service control	HVAC controller adjusts supply airflow and outdoor air fraction from temperature and CO_2 levels.
[26]	Thermal, Visual	Single building service control	Shading actuated based on solar radiation, temperature, and illuminance; HVAC and lighting are not co-optimized.
[54]	Thermal, IAQ	Single building service control	Occupancy-based HVAC enforces fixed temperature setpoints and a CO_2 limit using one system.
[57]	Thermal, Visual, IAQ	Decentralized	Separate loops for HVAC, windows, shading, and lighting keep PMV, CO_2, and illuminance within thresholds.
[51]	Thermal, Visual, IAQ	Decentralized	Decentralized control controls HVAC. Ventilation, Illuminance levels are considered as setpoint constraints in the simulation scenarios.
[27]	Thermal, IAQ	Decentralized	Separate fuzzy indices for thermal comfort and IAQ trigger domain-specific actions (e.g., fans, exhaust).
[32]	Thermal, Visual, IAQ	Centralized	1st Move roller shades to eliminate glare (DGI < 22). 2nd. Use HVAC to correct PMV into [−0.5, +0.5].
[52]	Visual	Centralized	1st Adjust shading to reduce daylight glare probability (DGP). 2nd. Reach daylight illuminance target. 3rd. Preserve outdoor view.
[25]	Thermal, Visual, IAQ	Centralized	1st Keep CO_2 in double-skin cavity <1000 ppm. 2nd. Hold cavity-air temperature within ±1 K. 3rd. Modulate blinds for daylight.
[55]	Thermal, Visual	Centralized	1st Control solar gains to meet indoor temperature target. 2nd. Keep illuminance levels.
[38]	Thermal, Visual	Centralized	Recommender system jointly evaluates thermal and lighting conditions to assign occupants to workstations.

traditional comfort models as input for the control logic [52,53,57].

Some studies apply the same metrics to inform both control decisions and performance evaluation. For instance, one approach uses personal comfort models based on occupant interaction frequency with thermostats and evaluates system performance by measuring the reduction of these interactions [49]. Results showed a reduction from 4–9 monthly adjustments to just one under the deployed control scheme. Similarly, control logic was designed around PMV and DGI thresholds and performance was evaluated using the same indicators [32]. Their integrated shading-HVAC controller maintained thermal and visual comfort for approximately 99% of the year within the defined acceptable ranges. Adopting a behaviour-driven approach, the number of HVAC and lighting overrides served as both inputs to the control system and key performance indicators [45]. This strategy effectively tied control adaptation to observed occupant behaviour reduction. A similar rationale was followed by assessing performance based on the frequency with which occupants remained within their preferred comfort bands, a metric that was simultaneously used within the BACS [35,56]. Reinforcement learning-based frameworks further illustrate this alignment where reward functions are defined using indoor environmental quality (IEQ) thresholds, such as PMV and CO_2 concentrations, and system success is evaluated by calculating the percentage of time conditions remained within these predefined comfort thresholds [59,64].

In contrast, other studies demonstrate occupant-centric performance evaluation metrics. These studies often apply predefined environmental thresholds in the control logic but rely on post-occupancy questionnaires or indirect behavioural proxies for evaluation. For example, thermal and visual environments were controlled using PMV and illuminance thresholds, but comfort was evaluated through occupant satisfaction ratings on a 7-point scale, creating a clear distinction between system operation and outcome measurement [57]. Similarly, ASHRAE Standard 55 satisfaction thresholds (≥80% of occupants satisfied) were targeted within the control logic, yet system performance was assessed only via post-occupancy surveys [53]. Visual comfort was based on subjective glare discomfort and user override behaviour collected through surveys, but the control logic remained bound to static thresholds such as PMV and DGI, without adapting to reported preferences [52].

