Building Automation Systems for energy and comfort management in green buildings: A critical review and future directions

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ABSTRACT

Building automation system (BAS) applications in green buildings (GB) is an ideal way to improve energy performance and reduce environmental impact. Although GB has been studied in-depth in recent decades, to date, BAS-in-GB research is inferior. Therefore, this study explores the nexus between BAS and GB to achieve a holistic understanding of this area based on 141 articles published from 2008 to 2022. This paper systematically illustrates 1) BAS applications in the lifecycles of GB; 2) BAS applications in supporting GB indoor human comfort: thermal comfort, visual comfort, ventilation comfort, and acoustic comfort; 3) the research framework for reducing the energy performance gap in GB; 4) five BAS and GB integration methods for energy efficiency; and 5) limitations, challenges and future research directions of BAS-in-GB domain. The results show that uncertainties, long-term prediction and control, BAS-supported sustainability goals, and privacy and security are the four main challenging research directions. This study is the first to provide essential guidance on integrating BAS with GB to enhance energy and comfort management.

Keywords: Building Automation Systems (BAS), Green buildings (GB), Energy efficiency, Occupant comfort, Energy performance gap (EPG), Integration methods, Sustainability

1. Introduction

The conception and technological approaches of green buildings (GB) have gotten broad attention due to the growth of environmental issues and the onset of the energy crisis. The architecture, engineering, and construction (AEC) industries account for nearly 40% of the world's energy, which is also responsible for 32% of CO_2 emissions, 50% of raw materials, and 71% of power use [1–3]. Therefore, countries worldwide advocate for developing GB to reduce energy consumption and CO2 emissions. However, because of subpar design and poor energy system management, they frequently fall short of the required energy performance targets during operation [4]. The energy performance gap (EPG) is the difference in energy consumption between predicted and actual operation. Building automation systems (BAS) application in GB can address this issue by regulating energy efficiency and maintaining a comfortable interior environment over the lifecycle of a building [5].

With the increased interest in GB in recent decades, the number of review articles on the subject is expanding. Integrating quantitative and qualitative review approaches can enhance the depth and breadth of understanding and comprehend the present research state and crucial research challenges [6]. According to previous review articles, GB is a high-performance building that may increase the quality of life while maintaining energy efficiency and reducing the influence on the surrounding environment across the life cycle [6–8]. In the literature, the implementation process, assessment methods, and sustainability performance are three major research streams in the GB domain. Digital technologies, such as building information modeling (BIM), the Internet of Things (IoT), and Artificial Intelligence (AI), are frequently used in the GB area. They enable the integrated administration of information and enhance sustainable performance. Various research has examined their applicability in GB, including BIM for green retrofitting [9], BIM for GB certification systems [7], and AI in GB [10]. These review papers help understand the GB body of knowledge. These studies also showed that the lack of automation control would lead to low energy efficiency and hinder the development of smart GB. BAS can fill this gap due to its ability to integrate multiple functions, including automated control, energy management, occupant comfort, security, and safety [11,12].

BAS are distributed systems that control and monitor electrical devices in a building, which include Heating, Ventilation, and Air-conditioning (HVAC), lighting, and alarm security systems [13]. BAS consists of three layers based on function: the field layer (interacting with sensors and actuators), the automation layer (device and process), and the management layer (plant level) [14]. BAS has gained popularity because of its balancing ability to improve occupant comfort and reduce EPG during building operations. [15]. As a recent development, BAS plays a vital role in the AEC sector, particularly in intelligent buildings. Existing review papers mainly focus on energy efficiency optimization [16], automation technology upgrading [17], and occupants' behavior modeling and simulation [18]. They also illustrated that BAS has many potential features to support GB development [19,20]. To sum up: 1) allow prediction of energy performance; 2) reduce time and expense; 3) simplify the measurement of performance indicators; 4) enable input of uncertain parameters; 5) provide comprehensive results. However, existing research has limitations on BAS and GB integration. It is still unknown how to address the following research questions:

RQ1. What is the current research status of BAS applications in GB?

RQ2. How to manage energy and comfort by integrating BAS with GB?

RQ3. What challenges and limitations exist in integrating BAS with GB?

RQ4. What are the next steps in BAS-GB research?

Therefore, this study aims to conduct a comprehensive review of BAS-in-GB to answer these research questions and benefit the development of GB. The research objectives are: (1) to investigate BAS-supported lifecycles and occupant comfort of GB to construct an EPG framework; (2) to identify and discuss BAS-GB integration methods; (3) to summarize research limitations and challenges; (4) to provide recommendations for future research.

The contributions are listed below. (1) To the best of the authors' knowledge, this is the first article that systematically analyzes the BAS-GB integration for energy and comfort management. 2) This study develops a research framework for reducing EPG. The framework can provide valuable references for researchers and managers. 3) The proposed integration methods expand our knowledge of achieving a trade-off between energy efficiency and occupant comfort. 4) The summarized challenges and recommendations can provide essential guidance for future studies.

The paper is structured as follows: Section 2 describes the research methodology. Then Section 3 introduces the BAS application in GB. Section 4 discusses hybrid approaches for integrating BAS and GB. Section 5 summarizes research challenges and future directions. Last, Section 6 shows the conclusions.

2. Research Methodology

The study adopted a mixed method combining two approaches, i.e., the bibliometric approach and systematic literature review (SLR), as shown in **Fig.1**. The research method includes seven stages: (1) identification, (2) screening, (3) eligibility, (4) included, (5) bibliometric analysis, (6) systematic analysis, and (7) synthesis. This study selects the bibliometric approach as a quantitative method to map and visualize dynamic features of the knowledge field and research trends. The SLR is a qualitative method that can effectively summarize research status, limitations, and future directions. The combination of the two approaches has advantages in providing robust, consistent, and impartial findings [21]. In interdisciplinary BAS-in-GB research domains, it can also increase the depth and breadth of understanding. Therefore, this study chooses mixed approaches.

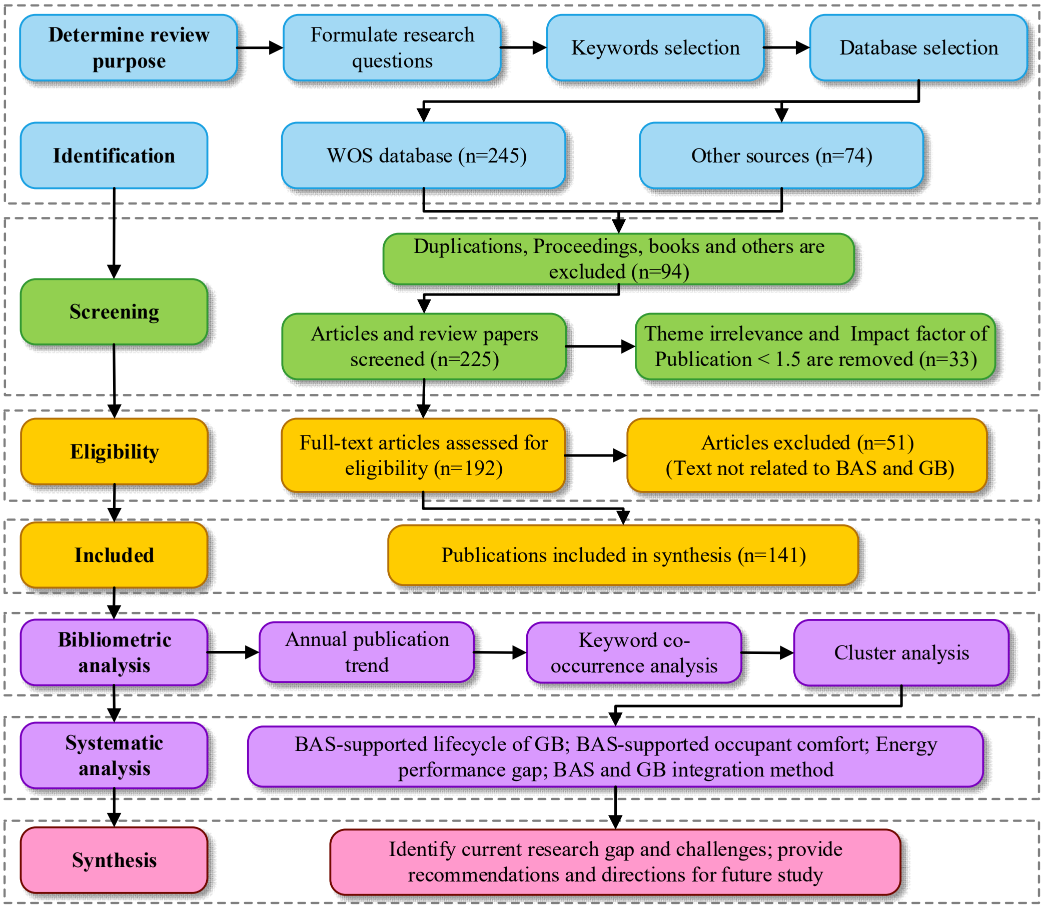


Fig. 1. Mixed-methods Systematic review procedure.

2.1. Literature filtration (stages 1-4)

This study chose a series of terms based on the subjects of BAS-in-GB. Existing research has shown that these keywords are valid [5,7,10]. **Table 1** lists all keywords.

Table 1 Keywords for systematic literature review.

String
(*"Green building"* OR *"Green construction"* OR *"High performance building"* OR *"High performance construction"* OR *"Sustainable building"* OR *"Sustainable construction"* OR *"Green*

project" OR *"Sustainable project"* OR *"Green technology"* OR *"High-performance building"* OR *"High-performance construction"* OR *"High performance project"* OR *"High-performance project"* OR *"Energy efficient buildings" OR "Energy performance"*)

AND

("Building management systems" OR "Building energy systems" OR "Building energy management systems" OR "Building automation systems" OR "Building Control Systems" OR "Building automation and control systems" OR "internet of things" OR "Artificial intelligence" OR "automation" OR "Energy management control systems" OR "Energy management systems" OR "Facility management systems" OR "Building Information Systems" OR "Maintenance Management systems" OR "heating, ventilation, and air conditioning systems")

The central database used in this article is the Web of Science Core Collection because this database provides peer-reviewed indexed publications which are well-regarded by researchers worldwide. Other databases were also incorporated to allow for a comprehensive examination of the BAS-in-GB area, which includes transdisciplinary themes. They are Science Direct, the American Society of Civil Engineers (ASCE) library, Electrical and Electronics Engineers (IEEE) Xplore, and the Association of Computing Machinery (ACM). The query terms also used the keywords such as "Green buildings," "Building automation systems," and "Energy management systems."

