



Occupant behavior and energy efficiency in higher education buildings: A systematic review

Mohammed Mahmood Katun *, Olawale Muhammed Popoola

Department of Electrical Engineering and Centre for Energy and Electric Power (CEEP), Tshwane University of Technology, Pretoria, South Africa

Abstract

This systematic literature review examines the impact of occupant activities and patterns on efficient energy utilization in higher education buildings. The building sector is a major global energy consumer, with education institutions contributing significantly due to their diverse functions and occupancy variability. Traditional building control systems, relying on fixed schedules, often lead to substantial energy waste as they do not account for actual occupancy. This paper synthesizes literature from 2015-2025, using PRISMA guidelines and Scopus as a primary database, ultimately analyzing 52 eligible articles. It identifies various approaches for learning occupant behavior, including dedicated sensors, Wi-Fi infrastructure, and advanced analytical techniques like machine learning and model predictive control. Key occupant activities negatively impacting energy efficiency include Heating, Ventilation, and Air Conditioning (HVAC) setpoint adjustments, fixed operating schedules and mismanagement of equipment and lighting. These behaviors result in significant energy waste, with HVAC systems and electronic devices being major contributors. The study highlights a research gap in understanding occupant activity and energy efficiency in student accommodation. Addressing these dynamic and often unpredictable occupant behaviors is crucial for achieving sustainable energy management in university campuses.

Keywords: Occupant Behavior; Energy Efficiency; Energy Consumption; Commercial Building; Higher Education Buildings

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Cite this article as: Katun, M.M. and Popoola, O.M. (2025), "Occupant behavior and energy efficiency in higher education buildings: A systematic review", *International Journal of Development and Sustainability*, Vol. 14 No. 7, pp. 476-497.

* Corresponding author. E-mail address: mahmoodmk@tut.ac.za

1. Introduction

The building sector is a significant global energy consumer, accounting for approximately 40% of total worldwide energy consumption and contributing to 30% or more of global CO₂ emissions (Gui et al., 2021; Kula et al., 2023; Rafiq et al., 2024; Safwat et al., 2024). This demand is continuously increasing due to factors such as growing populations and rising standards of living, which exacerbate challenges related to depleting fossil fuels, climate change, and sustainability (Jafarinejad et al., 2019; Rafiq et al., 2024).

Within the commercial building sector, education buildings are substantial energy users, representing a considerable contribution to overall energy consumption (Brucal et al., 2025; Elbellahy et al., 2024; Kula et al., 2023; Safwat et al., 2024; Taheri et al., 2024). Universities, in particular, function akin to "small cities" due to their size, diverse populations, and varied activities, encompassing laboratories, lecture halls, libraries, and administrative offices, all with distinct energy needs (Brucal et al., 2025; Gui et al., 2021; Safwat et al., 2024). These complexities often lead to energy being wasted. For instance, a report indicates that 30% of total energy consumption in commercial buildings is wasted (Rafiq et al., 2024).

A crucial, yet often overlooked, factor influencing building energy consumption is the presence and behavior of occupants (Leong and Essah, 2017; Michailidis et al., 2018; Rafiq et al., 2024; Zou et al., 2017). Systems like HVAC and lighting are major energy consumers, accounting for nearly 60% of all energy used in commercial buildings (Chaer et al., 2025; Kula et al., 2023; Rafiq et al., 2024). While most traditional building control systems rely on fixed, predetermined occupancy schedules, these schedules frequently differ significantly from actual occupancy patterns, resulting in substantial and unnecessary energy consumption (Ben-Nakhi and Mahmoud, 2017; Jagadeesh Simma et al., 2019; Zou et al., 2017). For example, studies have shown that average occupancy rates in university offices are rarely above 60% of maximum capacity, yet HVAC systems often follow static schedules, leading to considerable energy waste (Kula et al., 2023).