4. Discussion

4.1. Heterogeneous occupant demand modelling for multi-domain BACS

Across the reviewed literature, occupant demands are predominantly represented through top-down formulations. In both research and practice, “demand” is often defined via standard, and static setpoints for temperature, CO_2, illuminance, or relative humidity. These representations are straightforward to implement, but they can remain substantially misaligned with occupant requirements [66]. In our review, around half of these top-down formulations are implemented in not integrated BACS, where each domain is defined independently (thermal via PMV or air temperature, IAQ via CO_2 limits, visual via illuminance or glare). In these cases, domain interactions are not represented in either the occupant demand definition or the BACS decision logic. In contrast, integrated BACS in this review rely on unimodal demand representations, most often top-down, and combine or prioritise these within a single decision framework (e.g., rule hierarchies or scalarised objectives). As a result, domain interactions are handled at the policy level in integrated controllers, whereas they remain absent in not integrated BACS. We discuss how these policy level interactions are operationalised in the subsequent sections

On single-domain literature, thermal comfort literature has extensively studied inter-individual variability and contextual dependence [67]. Bottom-up approaches respond to this by learning occupant (or group) requirements from data, rather than relying on fixed setpoints. Within this review, the most common multi-domain bottom-up implementations are multimodal, most frequently capturing cross-domain effects in which air quality predictors (typically CO_2) are included to explain thermal comfort demand [39,40,42,43,49,68,69]. At the same time, evidence from thermal comfort suggests that fully personalised models are not always necessary: broad temperature ranges can satisfy a large share of occupants [70], and group-level bottom-up comfort models can perform comparably to personal comfort models in some contexts [71]. This suggests that research effort may be more effectively directed toward multimodal bottom-up models that capture IEQ interactions, rather than pursuing perfect individual personalization for the thermal domain.

The need for multimodal occupant demand models is reinforced by

Table 3
Overview of optimization-based control strategies, classified by formulation type, energy and occupant objectives, use of constraints, and accounting of multi-domain interaction. Legend: MO+C: Multi-Objective + Constraints, SO+C: Single-Objective + Constraints, SO: Single-Objective.

Refs.	Type	Control objectives related to energy parameters	Control objectives related to occupant	Constraints	Level of integration
[36]	MO+C	Energy costs	Indoor environmental quality (Air T., Lux, C02)	Lower illuminance, Lower/Upper air flow rate	Integrated
[45]	MO+C	Energy use intensity	Minimize thermostat and lighting override	Lower/upper temperature setpoint, Lower/upper illuminance.	Integrated
[35]	MO+C	Energy costs	Indoor environmental quality (Air T., AQI)	Lower/upper illuminance, Lower/upper air flow rate	Integrated
[33]	MO+C	Energy consumption (HVAC and lighting)	PMV and Indoor environmental quality (C02, Lux)	Upper/lower PMV, CO_2 and illuminance.	Integrated
[58]	MO+C	Power demand	Indoor environmental quality (Air T., RH, Lux, AQI)	Upper/lower PMV and CO_2	Integrated
[59]	MO+C	Energy consumption	PMV and C02 Levels	Lower/upper air temperature, illuminance, AQI	Integrated
[29]	MO+C	Power consumption	Indoor environmental quality (Air T., Lux, C02)	Upper/lower air temperature, illuminance, and CO2.	Integrated
[60]	SO+C	Energy use intensity	-	Lower/upper temperature setpoint, illuminance	No integrated
[41]	SO+C	Cost HVAC operation	-	Lower PIAQ, Upper/Lower PMV	No integrated
[31]	SO+C	Energy consumption (HVAC and Lighting)	-	Lower PGSV, upper/lower PMV	Integrated
[30]	SO+C	-	PMV	Lower/Upper air temperature, CO_2, illuminance	Integrated
[65]	SO+C	-	Indoor environmental quality (Air T., Lux, C02)	Lower/Upper air temperature, CO_2, illuminance	No integrated
[61]	SO+C	Power consumption	-	CO_2, daylight Factor, illuminance, air temperature, plugged Loads	No integrated
[63]	SO+C	Power consumption	-	Lower/upper air temperature, RH, CO_2, illuminance	Integrated
[62]	SO+C	Energy consumption	-	Lower/upper air temperature, RH, CO_2	No integrated
[46]	SO+C	HVAC energy consumption	-	Lower/upper air temperature, RH, CO_2, PM	No integrated
[48]	SO	-	Self-reported thermal comfort	-	No integrated
[43]	SO	-	Minimize window opening	-	No integrated
[64]	SO	-	Indoor environmental quality (Air T., AQI)	-	Integrated