This study followed five filter criteria to acquire high-quality publications: **i)** articles or review papers, **ii)** publication year from 2008 to October 2022, **iii)** journal impact factor ≥1.5, **(iv)** full text related to BAS and GB, **V)** elimination of duplication and irrelevance. Moreover, we added some proceeding articles published by ASCE to make the database more comprehensive. Initially, we filtered 319 publications by title, abstract, and keyword screening. Then we exclude most of them (178 publications) based on the filter criteria. Finally, we rigorously reviewed 141 publications that meet all the requirements. **Table 2** depicts the distribution of the 141 publications in the journals/database.

Table 2 Journals/database of reviewed articles

No.	Journals/database	Total searching	Reviewed paper	Percentage (%)
1	Energy and Buildings	57	34	24.11
2	Sustainability	41	15	10.64
3	Applied Energy	17	14	9.93
4	Renewable and Sustainable Energy Reviews	15	12	8.51
5	Building and Environment	15	9	6.38
6	Journal of Building Engineering	12	9	6.38
7	Automation in Construction	11	8	5.67
8	Energy	10	3	2.13
9	Journal of Cleaner Production	8	5	3.55
10	Journal of Construction Engineering and Management	7	3	2.13
11	Sustainable City and Society	5	5	3.55
12	Journal of Management in Engineering	5	1	0.71
13	Advanced Engineering Informatics	3	2	1.42

14	Journal of Computing in Civil Engineering	2	2	1.42
15	IEEE Xplore Digital Library	33	9	6.38
16	ASCE Digital library	64	7	4.96
17	ACM Digital Library	10	1	0.71
18	Science Direct Library	4	2	1.42
	Total	319	141	100

2.2. Bibliometric analysis (step 5)

2.2.1. Annual publication trends

Fig. 2 presents the annual publishing tendency of 141 peer-reviewed papers. It shows that there are only ten publications from 2008 to 2012. These publications attempted to find how the design automation strategies affect the energy efficiency of GB [22,23]. Then, the number of publications grew gradually from 2013 to 2017. After that, the number of publications considerably increased, indicating that the BAS-in-GB domain has attained ever-increasing attention.

Furthermore, it is essential to note that the frequency of articles published in 2022 is up to November. Generally, the exponential growth tendency in **Fig. 2** is evidence of growing interest in the BAS-in-GB field. It will continue to grow in the future.

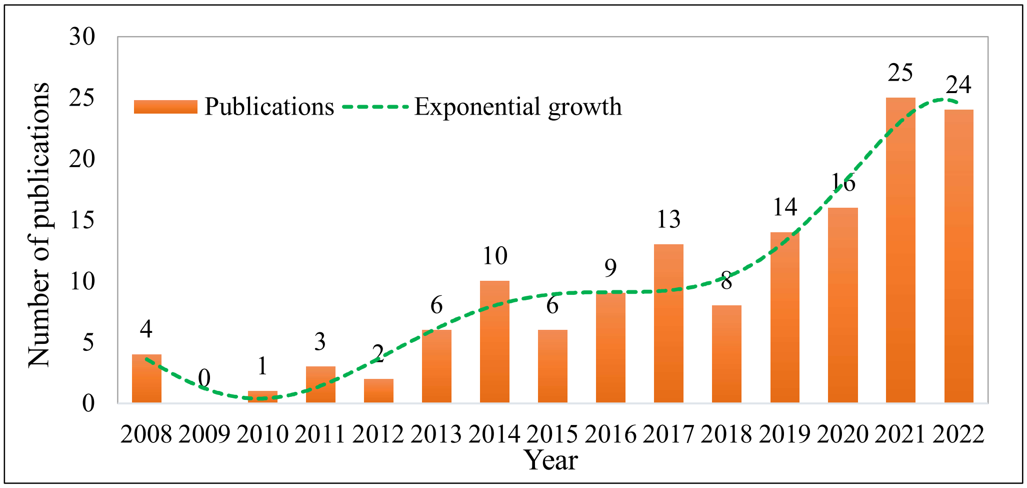


Fig. 2. Number of publications from 2008 to October 2022.

2.2.2. Keyword co-occurrence analysis

This research applied keyword co-occurrence analysis to identify the main focuses in the BAS-in-GB field. The co-occurrence analysis helps furnish a holistic understanding of investigated areas in a field. It can also visualize the development trends and intertwined correlations of research topics to support a comprehensive literature review. This study employed VOSviewer software to generate co-occurrence maps, as shown in **Fig.3**. The co-occurrence network consists of 54 nodes with 1084 links. Each node represents a keyword. The 54 keywords meet two filter criteria: (1) their frequency of recurrence is more than three, (2) no duplication. The size of nodes increases based on the frequency of their occurrences.

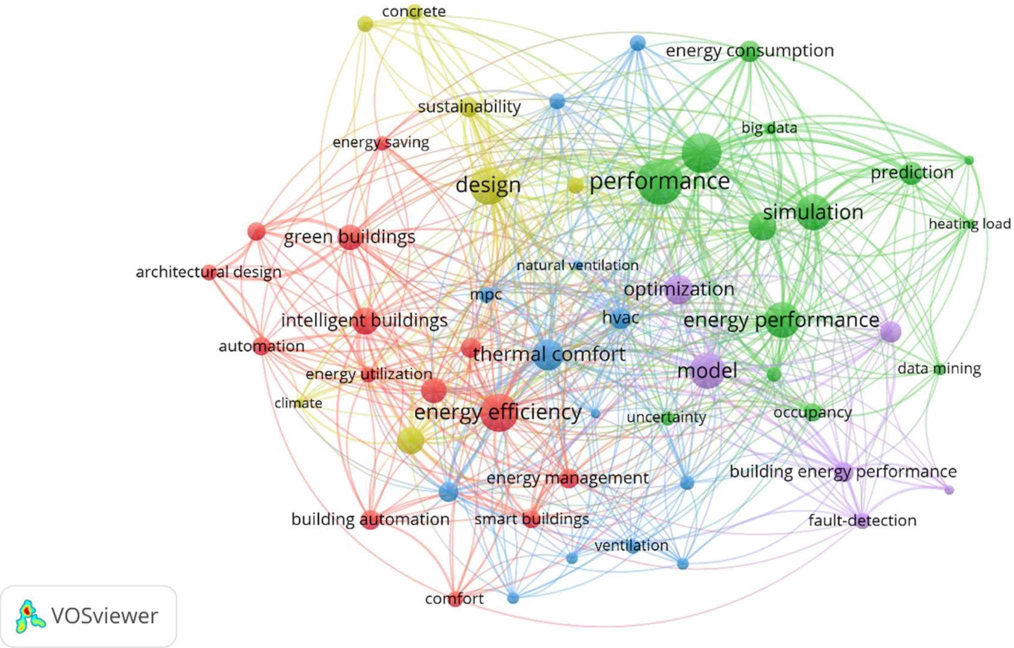


Fig. 3. Keywords co-occurrence network.

Table 2 presents 25 terms ranked by co-occurrence values. The overall link strength and average year published can show the degree of attention they have gotten each year. Greater link strength indicates that these keywords have more cross-connections with various study themes. High average citations suggest they have an enormous impact on other studies. For example, the keywords *"Energy performance," "Consumption," "Design,"* and *"Energy efficiency"* are ranked among the top five in the list, indicating their significance in the field of BAS-in-GB. In addition, the terms "*Model,*" "*Simulation,*" and "*Thermal comfort*" are top 10 of the list. This result demonstrates that many researchers frequently employ modeling and simulation techniques to enhance thermal comfort in the GB. Additionally, the phrase "*Building automation*" comes in last on the list, indicating that the investigation into the integration of BAS-GB is lacking.

2.2.3 Cluster analysis

This study conducts cluster analysis to identify research hotspots and reveals the knowledge structure of the BAS-in-GB field. As presented in **Fig. 3,** the VOSviewer program classifies these nodes (keywords) into five clusters by employing specific colors: red, green, blue, yellow, and purple. Specifically, keywords such as *"energy efficiency," "intelligent buildings," "green buildings," "building automation,"* and *"comfort"* from cluster 1 (red); *"energy performance," "simulation," "AI,"* "*data mining,"* and *"prediction"* from cluster 2 (green); *"model predictive control," "HVAC," "thermal comfort,"* and *"occupant behavior"* from cluster 3 (blue); *"design," "management," "sustainability,"* and *"climate"* from cluster 4 (yellow); *"model," "optimization," "machine learning,"* and *"building energy performance"* from cluster 5 (purple). Generally, the five primary research areas are as follows: (1) BAS application in the whole lifecycle of GB to improve energy efficiency; (2) prediction and control of HVAC systems to improve occupant comfort; (3) energy consumption simulation and prediction to reduce energy performance gap; (4)

GB-BAS integration methods application for sustainability management; (5) trade-off between energy performance and human comfort. The five study fields serve as a framework for systematic analysis in the following sections.

Table 2 The top 25 keywords in terms of occurrences.

Rank	Keywords	Occurrences	Total link strength	Cluster	Average year published
1	Performance	26	96	2	2019
2	Consumption	21	77	2	2019
3	Design	20	68	4	2018
4	Energy efficiency	20	72	1	2017
5	Energy performance	18	65	2	2019
6	Model	18	60	5	2019
7	Simulation	18	54	2	2018
8	Thermal comfort	15	74	3	2018
9	Optimization	14	54	5	2019
10	Artificial Intelligence	13	59	2	2017
11	Intelligent buildings	12	40	1	2016
12	Management	12	41	4	2017
13	Green buildings	11	36	1	2017
14	Office buildings	11	31	1	2016
15	Prediction	10	38	2	2018
16	Energy consumption	9	30	2	2017
17	HVAC	9	41	3	2018
18	Machine Learning	9	30	5	2021
19	Building Automation	8	18	1	2016
20	Building energy performance	8	29	5	2018
21	Energy management	8	27	1	2019
22	Internet of Things	8	17	1	2019
23	Model Predictive Control	8	37	3	2017
24	Sustainability	8	30	4	2019
25	Automation	7	22	1	2016

2.4. Systematic analysis (stage 6)

After bibliometric analysis, this study conducted SLR to offer in-depth insight into the BAS-in-GB research field. The five beforementioned research domains are the sites of penetration. Afterward, we divided the five clusters into two groups: BAS application in GB and BAS and GB integration methods. Specifically, the first group investigates how BAS supports GB's lifecycles, occupant comfort, and how to reduce the EPG. The second group presents and analyzes five integration methods extensively utilized for attaining sustainable performance. The subsequent two sections provide more details about SLR.