The emergence of smart buildings, enabled by Internet of Things (IoT) devices, automation systems, and Building Energy Management Systems (BEMS), offers a pathway to more efficient energy management through the availability of real-time data (Bellala et al., 2017; Hossain et al., 2020; Jagadeesh Simma et al., 2019; Simma et al., 2019; Wagiman et al., 2020). Modern machine learning (ML) algorithms and artificial neural networks (ANN) can process this data to forecast and schedule building loads effectively, leading to optimized energy utilization and cost reduction (Jafarinejad et al., 2019; Rafiq et al., 2024; Ramli et al., 2024). Incorporating real-time occupancy information allows for dynamic adjustment of systems like HVAC and lighting, which can significantly enhance energy efficiency and occupant comfort (Jagadeesh Simma et al., 2019; Kula et al., 2023; Rafiq et al., 2024). Studies have demonstrated that integrating real-time occupancy data can lead to substantial energy savings, with some approaches achieving up to 77% energy savings while improving comfort (Rajabi et al., 2022). For instance, WiFi-based occupancy schedules have resulted in at least 50% savings in HVAC energy consumption over static schedules in institutional buildings (Jagadeesh Simma et al., 2019).

Despite the recognized importance of occupant information, a "performance gap" frequently exists between the predicted and actual energy consumption of buildings (Alfalah et al., 2023; Kula et al., 2023). This gap is largely attributed to the inadequate consideration of dynamic occupant behavior during the design and operation phases (Alfalah et al., 2023; Jagadeesh Simma et al., 2019; Kula et al., 2023). While advancements in data collection (e.g., infrared video image sensors, WiFi networks) are improving the accuracy of occupancy data (Alfalah et al., 2023; Kula et al., 2023; Simma et al., 2019), there remains a lack of comprehensive, long-

term empirical research and standardized methodologies specifically focused on the impact of occupant activities on energy utilization in higher education buildings (Alfalah et al., 2023; Hossain et al., 2020). Many existing studies have concentrated on residential or commercial office buildings, or have been conducted over shorter durations, limiting their applicability to the unique context of higher education (Alfalah et al., 2023; Hossain et al., 2020; J. Yang et al., 2016).

This systematic review aims to bridge this knowledge gap by comprehensively analyzing and synthesizing existing literature on the impact of occupant activities on efficient energy utilization in higher education buildings by putting up the following research questions;

- What approaches are employed to learn occupant behavior and patterns in higher education institutions?
- What specific occupant activities have the most significant negative impact on energy efficiency on buildings in higher education institutions?
- What categories can be used to classify the energy-related challenges resulting from occupant behaviors?
- How are energy efficient practices and programs promoted in higher education institutions?

Furthermore, by examining various methodologies, findings, and challenges, this review seeks to provide a holistic understanding of the current state of research, identify key influential factors, and highlight opportunities for future advancements in achieving sustainable energy management in university and college campuses worldwide.

2. Methodology

This study was performed to present an understanding of occupant behavior in an academic environment. The methods and approaches used by researcher to learn and categorize occupant activities, impact on energy efficiency, and how energy efficient programs are promoted in higher education institutions was emphasized in the review. The systematic literature review employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Scopus search engine was used to collect data covering 2015-2025 for this study, and all selected documents were in English. The search for articles for this study was conducted on the 18th of June 2025.

The search for relevant articles was executed by exploring the title and keywords sections of the electronic databases mentioned above. The search strategy involved various combinations of keywords related to research area, using Boolean operators ("AND" and "OR") to combine the search terms. The search keywords used for the literature exploration were occupancy, occupant activities, energy utilization, energy management, commercial building and educational building. The following search query was used to identify and retrieve all articles related to the research topic: ("occupancy" OR "occupant activities" AND "energy utilization" OR "energy management" AND "commercial building" OR "educational building").

Inclusion/exclusion criteria: This review synthesized studies with varying methodologies and standards to capture the complexity of occupant behavior and energy usage. By examining diverse aspects, including occupant patterns, energy wastage, data collection technologies, efficient practices, and predictive models, we gained a deeper understanding of the research landscape and its implications for future research.