evidence that comfort responses and occupant behaviour are shaped by domain interactions rather than single-domain effects. For example, studies of window opening and shading show that behaviour is driven by multiple variables and trade-offs [72]. Increased daylight and view access can coincide with higher indoor temperatures and increased glare discomfort, illustrating that actions improving one domain can degrade another [73]. Other work similarly highlights that building context shapes combined IEQ perception in office environments [74]. Despite this, progress in multimodal bottom-up occupant demand models for BACS remains limited. We identified only one bottom-up study explicitly spanning thermal and visual domains [38], while most bottom-up developments remain confined to single domains, such as lighting control based on illuminance [75] or bottom-up shading models linking illuminance with occupant behaviour [76]. Façade control illustrates this gap clearly: occupants operate façades for multiple, often conflicting, reasons: brightness, glare control, view access, thermal comfort, air quality, and privacy [21,77,78]. Overall, these findings indicate that research efforts may be more effectively directed toward the development of multimodal models that capture complex IEQ interactions [18], rather than the pursuit of perfect individual personalization for the thermal domain.

Further research should address two gaps. First, it remains unclear when unimodal, top-down demand models are good enough for multi-domain BACS, because benchmarking against multimodal demand models under comparable control contexts is largely absent, especially in real building contexts. Second, multimodal bottom-up occupant demand models should expand beyond the thermal and air quality domains and be implemented and tested in BACS. In this review, most bottom-up multimodal work that also involves the visual or acoustic domains are not included in BACS control logic. This gap is particularly critical for façade-related decisions, where trade-offs across thermal, visual, and IAQ domains are most explicit [1]. Addressing it requires implementing multimodal demand models in control logic and evaluating their added value against unimodal baselines in both integrated and not integrated BACS.

4.2. The contextual barrier of multi-domain rule-based controls

Rule-based controllers remain among the most widely implemented control strategies because they are simple, transparent, and easy to adjust. In practice, rule-based control is still the dominant approach in real buildings [79]. This reality also influences more advanced control research: several AI-based controllers, including reinforcement learning, often use imitation learning from rule-based policies to accelerate training and improve stability [80]. Consistent with this, our review shows that rule-based control remains the most common policy design approach in multi-domain BACS. At the same time, rule-based control is best suited to settings with relatively simple objectives, where interpretability and predictability are prioritised over modelling complexity [81].

In not integrated rule-based BACS, rules are commonly implemented in parallel, with each service driven by its own thresholds and no explicit coordination across domains. In integrated rule-based BACS, multiple domains are handled within a single conditional or hierarchical rule set, where domain priorities are predefined by expert judgement. Here, a decision in one domain is conditioned on the state or limits of another. For example, shading actions intended to prevent glare are evaluated alongside their thermal implications through solar gains. In this review, the most common integrated pattern is prioritising glare control, then preserving daylight, while avoiding excessive heat gains [32,52].

Despite their operational appeal, engineered multi-domain rules introduce a contextual barrier. First, rule performance can be rigid and difficult to transfer across buildings or technologies. For example, studies reported that changing the shading technology increased occupant overrides under the same rule logic, suggesting limited transferability of expert tuned rules across setups [21,52]. Second, thresholds and priority orders vary substantially across studies, yet the rationale behind these choices is often not stated and is typically attributed to expert knowledge. This is problematic because recent preliminary evidence indicates that occupants show large variability in preferences across contexts and may weight thermal, visual, and air quality conditions differently depending on the situation [82]. A key open question is