3. BAS in GB Applications

Previous studies showed that even when buildings fulfill the GB assessment standards such as LEED, there is still considerable EPG [24]. Poor lifecycle management and uncertain occupant behavior are the two leading causes of this phenomenon. The BAS can improve energy efficiency throughout the whole GB lifespan, including four main stages: design, construction, operation, and renovations and retrofit [25]. It can also strengthen occupant comfort without increasing energy consumption. Accordingly, it is significant to investigate how to reduce EPG in GB by applying BAS. Section 3.1 presents the BAS application in GB lifecycles. Section 3.2 illustrates how to enhance occupant comfort through BAS. Section 3.3 develops a research framework that summarizes all solutions for minimizing EPG.

3.1. BAS application in GB lifecycles

3.1.1. Design stage

GB design includes external and internal environmental management [26]. In the external environment, BAS can evaluate the most advantageous sites and building façade through simulation tools for energy conservation. The location should be considered foremost during the design phase. Because several geometric elements, such as the local temperature, the land's natural features, and transportation, considerably influence energy performance [23]. For example, longer transportation distances typically result in higher fuel costs and more vehicle exhaust emissions. Sustainable facade design is another prominent application area. In this domain, BAS is beneficial for lowering construction costs, improving indoor air quality, and conserving energy [27].

In the internal environment, BAS is employed for fire safety [28], energy performance analyses [23,26], HVAC system optimization design [26], and demand-side management [29]. Moreover, scholars have focused on striking a balance between anthropocentrism and mechanical design [30]. Likewise, nature-based biomimetic design progress has become a stream incorporating aesthetics and functionality toward obtaining an intelligent green product [31]. In general, BAS application in the design stage is limited to energy consumption simulation. Therefore, future research should include more real-world examples to support the simulation results.

3.1.2. Construction stage

In the construction stage, environmental sustainability goals have received increased attention. For example, Alencar et al. [32] applied the Value-Focused Thinking methodology (VFT) to find fundamental factors in the construction stage, including electricity use, water recycling, and construction waste management. They demonstrated that durable and recycled materials could reduce resource waste when building envelope structures. Graziani et al. [33] investigated that the bent welded connectors could economize more electricity than traditional ones without sacrificing the structural integrity.

Additionally, the energy simulation approach is essential in improving energy efficiency. Mathews Roy et al. [34] simulated the building energy consumption of three types of cooling systems, i.e., variable refrigerant flow (VRF) system, variable air volume (VAV) system, and evaporative cooling system through eQuest software. They found that the evaporative cooling system consumes less energy than others.

Furthermore, automated techniques applied in construction safety management have received much interest. For instance, Mascaro et al. [35] developed a robotic walking excavator to automate building the wall using irregularly shaped rocks and rubble. The automated excavator can work in remote and extreme environments, making the building process safer and more efficient. In summary, most of the studies focused on the environmental sustainability of the BAS-in-GB domain. The concern about social and economic factors are very few.

3.1.3. Operation stage

Although GBs are designed based on sustainability certifications like BREEAM, LEED, and China's "Green Building Evaluation Standards." The EPG still exists. In some real cases, actual operation energy savings delivered only 28–71% of design expectations [36]. Therefore, high-performance energy management by employing BAS tools emerges from current research. Lertlakkhanakul et al. [37] devised a ubiquitous sensor networks framework to construct the semantic location of BAS to minimize building operation costs. Parise et al. [38] established a procedure based on European Standard EN15193 to evaluate the energy demand for lighting more accurately by considering the productive operating time and occupant behavior. Likewise, Miroshnichenko et al. [39] investigated the influence process of ambient conditions on heat transfer through mathematical simulation. The model they developed can anticipate the amount of energy required to guarantee indoor thermal comfort.

Safety management is equally as crucial as energy management in the operational phase. Building deformation monitoring plays a vital role in the occupants' safety domain. The conventional monitoring technique can only manually acquire data at certain intervals, which is tedious and time-consuming. Thus, researchers created a hybrid BAS-IoT method to address this issue [40,41]. The approach can monitor structural deformation and has advantages in real-time data acquisition, reliable data storage, and precise data analysis [42]. Moreover, BAS can assist in asset management to avoid energy waste and hazards such as pump failures, tank leaks, and creepage.

Energy efficiency analyses can benefit from BAS as well. Sang et al. [43] developed two evaluation indicators: coefficient of performance (COP) and energy efficiency ratio. AbdelAzim et al. [44] used Analytic Hierarchy Process (AHP) approach to develop weights for energy efficiency rating criteria. They illustrated that the 'Minimum Energy Performance' factor was mandatory for GBs assessment. In addition, Borowski et al. [45] developed a trigeneration heat and electricity monitoring system for a hotel building, which is more energy efficient than traditional systems. Generally, continuous building facilities monitoring and improving energy efficiency through BAS are critical solutions for reducing EPG.

3.1.4. Renovations and retrofit stage

Green retrofitting has been the subsequent step in dealing with EPG in recent years [46]. The BAS can help prioritize key performance parameters based on project types. Cost analysis, operational energy, and life cycle analysis are frequently used in the renovations and retrofit stage [9]. Rashid et al. [47] retrofitted a low-cost HVAC system incorporating an occupancy detection system to decrease building energy usage. Engelsgaard et al. [48] introduced an intelligent assessment tool, "IBACSA," which is comprehensive and user-friendly. The tool can quantify the specific impacts of upgrading and retrofitting. They demonstrated its validity in auditing various features in a university based on a qualitative-based multi-criteria approach.

Furthermore, low-impact retrofit solutions are particularly prevalent among researchers. Mauri et al. [49] simulated the relationship between energy consumption and the light transmission of windows by TRNSYS software. They illustrated that residential buildings could achieve up to 44% energy savings when they reduce windows' light transmission to nearly 32%. Ibaseta et al. [50] developed a novel architecture for BAS based on the Web of Things paradigm to address the interoperability issues between heterogeneous devices. They effectively verified the pilot through an innovative retrofit project in a two-story office building. Rahmawati et al. [51] investigated low Volatile Organic Compound (VOC) paint and LED bulbs applied in high-rise building refurbishment. They found that the two methods have advantages in improving indoor air quality and saving energy.

3.1.5. Summary of BAS-supported green building lifecycles

BAS can support various requirements in GB during the whole lifecycle, as shown in **Fig.4**. In the design stage, BAS enables 3D visualization analyses and simulations to assist designers in optimizing the HVAC system and project scheme. In the construction stage, BAS can offer sustainable material efficiency simulation, waste management, and safe construction processes to achieve sustainable construction objectives. In the operation phase, facility managers can monitor massive building equipment utilizing BAS-based micro-sensor networks to optimize energy usage. Moreover, BAS contains anomaly detection functions for building facilities, such as human health monitoring and fault detection. In the retrofit phase, BAS takes advantage of quantifying the specific impacts of upgrading and retrofitting building envelop, facilities, and appliances in GB. Generally, BAS benefits GBs' whole lifecycle by enhancing energy efficiency and lowering EPG.

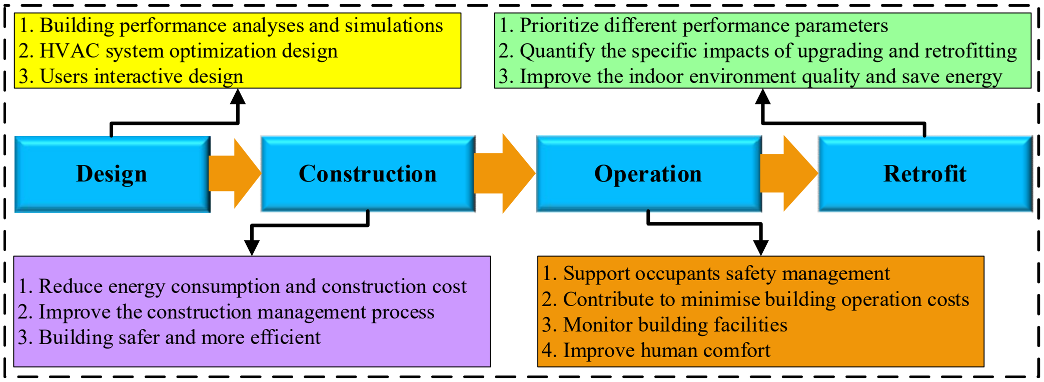


Fig. 4. BAS-supported GB lifecycles.

3.2. BAS-supported occupant comfort of green building

BAS begins with controlling HVAC, lighting, and other devices to reduce the energy consumption of GB. It progresses to automated adjust indoor environment quality (IEQ) parameters to improve occupant's comfort level [5]. These parameters include thermal, visual, ventilation, and acoustic comfort based on GB assessment criteria like LEED, BREEAM, and Green Star.

3.2.1. Thermal comfort

In GBs, human thermal comfort is a crucial sustainability metric. It includes a series of notoriously complicated parameters, such as indoor temperature, humidity, and mean radiant temperature [52]. Predicted mean vote (PMV) and predicted percentage of dissatisfaction are two primary thermal comfort assessment approaches in existing studies [2]. Kumar and Hancke [53] developed a wireless, smart comfort sensing system to measure them in real-time efficiently. The system has many desirable qualities, including portability, power efficiency, high reliability, and low system cost. Hu et al. [54] developed intelligent thermal comfort neural network to evaluate human thermal sensations, which outperforms canonical models, such as PMV and adaptive model.

Additionally, HVAC systems provide thermal comfort at the expense of consuming large amounts of energy [55,56]. Researchers tried to develop high-efficient HVAC systems to reduce power consumption and CO2 emission. However, most systems they introduced are costly due to complex automation control facilities. Another way to overcome the shortcomings is to integrate high-performance building envelopes and thermal energy storage systems [57–59].