The initial search yielded 263 documents, and for eligibility, studies from 2015 to 2025 were considered, dropping the documents to 200. Given the rapid evolution of BEMS and predictive modeling, this review prioritizes recent research (post-2014) to reflect the current state of knowledge on occupant behavior and energy usage in higher education buildings, ensuring relevance and accuracy. Based on this eligibility, Table 1. shows documents published by year. Out of the documents published within the study range, 2018 and 2022 recorded 12%; making the both year recording the highest publications. This may indicate a high level of research activity or significant data gathering. As of the time this search was conducted, the least goes to 2025 followed by 2024 recording 3.5% and 6.5% respectively. Declining effort in this area was recorded from 2023 to date although days are still counting for the year 2025.

Table 1. Documents published by year

Year	Number of document published
2015	20
2016	21
2017	19
2018	24
2019	16
2020	17
2021	23
2022	24
2023	16
2024	13
2025	7

The study further investigated the search based on document type. As revealed on the Figure 1., the highest percentage (49.5%) of number of publication came from journal articles followed by conference papers (45.0%) and the least was book chapter and conference review. The analysis also revealed that review only made up 3.5% of the documents, indicating the need for this study (a systematic review).

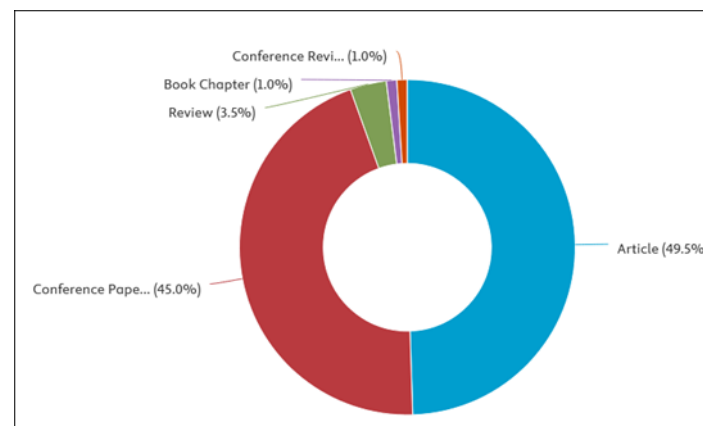
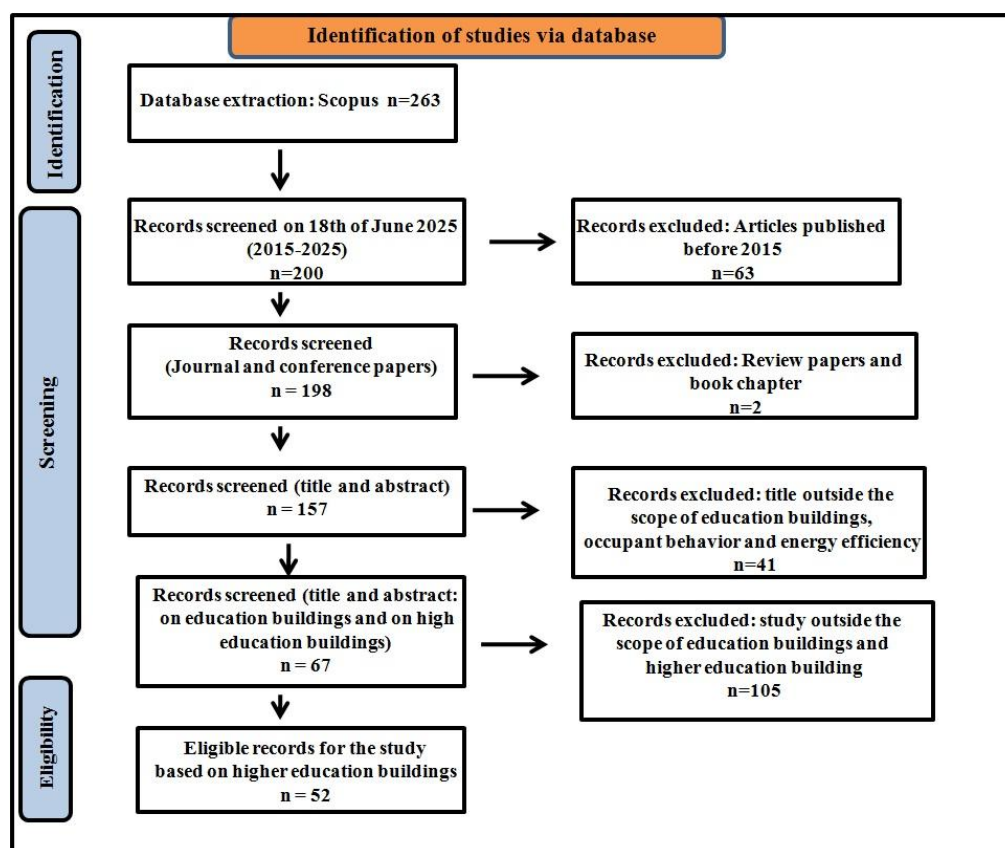