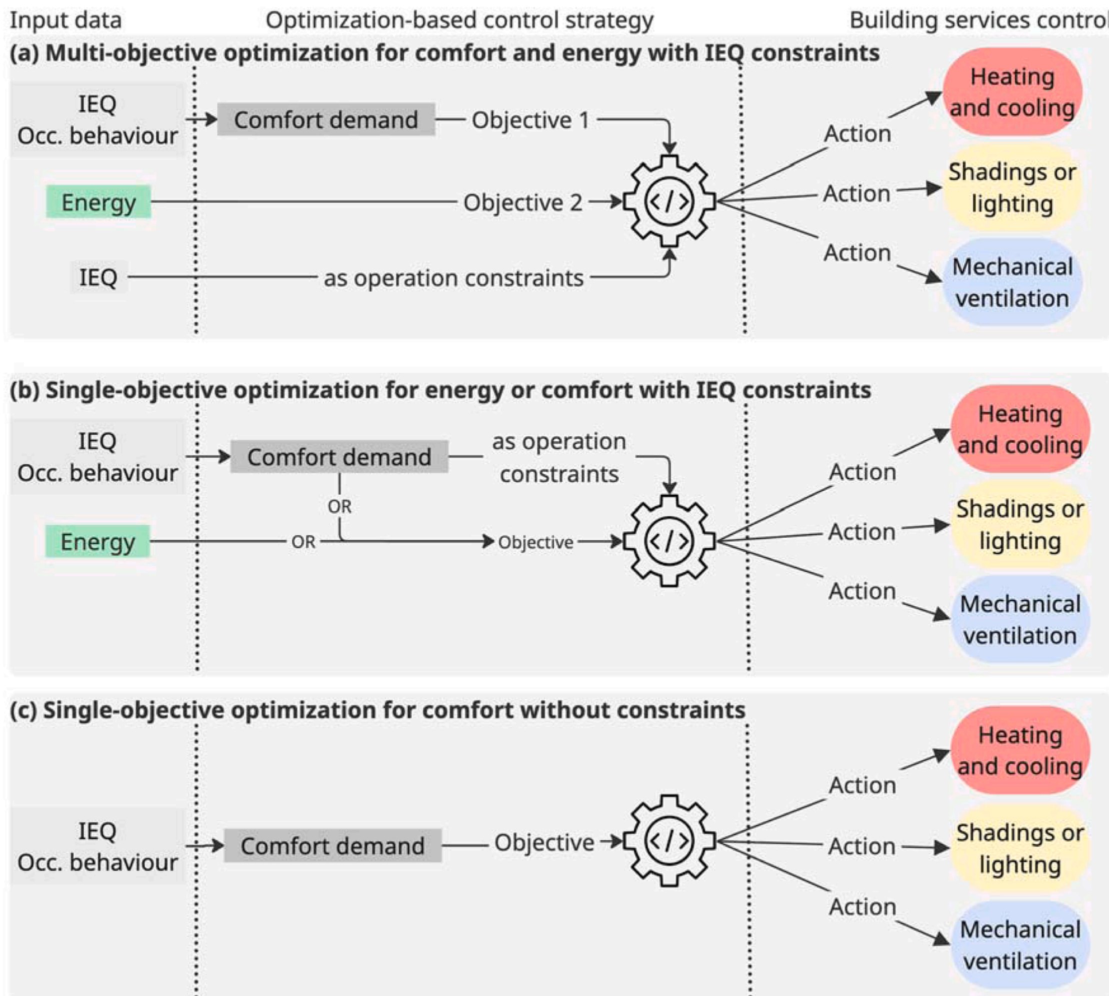

Fig. 12. Representation of three types of optimizations found in the literature. (a) Multi-objective optimization for comfort and energy with indoor environmental quality constraints. (b) Single-objective optimization for energy with indoor environmental quality constraints. (c) Single-objective optimization for comfort without constraints.

therefore whether the prioritisation schemes and thresholds used in rule based integrated control align with occupant preferences and how this alignment changes with context.

Future work should focus on closing this gap by making rule-based policies more evidence based and context aware. One direction is to infer threshold values from observed behaviour, for example by learning setpoints and acceptable bounds from overrides and using these as adaptive thresholds rather than fixed expert values, previously done for single-domain building services [75]. A second direction is to elicit prioritisation over competing IEQ factors, for example through questionnaires that capture trade-off hierarchies, and then translate these into policy logic. A third direction is to infer priorities and context dependence from field time-series data using causal or preference inference methods, with the goal of identifying when occupants trade glare for view, or thermal comfort for fresh air, and how these trade-offs shift across seasons, building types, and façade technologies. Together, these steps would support controllers that remain interpretable but less contextual and rigid, and ultimately better aligned with occupant demands.

4.3. Advocating for transparency in policy design of optimization-based control systems

Optimization-based controllers are a more engineered alternative to rule-based logic for BACS. In multi-domain BACS, comfort and energy targets are often aggregated into a single scalar objective using weighted-sum formulations, where thermal, visual, and IAQ terms are normalized and combined using fixed IEQ weights. Reinforcement learning controllers follow a similar structure by optimising a single scalar reward that embeds the relative importance of domains through pre-defined reward weights.

A first limitation is that these scalarised formulations can be opaque and difficult to interpret. The effective trade-offs across domains are largely determined by the chosen weights, penalty functions, and normalisation, yet these design choices are rarely justified or analysed. In multi-domain objectives, the domain with the largest deviation or highest penalty can dominate the optimisation, but this dominance is seldom communicated in terms of what it implies for comfort prioritisation. This is particularly problematic because occupants do not necessarily weight thermal, visual, and air-quality conditions equally, and their priorities can shift with context [82]. When equal or ad-hoc weights are used without evidence, it remains unclear whether the optimisation aligns with occupant preferences or instead over-penalises deviations in some domains while under-representing tolerance in others.