Intelligent ventilation systems can also improve indoor air quality and provide thermal comfort for building occupants. The systems mainly adopt intelligent feedback techniques and sensor fusion algorithms to detect HVAC systems and occupancy [60,61]. In addition, making the most of natural resources may provide thermal comfort while remaining economically viable. Examples of this include adaptive envelopes [58], hybrid ventilation systems [62], and earth-based construction materials (EBCMs) [63]. Furthermore, simulating the ground heat transfer and considering weather forecast uncertainties can avoid future thermal imbalance in GBs [39,64].

3.2.2. Visual comfort

BAS creates visual comfort in adaptive building envelopes, lighting systems, and user interfaces. Initially, the intelligent façade can respond to environmental changes in real time. Several customized components, such as blinds, sunshades, and windows, can adapt to nature's light to maximize visual comfort. These components incorporate outdoor solar radiation measurement to assist users in adjusting inside illumination [58].

Moreover, the BAS can control the amount of daylight through an internal Venetian blind system and feedback to the lighting systems. Subsequently, simulation software such as "Grasshopper" and "Honeybee" evaluate power consumption by inputting lighting parameters such as solar radiation, sunshine duration, and electric lighting [65]. They can also calculate daylight distribution and visualize the 3D visual environment [66].

Ultimately, BAS support develops detecting algorithms to simulate occupants' interaction with the building. For example, BAS simulation software employs an image processing algorithm to detect occupancy behavior regarding turning on/off the lighting devices for energy savings [38]. The software "Daysim" enables users to simulate interactive lighting systems through active or passive control [66].

3.2.3. Ventilation comfort

People spend more than 90% of their time indoors. Thus, the IEQ plays a significant role in occupants' health and comfort [67]. Frequently natural or mechanical ventilation can improve the air exchange rate between indoor and outdoor environments and remove pollutants in the buildings. In hot regions, such as Malaysia and Australia, a single natural ventilation system is hard to chill the air. As a result, these hot areas must install numerous air conditioning units that consume a lot of electricity.

Additionally, BAS can assist in delivering intelligent ventilation control systems to precisely maintain low levels of power usage and appropriate ventilation air rates [68]. BAS can also provide monitoring systems to measure indoor air parameters, e.g., air temperature, air change rates, pollutant transport, and exposure [55]. In recent years, researchers have integrated the monitoring system with IoT and Big Data techniques to accurately control the pollutant gases like SO2, CO, O3, and NO2 [4].

3.2.4. Acoustic comfort

Acoustic comfort substantially impacts IEQ, and most research focuses on improving materials' sound insulation performance [65,69]. However, few studies concentrate on the BAS application for acoustic analysis [18,27]. The acoustic effect comes from both internal and external sources. External acoustic includes vehicles, neighbors, and engineering construction, whereas domestic activities and appliances are sources of internal acoustic [69]. The application of double-window and double-skin can decrease the effects of external noise. The internal acoustics parameters are difficult to identify because of diverse human activities [70].

Furthermore, it is challenging to gather acoustic comfort data due to complex data files. Meerbeek [65] collected the data through semi-structured interviews by asking occupants whether they felt comfortable. Pauwels et al. [71] introduced a domain ontology integrating an instance model to check whether the actual acoustic is in line with European acoustic regulations. Nevertheless, recent studies have revealed that IoT-based BMS was able to construct a holistic energy efficiency assessment framework, including acoustic comfort indicators [72–74]. Similarly, Gupta et al. [75] introduced the AI-based BMS framework to extract the features of each acoustic signal.

3.2.5. Summary of BAS functions for human comfort in green building

BAS applications are designed not only for energy savings but also for occupancy comfort. Indoor environment quality parameters, e.g., thermal comfort, visual comfort, ventilation comfort, and acoustic comfort, influence human comfort level. These parameters could be measured by BAS accurately. **Fig. 5** depicts the critical BAS-supported measurement indicators. According to the BAS application mentioned above, thermal and ventilation comfort are more concerned than visual and acoustic comfort. Although BAS provides an efficient and effective analysis tool for IEQ assessment, these comfort variables are separate and cannot evaluate human comfort sensations adequately [54]. Moreover, previous studies have yet to treat these variables in an all-inclusive way to reduce interactive influence [76]. Future research could focus on an integrated green BAS that would improve the human comfort level in the room environment.

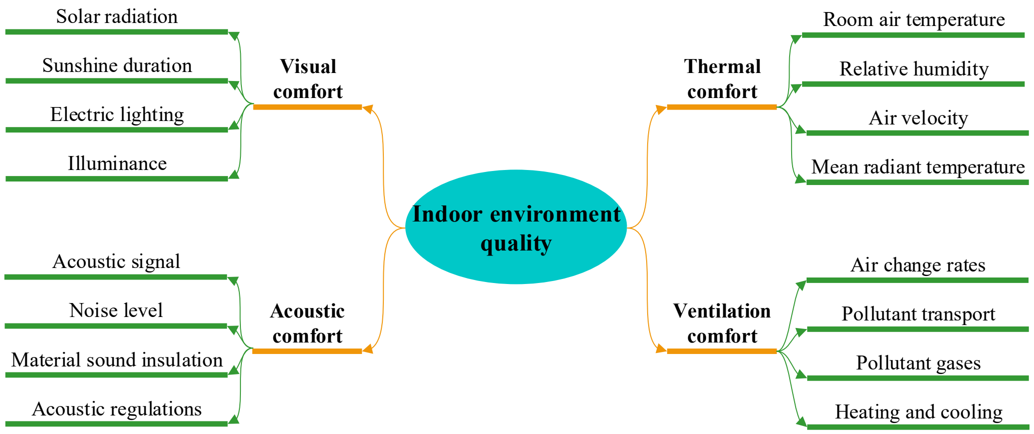


Fig. 5. BAS-supported IEQ parameters for GB.

3.3. BAS-supported research framework to minimize EPG in GB

According to SLR in sections 3.1 and 3.2, BAS plays a crucial role in enhancing GB’s energy efficiency and occupant comfort. Although building energy performance has been modeled and simulated using BAS tools in the design stage, deviation exists from uncertainties, e.g., climate conditions and occupant behavior in the operation stage [77]. These uncertainties will increase the risk of additional energy usage and lead to EPG.

In summary, existing research has made substantial efforts to minimize EPG. For example, predict and control energy performance [34,39,56,78,79], anticipate occupant behavior [18,30,80–82], and reduce energy consumption [12,44,83–85]. **Fig. 6** presents a research framework for minimizing EPG based on SLR findings from sections 3.1 and 3.2. The diagram shows 16 solutions assigned to four building phases. The three generic solutions in the center of the diagram are consistently valid throughout the building lifecycle.

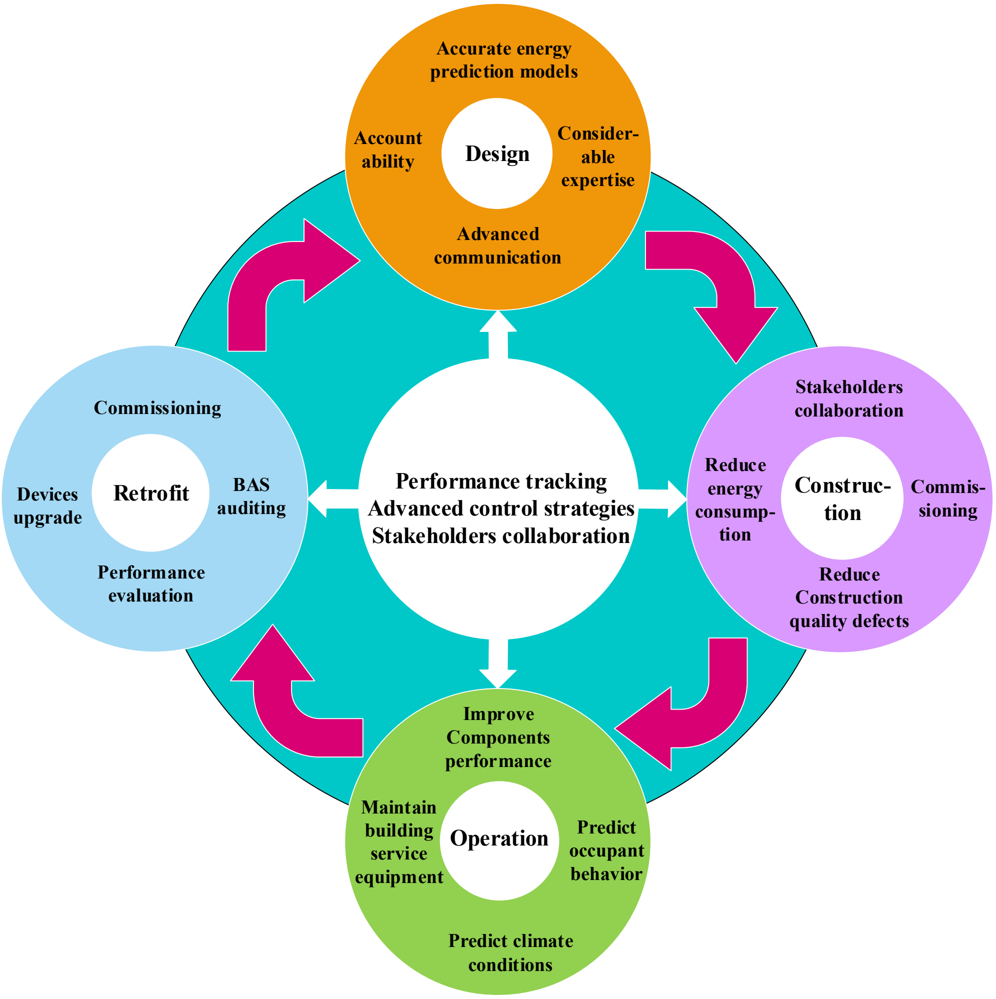


Fig. 6. Research framework for reducing EPG.

4. BAS and GB integration methods

Energy and comfort management is the key to reducing EPG. Therefore, this section initially discussed how to predict and control energy efficiency. Next, we analyzed how to achieve a trade-off between energy consumption and occupant comfort in GB. **Fig.7** shows five BAS-GB integration methods widely employed in the reviewed papers. This research will not present other approaches because they cannot fulfill trade-off objectives.