Figure 1. Percentage of document type (source: scopus.com)

Table 2. Selection and exclusion criteria

Selection criteria	Exclusion criteria
Articles published between 2015-2025	Articles published before 2015
Publication in English language	Articles not in English language
Research published in academic journals and conference proceedings	Review, conference review and book chapter
Relevance of the title and abstract to occupant behavior, occupant activities, energy efficiency, predictive models, occupancy and data collection technologies in education buildings.	Studies outside the scope of education buildings
Studies that were specifically done on higher education buildings	Studies outside the scope of higher education buildings

**Figure 2.** PRISMA flow-chat: An illustration of data collection approach

We subjected the remaining articles to a four-stage screening process, beginning with 198 journal and conference papers. Subsequent review of titles and abstracts narrowed the selection to 157, followed by the

exclusion of research unrelated to education buildings, leaving 67 articles. Ultimately, only studies focused on higher education institutions were included, resulting in the 52 eligible articles depicted in the PRISMA flow chart (Figure 2). This rigorous methodology allowed for precise identification of research gaps and effective addressing of research questions, yielding a reliable foundation for practical recommendations and future research directions. Table 2 shows the selection and exclusion criteria in detail.

3. Result and interpretation

This paper systematically analyzed 52 articles, focusing on themes such as occupant activities, comfort, presence, data collection, sensor technologies, forecasting models, control systems (for occupancy, energy, HVAC, and other appliances), and IoT-based systems. This comprehensive study revealed common research objectives, methodologies, and experimental setups. The objectives across all 52 reviewed articles can be summarized into five key areas:

- To understand occupancy, their activities, patterns and comfort in higher education buildings.
- To study different methods of occupancy presence and data collection technologies.
- To understudy control technologies and their impact on energy efficiency in higher education buildings.
- To simulate an energy efficient building without compromising occupant comfort and lastly,
- To test and identify the best performing models to predict occupant presence and electricity consumption.

The reviewed studies primarily leveraged simulation software, forecasting models, IoT and sensor technologies, questionnaires (as used in (Allab et al., 2017)), energy meters, and smart technologies to conduct their experiments. For example, several articles ((Ascione et al., 2015; F. Sangogboye et al., 2018; J. Yang et al., 2016)) utilized EnergyPlus software to model educational buildings, aiming to optimize energy use. Various sensors were deployed to record occupant presence and environmental data. Furthermore, machine learning, deep learning, and hybrid models were commonly employed across experiments to predict both occupant presence and energy consumption. Among the 52 articles analyzed, the experimental locations varied, with offices (38.33%), classrooms/lecture halls (33.33%), and laboratories (16.67%) being the most frequently cited. A smaller portion (11.67%) involved ambiguous locations. It's noteworthy that, to our knowledge, none of the studies explicitly focused on student accommodation or hostels.