A second limitation concerns the link between preferred states, and the actions occupants accept. Current bottom-up demand models are typically formulated to predict a preferred environmental state, such as an air temperature target, but they rarely represent the action pathway by which occupants prefer to reach that state. In buildings, the same comfort outcome can often be achieved through multiple services, for example by adjusting HVAC setpoints, moving shades, or opening a window. If an automated controller selects an actuator that conflicts with an occupant's priorities, occupant–automation conflict can arise and overrides become more likely [83,84]. This gap is reflected in our review: studies rarely address actuator choice explicitly when multiple services can satisfy the same comfort objective, such as shading versus lighting for daylight, or window opening versus mechanical ventilation for air quality. Reinforcement learning can, in principle, learn state–action policies directly [82], yet most applications remain focused on a single domain and do not attempt to represent the domain trade-offs that drive occupants' actions, such as view preservation versus glare control.

These gaps point to the need for optimisation and learning frameworks that are both transparent and occupant centred. Future work should make domain weighting and trade-offs explicit and interpretable, learn state–action preferences and actuator hierarchies from occupant data, and calibrate objectives dynamically using real-time occupant feedback. Recent demonstrations of imitation learning for lighting control illustrate one pathway toward such occupant-aligned policy design [75]. Advancing these directions is likely to be essential for the wider adoption and long-term acceptance of integrated multi-domain BACS.

5. Conclusion

We examined how multi domain occupant demands are defined and operationalised within Building Automation and Control Systems (BACS). The evidence remains strongly thermal centric. Visual and air quality demands are included more often but are represented inconsistently across studies. Acoustics is rarely considered, and never actively controlled. This review also shows that multi-domain scope does not imply high level of multi-domain integration. Many studies include several IEQ variables yet implement not integrated BACS where each domain is handled independently. When integration is reported, it is most often achieved at the policy level by combining separate unimodal demand definitions rather than by modelling interactions within the occupant demand representation itself.

A central finding is the heterogeneity of occupant demand modelling. Top-down demands dominate and are typically defined through standard setpoints and static thresholds. These definitions are simple to deploy but can remain misaligned with occupant requirements and do not adapt to variability across occupants and contexts. Bottom-up approaches offer a pathway to learn demands from data, but in the reviewed literature they are still concentrated on thermal and air quality interactions and are rarely implemented and tested in BACS, particularly when visual or acoustic variables are involved. In addition, most demand models predict preferred environmental states rather than the preferred action pathway. When the same target can be achieved through multiple services, the lack of an explicit state-action service link can lead to occupant overrides when the chosen actuator does not match occupant priorities.

On the policy design side, both dominant strategies face barriers. Rule-based control remains common because it is transparent and practical, yet integrated rule policies often depend on expert tuned priorities and thresholds that can be highly contextual and weak across technologies and buildings. Optimization based controllers can coordinate multiple objectives, but weighted sum formulations and reward-based learning often embed trade-offs in fixed weights and penalty functions that are rarely justified or interpreted. In both cases, the prioritisation of thermal, visual, and air quality demands is often implicit rather than explained, making it difficult to assess whether the resulting behaviour aligns with occupant preferences, especially as these preferences can shift with context.

Overall, this review does not aim to prescribe strict guidelines on how multi-domain control should be implemented. Instead, it clarifies why multi-domain occupant demands matter for BACS, where current approaches fall short, and where research effort is likely to have the highest impact. The field needs direct benchmarking of unimodal versus multimodal demand models under comparable control contexts, wider implementation of bottom-up multimodal demands in BACS beyond thermal and air quality, and policy designs that make priorities and service choices transparent and adaptable. Progress on aligning occupant demands with automation will likely depend on addressing the domains where comfort is most sensitive, such as daylight availability, glare perception, and noise, where fast dynamics, and weak reliance on occupant adaptive behaviour make static thresholds and rigid policies insufficient.

CRediT authorship contribution statement

P. Martinez-Alcaraz: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **P. de la Barra:** Writing – review & editing, Investigation, Conceptualization. **C.P. Andriotis:** Writing – review & editing, Supervision, Investigation, Conceptualization. **U. Knaack:** Writing – review & editing. **A. Luna-Navarro:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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