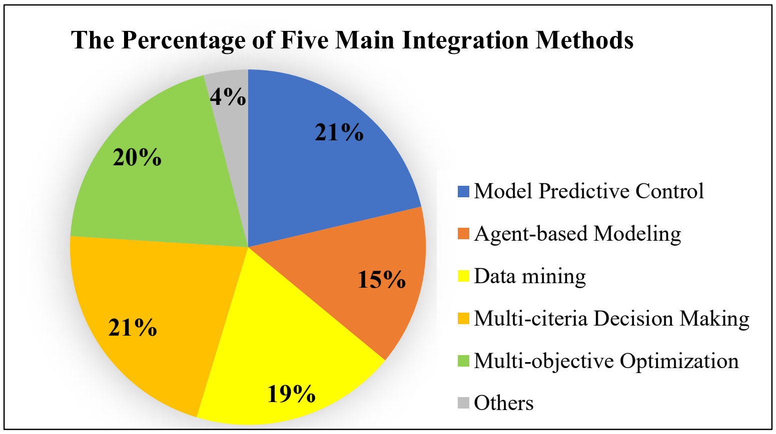


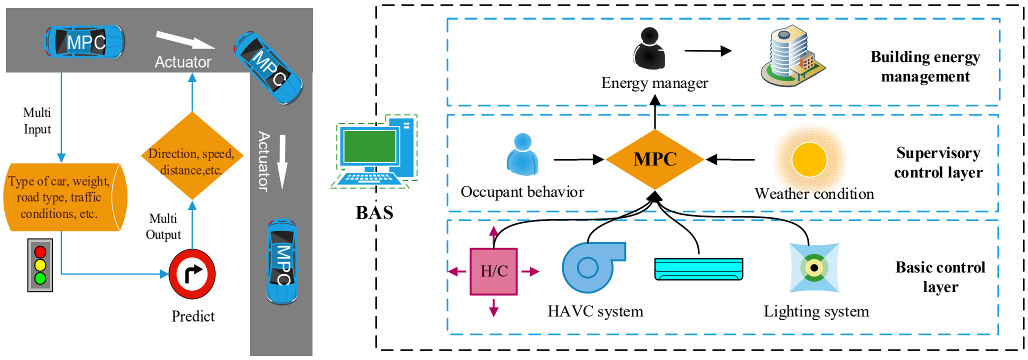
Fig. 7. The percentage of five main integration methods in the reviewed articles.

4.1. How to predict and control energy efficiency in GB?

Proportional-Integral-Derivative (PID) and Model Predictive Control (MPC) are the two main energy performance prediction and control models for GB to achieve sustainability goals. However, GB is characteristic of unique and dynamic [86]. Uniqueness indicates that each building has an exceptional location, material, setting, and design standards. Various stakeholders' demands result in dynamics such as construction cost, sustainability goals, and energy usage. These requirements are constantly evolving throughout the whole lifecycles of GB. As a result, simulating the energy efficiency of GB is sophisticated that conventional PID controllers cannot manage BAS efficiently [87]. Therefore, this study introduced an MPC approach to address this issue effectively.

4.1.1. Model Predictive Control (MPC) Concept

MPC is a simulation model in the building industry used for energy efficiency prediction and control. **Fig. 8a** illustrates MPC with a classic example of driving a vehicle around. To begin with, the model must consider fundamental variables that influence fuel consumption. Some of these factors are the type of automobile, weight, and aerodynamics. It is the same in GB, and we can improve the envelope by using new insulating materials and double-layer windows to minimize energy consumption [88]. In addition, in the car example, interminable unpredictable situations such as traffic lights, traffic jams, and the number of passengers are hard to regulate. For GB, these variables would be weather conditions and occupant behaviors which are predicted but not controlled. Finally, vehicles can make regular trips to be more comfortable or faster based on people's experience. Before the automobile crosses the curve, MPC controllers can calculate various control actions. Then the best suitable action (direction, speed, and distance) will be taken by modeling the automobile trajectory throughout numerous sample intervals. In a nutshell, it is similar to driving while looking ahead. In a building (**Fig. 8b**), MPC utilizes an intelligent algorithm to consider the energy consumption from the HVAC and lighting systems. It can also consider a forecast of occupancy behavior and climate conditions to achieve optimal energy management [87].



(a) Model Predictive Control (MPC) (b) MPC in building automation system (BAS)

Fig. 8. Typical control structure of MPC.

4.1.2. Application of Model Predictive Control (MPC) method

In literature, modeling and optimization techniques are widely used in MPC to improve energy efficiency in GB operation. There are three main optimization models: physics-based (white box), data-driven (black box), and gray box (hybrid) [16].

Physics-based (white box) model: The physics-based model is also called the white box model. It is established based on underlying principles of physics, such as mass and energy balances [89]. Current research widely applies the model to optimize the HVAC system design. The physics-based model can simulate the energy performance and indoor environment through soft tools: EnergyPlus [90], TRNSYS [49], eQuest [34], or Modelica [91]. Examples of the application include indoor air quality comfort [92], ground heat exchanger [64], prediction of building heating and cooling demands [93], maintaining thermal comfort through hybrid ventilation [94], and occupancy-based building climate control [19].

Data-driven (black box) model: Mathematic equations are the basis of the data-driven model. The model optimization needs to collect massive time series data from actual practice [16]. In the model identification process, statistics and machine learning techniques (e.g., artificial neural network (ANN), multiple linear regression (MLR), support vector machine (SVM)) enable input/output variables without prior knowledge. In the GB field, these approaches have been widely used for structural health monitoring [10,16,95], building energy consumption [52,87,89], occupant behavior prediction [61,80,82,96,97], fault detection and real-time diagnostics [75,93,98,99].

Gray-box (hybrid) model: Gray-box (hybrid) model is a compromise between physics-based and data-driven models, which is appropriate for accurate and high-speed calculations in MPC. The gray-box model can also benefit deterministic and stochastic frameworks. Researchers can build the model structure using parameter estimation algorithms and expert knowledge [16]. Thus, the gray-box model is effective for HVAC systems when adequate training data is lacking. Additionally, several studies employ a resistance and capacitance (RC) network analog to create a gray-box model for achieving energy savings in GB [19,100,101]. Furthermore, GB dynamics are very complex, and most optimization problems are non-linear, leading to non-convex. Therefore, non-linear programming (NLP) and mixed integer linear programming (MILP) formulation are taken into account to improve energy performance [87,89].

4.1.3. Discussion of Model Predictive Control (MPC) method

MPC shows its flexibility in BAS process control while considering the GB dynamics. Its integration with BAS has significant potential for minimizing the impacts arising from uncertainties and maximizing energy performance. Another benefit of this method is that it can predict future disturbances and conflicting events, such as inefficient behavior and harsh climate, and then give optimum management [101]. In addition, the hybrid model is a blend of inductive and deductive models. As a result, it is beneficial to handle non-linear, dynamic, and implicit models derived from real-world data [16].

There are also some limitations in MPC: Initially, it needs a large amount of effort to build a suitable model, which increases the investment. The current study indicated that designing and calibrating an adequate model is the most costly activity, accounting for around 70% of the overall project expenses [102]. Next, it presents high requirements for energy managers who need more expertise. Therefore, they need an additional training schema to operate and maintain the MPC. Moreover, the model requires massive data, including weather conditions and occupant behavior which are difficult to be measured in GB. Last, it requires additional computation capacities of hardware.

4.2. How to achieve a trade-off between energy efficiency and occupant comfort?

Another general objective of BAS is to improve occupant comfort while reducing energy consumption which is inconsistent with the social sustainability goal in GB [103]. Uncertainties present in GB primarily originate from energy system operation, external environment, and occupant activity. The uncertainty typically leads to low energy efficiency and makes it difficult to achieve the trade-off goal. Additionally, occupant behavior is a critical determinant of building energy usage. Consequently, current studies have developed several modeling and simulation approaches to address uncertainty elements in BAS. This section will investigate four main integrated methods: agent-based modeling (ABM), data mining (DM), multi-criteria decision-making (MCDM), and multi-objective optimization (MOO).

4.2.1. Agent-based modeling

Fig. 9 shows the classical framework of Agent-based Modeling (ABM), consisting of inputs (building and occupancy) and outputs (comfort) modules. In this framework, local agents represent building devices and control thermal, visual, ventilation, and acoustic comfort [104]. Central agents are responsible for optimizing and controlling the energy performance of the GB through an optimization algorithm. It can communicate with occupants through a graphical user interface and comfortably maintain indoor environmental parameters [15].

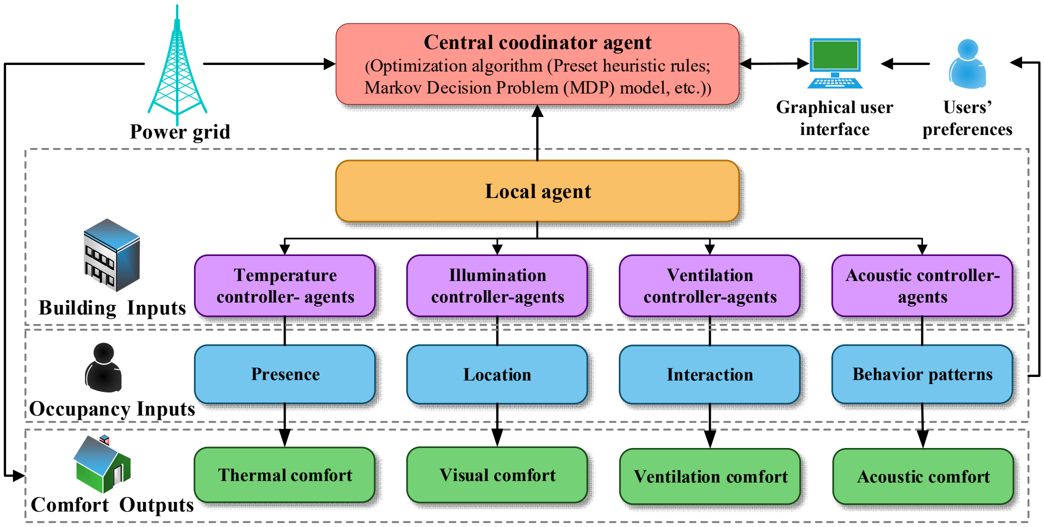


Fig. 9. Classical framework of Agent-based Modeling (ABM).