Student accommodation has a unique energy profile due to its high density, varied occupancy, and shared facilities. Unlike typical residential buildings, it has higher baseline energy use around the clock, worsened by student habits like leaving lights on and a general lack of energy awareness (Alamel, 2021; Ayeleru et al., 2017; Jamaludin et al., 2017). This suggests a significant research gap concerning the impact of occupant activity on energy efficiency in student housing within higher education buildings. Additionally, Heating, Ventilation, and Air Conditioning (HVAC) systems were more frequently investigated compared to other appliances and plug loads in the reviewed articles.

3.1. An overview on the methodologies

The articles employ diverse methodologies. Some focus on data-driven models for load forecasting and optimization, using hybrid ML (LSTM, XgBoost, Random Forest, Linear Regression) (Rafiq et al., 2024), fuzzy

logic with Rough Set Theory (Brucal et al., 2025), or various ML algorithms (ANN, DNN, SVR) (Ramli et al., 2024). Others utilize building energy modeling with tools like TRNSYS18 or EnergyPlus to evaluate retrofits, green roofs, or specific scenarios (Aparicio-Fernández et al., 2023; Ascione et al., 2015; J. Yang et al., 2016; Z. Yang et al., 2015). A significant segment involves IoT and sensing technologies for real-time environmental monitoring (Hossain et al., 2020), non-intrusive occupancy detection via WiFi (Zou et al., 2017), or Bluetooth Low Energy (BLE) for plug load management (Tekler et al., 2022). Methodologies also include experimental research with Post-Occupancy Evaluation (POE) surveys (Elbellahy et al., 2024; Hossain et al., 2020), regulated laboratory testing for sensor reliability (Kula et al., 2023), and data collection protocols where actual data is scarce (Safwat et al., 2024).

However, among the methodologies synthesized, Rafiq et al.'s hybrid Machine Learning for load prediction stands out for combining different algorithms (LSTM, XgBoost, RF, LR) utilizing real-time occupant information for high accuracy, directly impacting energy optimization and cost savings (Rafiq et al., 2024). Meanwhile, the research did by Tekler et al. on IoT-based Plug-Mate provide a holistic, non-intrusive system for plug load management, a less-research area, achieving significant energy savings (51.7%) and high user satisfaction through advanced automation (Tekler et al., 2022). Kula et al.'s standardized laboratory methodology for occupancy sensor reliability is crucial and exceptional, providing a uniform testing method for data integrity vital for all occupancy-driven controls (Kula et al., 2023). However, the reviewed articles revealed several methodological limitations, which can be summarized thus:

- Data gaps: Many studies were based on simulated or hypothetical data rather than actual energy consumption records.
- Limited generalizability: Many research focused on specific building types or environmental condition, narrowing their broader applicability.
- Technical constraints: Automated occupancy sensing systems were often obstructed by reliance on user devices or detection errors.
- Scalability challenges: Manual system calibrations and computational complexities presented major obstacles to real-world implementation and scalability.

These constraints underscore the need for more robust and generalizable research methodologies to advance the field.

4. Findings on the questions

This section comprehensively presents the findings on the research questions. To achieve this, the 52 articles were critically evaluated to identified and understand the effective way to articulate the response to the research questions.

4.1. Findings on the first question: Understanding occupant behavior and patterns in higher education institutions

Building management systems (BMS) have increasingly integrated sophisticated approaches to learn and adapt to occupant activities and behaviors, moving beyond static schedules to dynamic, data-driven controls

(Jafarinejad et al., 2019; Kula et al., 2023; Winkler et al., 2020). This is crucial for optimizing energy efficiency and maintaining comfort in higher education buildings. Key approaches employed to collect data to learn occupant behavior and patterns include:

Occupancy sensing technologies:

- Dedicated sensors such as infrared video image sensors, thermal and vibration sensors, CO₂ sensors, and PIR sensors are used to extract real-time occupant presence, counts, and locations (Alfalah et al., 2023; Allab et al., 2017; Bourdeau et al., 2018; Clausen et al., 2021; Merabtine et al., 2018; Rajabi et al., 2022; F. Sangogboye et al., 2018; Winkler et al., 2020; Zou et al., 2017). These provide high-accuracy data, up to 98% for infrared video image sensors (Alfalah et al., 2023). BMS data from HVAC systems, such as damper or reheat valve positions and CO₂ levels, can act as "occupancy indicative sensors" to infer presence (Ardakanian et al., 2018; Merabtine et al., 2018).
- Wi-Fi Infrastructure: A widely adopted non-intrusive method leverages existing Wi-Fi networks to detect, count, and track occupants (Alfalah et al., 2023; Auquilla et al., 2016; Bellala et al., 2017; Heidarinejad et al., 2017; Jagadeesh Simma et al., 2019; Markus et al., 2021; Rafsanjani et al., 2018; Zou et al., 2017). This provides fine-grained, real-time data on presence and movement (Rafsanjani et al., 2018), addressing limitations of traditional sensors. Systems like WinOSS have demonstrated high detection accuracy, such as 98.85% (Zou et al., 2017). Wi-Fi connection/disconnection events can be viable indicators of energy load changes (Rafsanjani et al., 2018). Studies show Wi-Fi based occupancy schedules can lead to at least 50% savings in HVAC energy consumption over static schedules. However, privacy concerns exist with MAC (Media Access Control) addresses (Jagadeesh Simma et al., 2019). CO₂ sensors are also used to infer occupancy levels for ventilation control (Matthew et al., 2021; Rajabi et al., 2022).
- Other Sensors: Wired network connections can provide fine-grained, cube-level occupancy information (Bellala et al., 2017). Methods based on computer interactions (e.g., network traffic) are also utilized (Auquilla et al., 2016). Door Access Systems (DAS) requiring swipe cards, these systems can provide accessibility to occupancy patterns in specific facilities like offices and labs (Heidarinejad et al., 2017).

Advanced analytical techniques:

- Machine Learning (ML) and Deep Learning (DL) models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XgBoost), Support Vector Regression (SVR), and Random Forest (RF) are extensively used for load forecasting, occupancy prediction, and identifying complex non-linear building behaviors (Jafarinejad et al., 2019; Khalil et al., 2021; Mortazavigazar et al., 2021; Rafiq et al., 2024; Ramli et al., 2024). Multi-label classification (MLC) is used for predicting room occupancy (F. C. Sangogboye et al., 2016). Hidden Markov Models (HMMs) are employed for unsupervised occupancy estimation from network data (Bellala et al., 2017). Support Vector Machines (SVM) show robust performance in occupancy prediction (Bellala et al., 2017; F. C. Sangogboye et al., 2016). Techniques like Principal Component Analysis (PCA) and K-means clustering are used to classify ACU (Air Conditioning Unit) power consumption and identify distinct operational patterns based on variables like temperature, humidity, and occupancy (Brucal et al., 2025). K-means groups raw occupancy data into cohesive patterns and profiles, identifying influential drivers like

academic terms or examination periods in universities (Alfalah et al., 2023). Model Predictive Control (MPC) systems integrate real-time and predicted occupancy, weather forecasts, and building models to optimize HVAC operations, allowing for pre-conditioning and significant energy savings (Clausen et al., 2021; Merema et al., 2022; Winkler et al., 2020). Blended Markov Chains (BMC) are used for occupancy prediction within MPC frameworks (Winkler et al., 2020).