The ABM integration with BAS can prompt energy saving, optimization, and user comfort. The ABM is characteristic of autonomy, flexibility, homogeneity, and rule-based [17]. It enables simulating the internal and external interaction and evaluating the effects on the BAS. In addition, ABM is the basis of applying artificial intelligence (AI) techniques in BAS, for instance, data mining, ANN, and intelligent decision-making. Furthermore, ABM is crucial to accomplishing multiple goals in innovative energy management. For example, Mousavi et al. [17] developed a new hybrid method by integrating Function Block (software paradigm for industrial automation), intelligent software agents, and semantic web technologies to address BAS complexity arising from heterogeneous components, highly dynamic, and high-level intelligence. The work of Nguyen et al. [105] also revealed that occupant behaviors in buildings could be predicted based on ABM for intelligent energy management.

ABMs for occupant behavior investigations have several foci. The majority of studies have focused on how people and building systems interact. For example, Yang and Wang [15] developed a multi-agent-based control framework to address the conflicts between building energy consumption and occupants' comfort. In the beginning, their model divided the whole BAS into several subsystems, helpful in controlling and coordinating multi-agent systems. Then, they created a collection of distributed agents to imitate the occupants' preferences and needs, combining a central agent and a local agent. Finally, they constructed the epistemic, deontic, and axiological (EDA) paradigms. As a result, the agent can make choices based on a thorough investigation of various environmental elements.

The ABM is a promising method for integrating various HVAC, lighting, and security systems. It permits the reduction of the disparity between the natural environment values and the user's selected parameters that define the overall comfort level [12]. It can optimize energy management, simulate occupant behavior, and provide intelligent control strategies to reconcile the tension between the human level of satisfaction and power usage, further improving both environment and social sustainability performance in GB.

Shortcomings also exist in the present ABM. First, building agents and human agents lack autonomy in many cases. It will lead to only controlled indoor environment sensors by agents with authorization. Next, most agents cannot communicate with external environments (software runs out of the BAS). The reasoning technique limits autonomous decisions based on external real-time data. Last, the validation of agent-based simulation, especially stochastic occupancy modeling in a real-world GB project, still needs to be improved.

4.2.2. Data mining

Data mining (DM) is a growing topic in the GB industry that can effectively save time and intelligently identify and analyze energy consumption records available from BAS [106]. It can extract hidden information from semi-structured and unstructured data sources by employing intelligent algorithms. **Fig. 10** depicts the DM procedures and applications in GB [107]. This technique has advantages in revealing energy consumption patterns and occupants' preferences compared to traditional statistical models. Artificial neural networks (ANN) and SVM are two common data mining algorithms widely used in GB energy performance systems because of their advantages in addressing complex and non-linear system dynamics [11]. Generally, the DM consists of four steps to analyze energy consumption patterns [106,108], they are: (1) collect data from BAS; (2) pre-process the time-series data and address missing values; (3) analyze the data using the k-means clustering method; (4) interpret cluster analysis results.

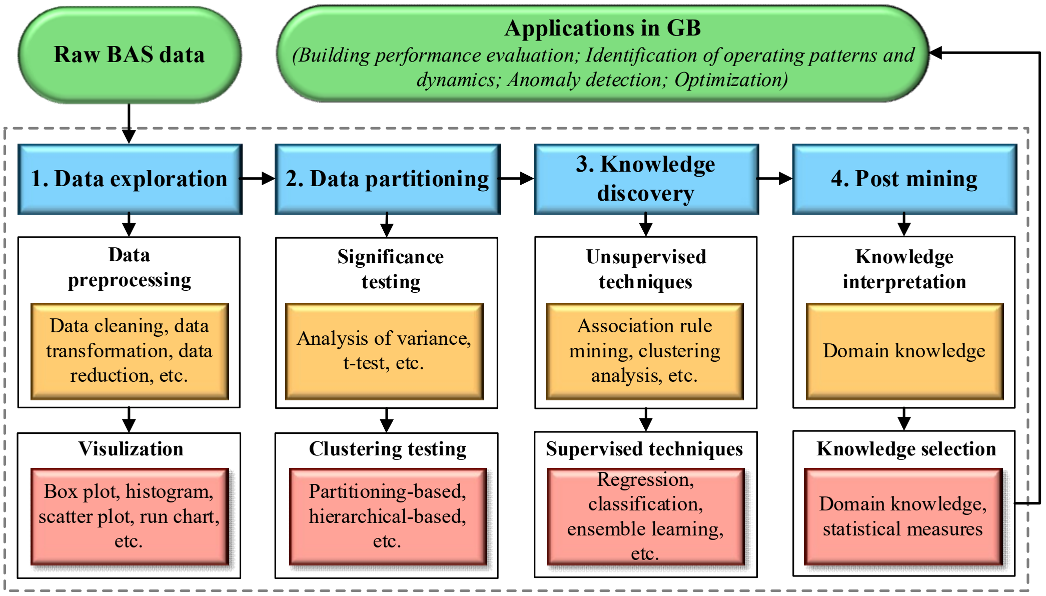


Fig. 10. Framework of DM method in GB.

Numerous studies applied DM to discover building energy consumption and saving strategies. The research of Chen et al.[96] supported that users would regulate their behavior patterns to decrease energy consumption if provided knowledge about the energy-saving activity. In their work, they used pervasive computing techniques to analyze electricity usage and related activity to find correct energy-efficient behavioral patterns. Then they validated the interactive influence between energy consumption and occupants' behavior using DM algorithms based on intelligent home testbeds. Afroz et al. [16] systematically analyzed the ANN application in the HVAC system, such as the heating/cooling load prediction, the performance of chillers, indoor environment optimization, and dynamics modeling.

In addition, Amayri et al. [82] integrated machine learning and DM techniques to improve the database quality collected from human behavior in buildings. They adopted a supervised learning approach and Multi-Layer Perceptron (MLP) to construct an occupants' interaction framework. A novel concept, 'spread rate,' was introduced in their research, which can improve the occupancy estimation results and avoid useless interaction with users. Similarly, Alam et al. [106] used an unsupervised data mining approach, 'k-means clustering,' to examine the energy usage trends in educational facilities. They demonstrated that malfunctioning sensors, more extended occupancy, or switch-off mode would affect EPG.

The studies mentioned above explain the interaction patterns of energy consumption and occupant behavior in GB by applying DM techniques. The method possesses several advantages, such as addressing complex non-linear relations between human activity and HVAC systems, discovering hidden energy consumption patterns, and being user-friendly to many researchers. However, several limitations exist. First, no derivation of the produced model is achievable for either DM technique. Next, the performance will become worse when circumstances diverge from training settings. Finally, it is always time-consuming to apply to these programs online.

4.2.3. Multi-Criteria Decision Making

Multi-Criteria Decision Making (MCDM) is a systematic analysis framework that develops scientific evaluation criteria to solve optimization problems in a group of alternatives [27]. As illustrated in **Fig. 11**, there are four decision-making processes using MCDM approaches [109]. This new research paradigm is built based on the trade-off objectives of power usage against human comfort. Two conflict indicators are initially selected based on a literature review, workshop, or expert interview. Then, the decision-making matrix is constructed based on the weighing methods, which directly impact the final decision. After that, the alternatives are evaluated and ranked. Finally, designer assesses whether the results meet the trade-off objectives.

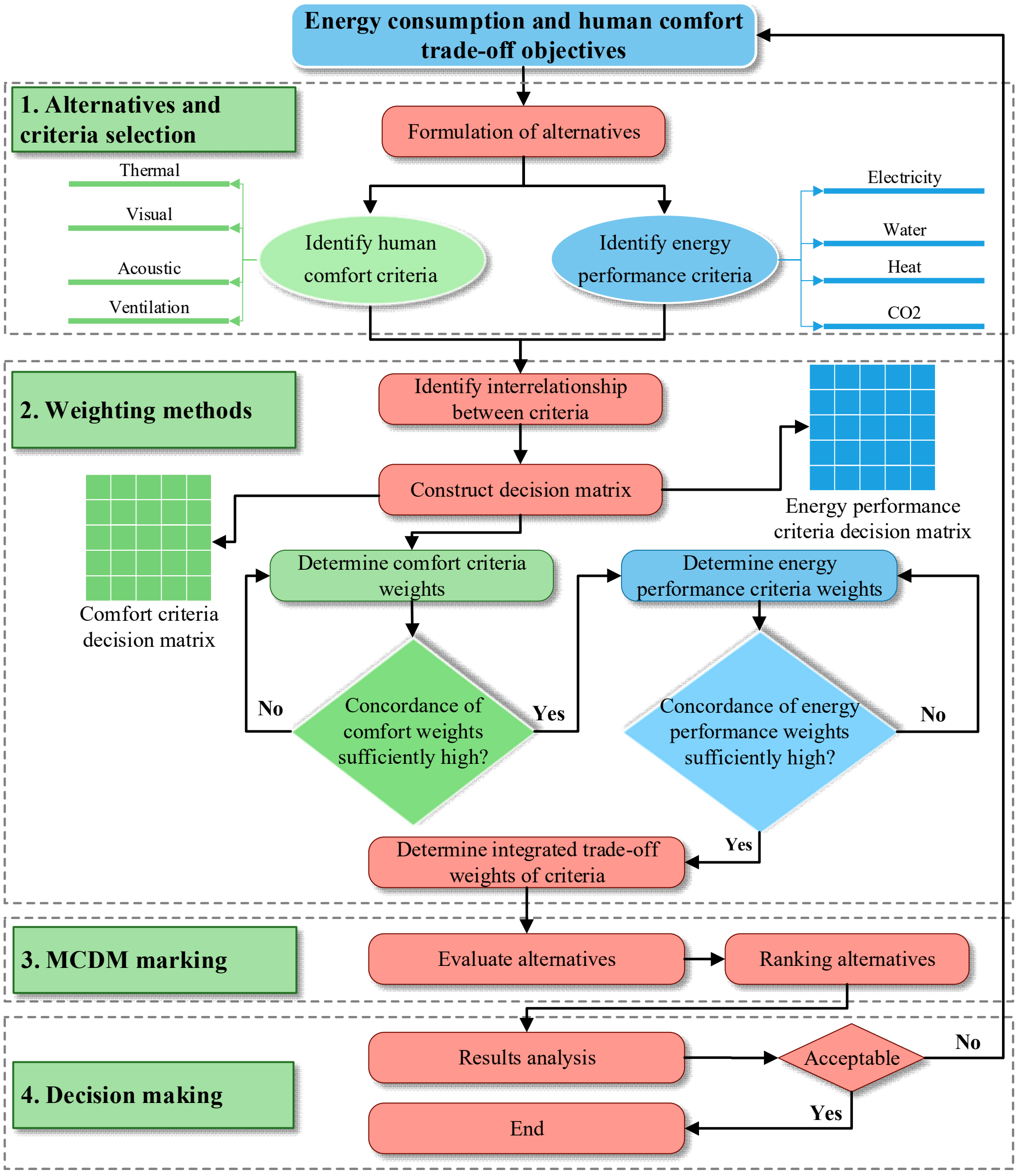


Fig .11. MCDM process for achieving a trade-off between energy efficiency and occupant comfort.

Researchers have tried to find the most suitable MCDM techniques for intelligent decisions [110]. For instance, Kuo et al. [111] employed fuzzy analytic hierarchical process (FAHP) methods to evaluate the policy efficiency of intelligent GB in Taiwan from 1999 to 2015. Then they collected data through questionnaire surveys and expert interviews. After that, they incorporated a fuzzy transformation matrix (FTM) into FAHP to measure the contributions of each policy. Finally, they verified the weighting results using empirical methods. They found that the effectiveness of policy incentives in the design stage outperforms that in the operation stage. Similarly, Moghtadernejad et al. [27] systematically analyzed nine standard MCDM methods and classified them from two perspectives: problem-solving technique and mathematical nature. The investigation showed that the Choquet Integrals method outperforms other mainly used methods, fuzzy sets, AHP, and TOPSIS, in designing sustainable façades.

Furthermore, in the building energy management domain, Starynina and Ustinovichius [112] applied the SyMAD-3 method based on MCDM to determine the most effective modification from composing alternatives. This method could assess the structure parameters of buildings and estimate the energy demand for decision-makers. Notably, the hybrid MCDM methods can calculate energy usage faster and more accurately by reducing the impacts of uncertainty factors generated by human behaviors.

Generally, MCDM techniques like fuzzy sets and AHP are easy-to-understand for decision-makers. They can effectively assist energy system management which may be difficult when facing conflicting goals between energy consumption and occupant comfort [113]. However, there are also several drawbacks. First, this technique needs to choose reliable energy performance and occupants' comfort criteria based on sufficient experience in the particular field. Moreover, interviewing experts and obtaining a consensus may be difficult because they have various research backgrounds. Last, criteria weighting and ranking results may need to be more consistent when changing the expert panel.

4.2.4 Multi-objective optimization (MOO)

The multi-objective optimization (MOO) method has been widely applied in GB energy optimization to coordinate conflicting factors and achieve the trade-off objectives before-mentioned [114]. **Fig. 12** illustrates four steps included in this optimization method. The inputs are time series data, including energy consumption, weather conditions, and occupant behaviors, extracted from the GB modeling software Autodesk series. Then the GB energy model is modeled through simulation programs such as TRNSYS, Energy Plus, and Design Builder. Modeling optimization is followed by optimizing parameters, finding objective functions, and applying optimization algorithms. These algorithms include a Genetic algorithm (GA), Non-dominated Sorting Genetic Algorithm (NSGA-II), and Particle swarm optimization (PSO) [115]. Finally, designers evaluate optimization values to achieve the energy savings and occupants' comfort trade-off objective.

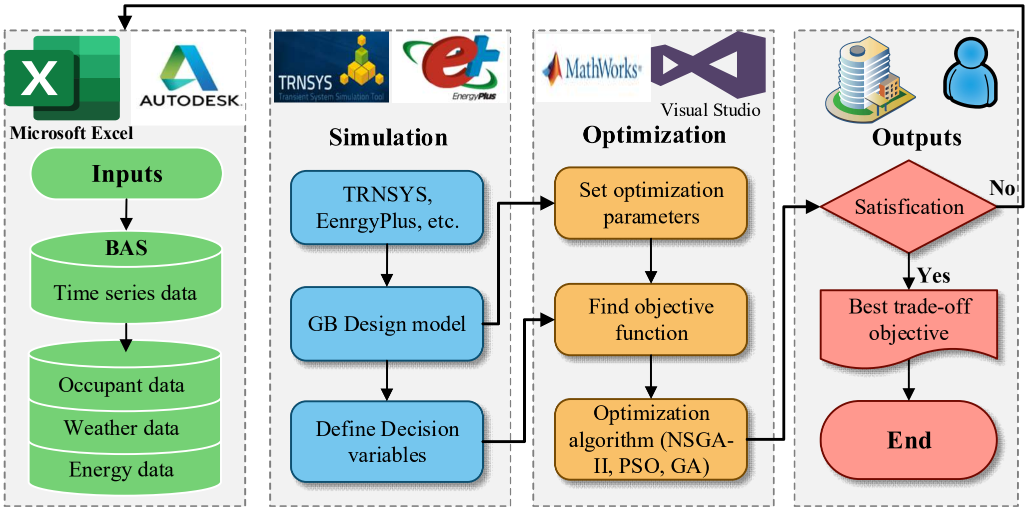


Fig .12. GB Multi-objective optimization method based on BAS.

The MOO method has advantages in controlling and balancing conflicting objectives in the complex BAS [15]. Previous studies have found that it can also support achieving multiple sustainability objectives (social, economic, and environmental) in GB. For example, Lin et al. [116]

introduced a MOO method to treat building envelope and BAS in GB. Their work optimizes the design configurations by reducing envelop energy loading and improving air conditioning performance. They found the solution compelling through a case study. The findings showed that the MOO approach decreases CO2 emissions by 58.3% while only increasing costs by 5.3%.

Similarly, to increase the power exchange efficiency based on solar, Middelhauve et al. [117] used the MOO method to identify the most appropriate orientations of photovoltaic panels. Although the design cost rose by 8.3%, the peak power could be reduced by 50% when exchanged with the power grid. Yan [118] argued that adding green criteria to the MOO approach in addition to sustainability and affordability objectives is necessary. He applied the fraction of energy values to calculate their priority efficiently, which can also trade off the three types of optimization objectives.

The main advantages of MOO are as follows: (1) It considers energy consumption, weather conditions, and occupants' comfort in parallel and provides valuable data to designers. As a result, it has strengths in identifying the best-compromised solutions by comparing key indices. (2) MOO can solve data integration issues in the BAS, which includes numerous, dynamic, and various energy operation data. However, there are also some limits. (1) Occupant behavior preferences play an essential role in GB energy performance. (2) Existing simulation and modeling software fail to interpolate occupant behavior variables. (3) The present optimization algorithm has yet to adopt holistic optimization methods to address the whole BAS and occupant comfort.

4.3. *Summary of BAS and GB integration methods*

In the current research, BAS provides an effective energy performance model and occupant behavior prediction method for GB energy and comfort management. Precisely, to predict and control GB energy consumption, MPC and SMPC are widely employed. These models are characteristics with multi-input multi-output (MIMO), unruled-based, real-time prediction, and control coupled with environmental sustainability assessment in GB. ABM, DM, MCDM, and MOO are the four main methods for modeling energy performance and occupant behavior. These methods cannot only help achieve a trade-off between energy efficiency and occupant comfort but also improve the sustainability level in GB. **Fig.13** shows the five integration methods applied for GB trade-off objectives.

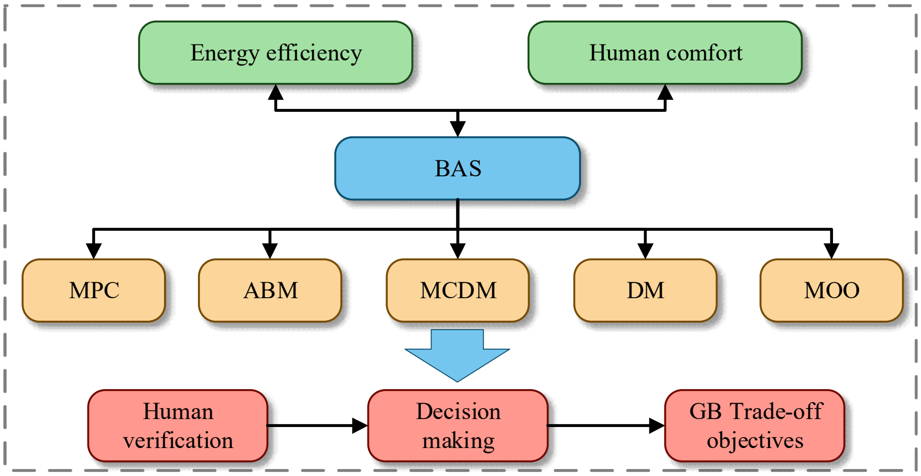


Fig. 13. BAS and GB integration methods

5. Challenges and recommendations

Although the five main BAS-GB integration methods have many benefits for minimizing EPG and achieving trade-off objectives, challenges and limitations also exist. The following sections will discuss four main challenges and related research recommendations to provide a valuable reference for future work.

5.1. Uncertainties affecting energy efficiency

Uncertainty is one of the significant challenges for achieving a trade-off between energy consumption and occupant comfort in GB based on BAS. Previous research has shown that occupant behaviors, building operation, and weather conditions are three main uncertainties resulting in GB energy performance discrepancy [87,119]. As shown in **Fig.14**, building operation status is influenced by weather conditions and occupant behaviors. Moreover, users' behaviors may change in response to weather conditions. For example, occupants will close the window and turn on the air conditioner on a hot day to cool themselves. This behavior will improve thermal comfort and increase electricity consumption at the same time. This causal relationship between them provides a foundation for energy efficiency simulation. Therefore, further research needs to enhance current integration methods to include all three forms of uncertainty.