- Sensor fusion techniques, such as those in the MODES framework, combine inputs from multiple sensor types (e.g., thermal and vibration) to achieve more accurate occupancy estimations, improving individual sensor deficiencies (Kula et al., 2023; Rajabi et al., 2022). Non-Intrusive Occupant Load Monitoring (NIOLM); A novel approach that couples Wi-Fi-based occupancy data with power changes in aggregated building-wide energy data. It uses density-based clustering (DBSCAN) and discriminant analysis (QDA) to disaggregate energy consumption down to individual occupant behaviors (Rafsanjani et al., 2018).
- Agent-Based Systems and Fuzzy Logic: These intelligent systems are employed to dynamically schedule HVAC and other systems, adapting to conditions like weather and university event schedules (Al-Daraiseh et al., 2015; Xie et al., 2018). Fuzzy Logic (FL), often enhanced by Rough Set Theory (RST), forms the basis of intelligent control systems that automatically adjust ACU setpoints. These systems utilize real-time indoor and outdoor environmental and room occupancy data. FL simulates human thought processes to effectively manage intricate scenarios, including fluctuating occupancy levels. RST specifically streamlines fuzzy control by eliminating rule redundancy (e.g., a 99.72% reduction in instructional rooms), substantially enhancing computational speed (96.40% faster) and precision in ACU setpoint optimization. This has demonstrated daily average power savings of 25.56%. Occupancy is a critical input, classified into categories such as "empty," "low," or "maximum capacity," alongside personal factors like clothing insulation and metabolic rate (Brucal et al., 2025).
- Statistical Analysis: Regression and correlation analyses are performed on historical data, including electricity use and occupancy, to identify patterns (Bourdeau et al., 2018; Kim et al., 2017). This helps link electricity consumption to occupancy (Kim et al., 2017).
- Building Energy Models (BEM/BPS): These models, such as those developed in EnergyPlus or TRNSYS, are calibrated using derived occupancy and plug-load schedules to accurately predict energy performance (Allab et al., 2017; Kim et al., 2017; F. Sangogboye et al., 2018; J. Yang et al., 2016).
- Transfer learning approaches improve occupancy prediction accuracy even with limited historical data by leveraging knowledge from similar rooms or buildings (Khalil et al., 2021).

Passive data sources:

Data like classroom timetables, administrative work hours, and special events provide advance information on occupant levels, locations, and numbers, enabling efficient HVAC scheduling without real-time sensing infrastructure (Taheri et al., 2024; Wilson et al., 2022). This allows for a lower setpoint temperature during non-occupancy periods, with preheating initiated to reach a comfortable level by the time occupants arrive, thereby optimizing energy consumption without compromising comfort. This approach has led to a 14.98% reduction in energy consumption in some case studies (Taheri et al., 2024).

Survey data sources:

Post-Occupancy Evaluation (POE) surveys and Computerized Maintenance Management System (CMMS) data (complaint logs) gather subjective feedback on comfort and identify anomalies or behavioral patterns affecting building performance (Day et al., 2020; Elbellahy et al., 2024; Hossain et al., 2020; Markus et al., 2021). The photovoice method allows occupants to visually document experiences (Day et al., 2020). Thermal comfort surveys are used to gather subjective feedback from occupants, aligning with models such as Fanger's predicted mean vote (PMV), to refine control strategies based on actual comfort preferences (Brucal et al., 2025). These diverse approaches signify a comprehensive shift towards dynamic and data-driven energy management.

Finally, BMS and associated technologies have made significant strides in optimizing operations to account for occupant activities and behaviors, particularly within higher educational buildings. These methods collectively enable BMS to dynamically respond to occupant presence, optimizing energy use and enhancing indoor environmental quality (Franco et al., 2021; Tekler et al., 2022). This evolution moves beyond rigid, rule-based systems to more dynamic and adaptive approaches. They provide a deeper understanding of dynamic occupancy patterns, enabling more optimized energy management and improved comfort in buildings (Al-Daraiseh et al., 2015; Heidarinejad et al., 2017; Michailidis et al., 2018; Xie et al., 2018; Zhou et al., 2017).