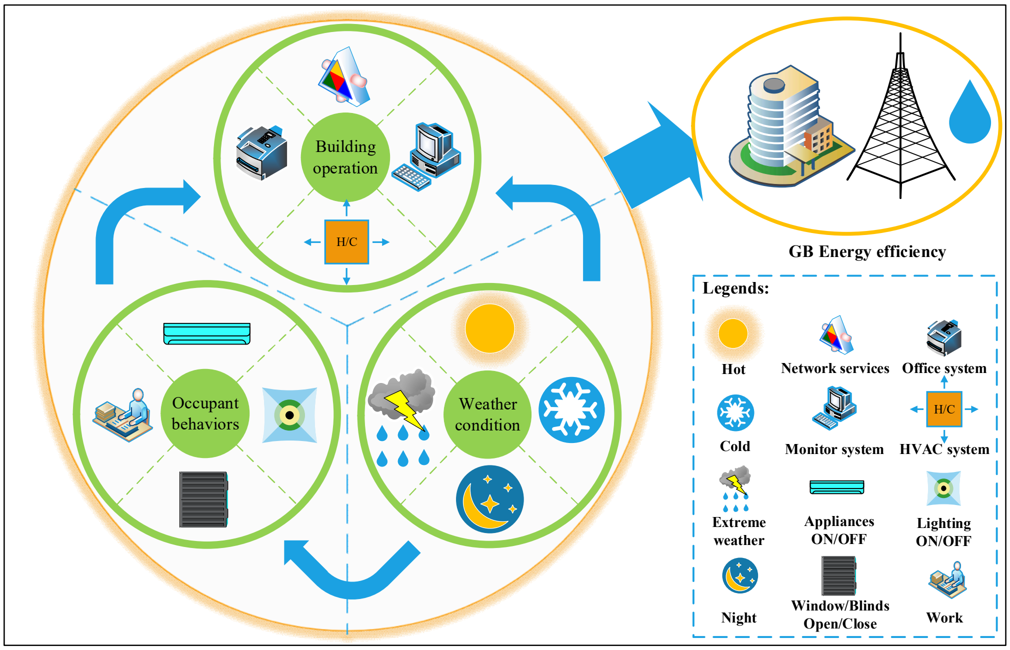


Fig. 14. Three main uncertainties affecting GB energy efficiency

Specifically, occupant behavior is characteristic of highly complex, dynamic, and stochastic in GB [12,82,96]. Researchers employed hybrid ABM, DM, and MPC methods to predict occupant behavior accurately. These studies showed that occupancy or occupant behavior prediction is challenging, and the driving factor is indeterminate [80]. Scholars have developed three fundamental techniques to improve prediction performance: data acquisition, modeling/simulating techniques, and evaluation [18,120,121]. Moreover, future work should create integrated platforms to collect historical data, such as temperature, humidity, and occupants' preference. The platform can construct links with BAS through a central database. It can also support causal analysis of occupant behavior on energy efficiency, help predict and optimize energy usage, and provide real-time BAS management strategies through feedback mechanisms [60,103]. Furthermore, researchers can adopt a series of software agents as intelligent control devices that provide a friendly human interface for decision-making [74].

Regarding modeling and evaluation techniques, MPC, ABM, DM, MCDM, and MOO implemented in BAS mentioned in section 4 have gained much attention in recent decades. Remarkably, the stochastic MPC framework enables taking all three uncertainties into account based on probability distributions theory and outperforms the deterministic MPC. Although it can provide more reliable energy consumption results [122,123], the three main uncertainty factors mentioned before will also lower its performance [13,101,103]. In addition, researchers should deeply understand integration methods such as ABM, DM, MCDM, and MOO to address uncertainties and achieve GB sustainability. Furthermore, different sensors, devices, and simulation software must work together, leading to interoperability issues. Future studies could apply semantic techniques [124] and develop immersive VR applications based on open-source software tools [95] to address these issues. Last, it is challenging to accurately simulate occupant behavior, weather condition, and building operation status because data acquisition is too tricky. Therefore, further research should acquire more actual and real-time data from residential and commercial buildings to remedy the problem.

5.2. Long-term Predictive Control for energy performance

Energy consumption in the operation stage of GB is primarily responsible for energy usage throughout the lifecycle. Therefore, it is critical to predict and control energy efficiency from a long-term perspective. However, existing forecast methods can only input short-term occupancy data and weather conditions, i.e., hours, weekdays, and months [12,98,125]. Such models can record the occupant behavior in response to indoor environment quality, weather conditions, and adjustments on BAS. However, the strategy is only effective for achieving short-term trade-off goals of energy savings and occupant comfort [64,78]. Future research can combine the regional climate characteristics into their simulation models. For instance, the United States has temperate and subtropical climates, the United Kingdom features a temperate maritime climate, and China is characteristics of hybrid climates [126]. Furthermore, considering human activity events, such as work meetings and academic conferences, can improve the accuracy of long-term predictive analytics of energy performance in GB.

During the lifecycle of GB, BAS plays a vital role in energy savings, occupant comfort improvement, and cost reduction, as mentioned in section 3.1. It enables applying intelligent technologies and metering systems to acquire vast amounts of metadata from BAS to monitor and control building facilities [10]. Despite the advantages of BAS in terms of long-term energy performance management, its widespread use in buildings remains a challenge. Future publications can focus on enhancing the interoperability of various platforms, such as BIM, IoT, and DM [127]. BAS integration with them could offer complementary functions and accelerate the digitalization of GB projects. However, most of the research is still at the conceptual stage. Hence, a potential research direction can be integrating BAS with other modeling approaches using advanced technologies, such as semantic web technologies, digital twins, and AI [10,127,128]. Furthermore, future work should consider end-user interactions and feedback in BAS to facilitate increased acceptance [5]. Finally, standardized data acquisition methods are worth investigating to reduce data collection costs.

5.3. BAS-supported GB Sustainability Goals

GB sustainability goals have three main dimensions, social, economic, and environmental [86]. Existing research mainly concentrates on energy efficiency optimization and occupancy/occupant behavior modeling, which is more related to environmental sustainability [36,39,78]. However, these studies only calculate energy consumption without incorporating the evaluation of CO_2 emissions [129]. The lifecycle assessment (LCA) technique can calculate the kg CO_2 emitted accurately and mitigate its impact on the natural environment by providing feedback to design makers [130]. However, the LCA method must be more flexible when design changes occur in GB [131]. Accordingly, the major challenge is integrating this approach with BAS, MCDM [110], and FAHP [132] to assess building energy conservation comprehensively [109]. Therefore, future research should develop an integrated platform to evaluate energy efficiency in GB dynamically.

In addition, social and economic sustainability has yet to gain enough attention in the existing BAS-GB domain. A few researchers have attempted to explore stakeholder collaboration for reducing the EPG, which is in line with social sustainability. Seamless knowledge transfer and expertise still need to be improved among stakeholders. Notably, the attention to real-time energy optimization via storage in GB is rising [133,134]. More real-time energy storage and usage data can be acquired from smart grids to promote the development of the energy markets worldwide. This issue may be an effective solution for reducing energy usage costs to achieve economic sustainability.

For this reason, the energy storage integrates with BAS in GB will become available at a commercial level in the future. The following are several challenging integration framework developments worthy of future research. (1) The energy transfer framework for cost-effective design [114]; (2) The closed-loop digital twin framework for advanced project management [128]; (3) The building real-time air quality monitoring framework for occupants' health. In conclusion, future work should develop more integrated frameworks to encompass social and economic sustainability.

5.4. Privacy and security

Tracking human activity through the BAS effectively explores the relationship between energy consumption and occupant behaviors [72]. Smartphone scanning sensors, videos, and cameras can acquire vast volumes of dynamic data in the monitoring process. Operation managers can identify the number of people and their indoor behaviors through these intelligent devices. Indeed, such tracking can provide rich occupant behavior information for high energy efficiency decision-making. However, the approach leads to human activity under real-time supervision, e.g., work, study, and social activities. Therefore, tracking occupants' behavior without invading their privacy is challenging. Another challenge is that large amounts of data need to be recorded and rated for real-time processing, even exceeding the capability of smartphones and cameras. Future studies can use heat maps, low-resolution images, and low-quality videos to obtain only vague information about individuals.

Furthermore, current studies construct Personalized Comfort Models (PCMs) to predict and evaluate occupant thermal comfort, incorporating human thermo-regulation factors [135]. Specifically, the model's inputs are physiological signals, e.g., skin temperature, heart rate, and metabolic rate. This model is complementary to the traditional temperature measurement. The application of PCM faces two challenges. The first is that wearable sensors are expensive, especially when testing many people simultaneously [136]. Another is the privacy and security concerns due to tracking physiological signals [124]. Therefore, other thermal comfort measurements, such as air temperature, humidity, and air velocity, can be integrated with BAS as alternatives for future research.

6. Conclusions

This paper reviews the BAS for energy and comfort management in GB, combing the bibliometric and systematic analysis methods. The quantitative approach analyzes the annual publication trends, keyword co-occurrence, and cluster based on 141 articles in the BAS-GB domain. Additionally, this study systematically analyzes the BAS application in the GB domain and BAS-GB integration methods. The results indicate that BAS can minimize EPG and improve occupant comfort throughout the lifecycle of GB. Furthermore, this work discusses five primary BAS-GB integration methods, including MPC, ABM, DM, MCDM, and MOO. Integrating these methods with BAS can achieve a trade-off between energy efficiency and occupant comfort. Last, this review presents challenges and recommendations for future research.

The main contributions of this review are as follows: First, the paper provides theoretical developments for BAS application in GB lifecycles and occupant comfort. It reveals that BAS is a promising tool that can effectively prompt the development of smart GB. Next, this review develops a research framework for reducing EPG in GB. Moreover, this study contributes to developing five integration methods (MPC, ABM, DM, MCDM, and MOO) by combing the BAS technique. These methods will support constructing an integrated platform for achieving a trade-off between low energy consumption and high occupant comfort in GB.

Finally, recommendations for future research are proposed based on limitations analysis. They are: (1) improve existing integration methods to contain all three types of uncertainties (occupant behaviors, building operation, and weather conditions); (2) actually simulate the energy consumption in a long-term lifecycle of GB; (3) improve the interoperability of BAS using semantic web technologies; (4) standardized data acquisition methods to reduce data collection cost; (5) construct BAS-GB integration frameworks for achieving social, economic and environmental sustainability goals; (6) develop big data storage techniques and monitor occupants comfort without privacy and security concerns.

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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