4.2. Findings on the second question: Specific occupant activities that have the most significant negative impact on energy efficiency in higher education institutions

Buildings are significant global energy consumers (Clausen et al., 2021; Rafiq et al., 2024). A large share of this consumption is due to Heating, Ventilation, and Air Conditioning (HVAC) systems (Merema et al., 2022; Rafiq et al., 2024; Rajabi et al., 2022; Winkler et al., 2020). Inefficient operation, often linked to occupant activities and behaviors, contributes to significant energy waste. For example, a considerable amount of total energy consumption is wasted in commercial buildings (Rafiq et al., 2024). Certain occupant activities and corresponding operational challenges that adversely affect energy efficiency include:

HVAC setpoint adjustments and fixed schedules:

Occupants and building managers frequently adjust HVAC and setpoints of air conditioning (AC) systems or maintain temperatures higher than recommended, with a 1°C increase potentially raising energy consumption by approximately 12% (Brucal et al., 2025; Heidarinejad et al., 2017; Merabtine et al., 2018). Many buildings operate HVAC systems on fixed, static schedules irrespective of actual occupancy, leading to unnecessary conditioning of empty or partially occupied spaces (Ardakanian et al., 2018; Bellala et al., 2017; Kula et al., 2023; Wei et al., 2018; Wilson et al., 2022; Winkler et al., 2020). This means spaces are conditioned and ventilated even when unoccupied or sparsely populated (Kula et al., 2023; Wilson et al., 2022; Winkler et al., 2020). ACUs are major energy consumers in educational buildings, accounting for approximately 47% of the total energy consumption (Taheri et al., 2024). Occupant thermal comfort preferences directly influence ACU settings, with demands for cooler conditions leading to increased energy use (Brucal et al., 2025). For instance, a

university's lecture halls might have significantly reduced usage in summer, but HVAC continues to operate based on general schedules. This approach can waste 15-30% of the energy produced by HVAC systems (Wilson et al., 2022). This "naive" scheduling is less efficient than dynamically adjusting to actual occupancy patterns (Ardakanian et al., 2018). Furthermore, energy management systems often keep air handling units (AHUs) running 24/7 or during weekends to ensure comfort for the start of the week, leading to wasted electricity (Allab et al., 2017; Merabtine et al., 2018).

Equipment and lighting mismanagement:

Occupants commonly leave equipment and lights on during unoccupied periods, contributing significantly to energy waste which largely affecting electricity consumption in educational buildings and schools (Azar and Al Amoodi, 2016; Bourdeau et al., 2018; Safwat et al., 2024). Miscellaneous electric loads (MELs), though individually small, collectively account for up to 36% of commercial building energy consumption (Rafsanjani et al., 2018). After-hours use of equipment and lighting is particularly impactful in buildings with longer unoccupied periods, such as classrooms during evenings and weekends (Azar and Al Amoodi, 2016). Inefficient auxiliary devices and high standby energy use for lighting control systems can also negate potential energy savings, with standby power accounting for up to 30-55% of total lighting energy (Gentile and Dubois, 2017). A primary factor is the prolonged operation of electronic devices, particularly personal computers (PCs). For instance, studies indicate that PC power consumption accounts for the highest percentage (42.71%) in offices. Simulation laboratories, in particular, consume more energy (41.14%) than other labs due to PCs being left working for extended periods. This direct occupant behavior results in substantial energy wastage (Safwat et al., 2024).

Adaptive behaviors for thermal comfort:

To achieve comfort, occupants may engage in energy-intensive behaviors. This includes opening windows and doors during cold weather to compensate for overheating or poor air quality, which increases heating and ventilation loads (Allab et al., 2017; Bourdeau et al., 2018; Jafarinejad et al., 2019; Markus et al., 2021; Merabtine et al., 2018). Additionally, the use of personal electric heaters to counter under-heating in offices or achieve desired warmer temperatures can drastically increase energy consumption (Allab et al., 2017; Bourdeau et al., 2018).

Occupancy variability:

Educational and university buildings, especially those with mixed-use spaces like laboratories and classrooms, exhibit highly dynamic and unpredictable occupancy patterns (Al-Daraiseh et al., 2015; Bourdeau et al., 2018; Kim et al., 2017; Leong and Essah, 2017). This variability challenges traditional building management systems that rely on simplistic occupancy models, making optimal energy consumption difficult without adaptive control strategies (Al-Daraiseh

et al., 2015). Effective energy management requires accounting for these occupant behaviors and integrating adaptive control mechanisms that respond to real-time occupancy (Azar and Al Amoodi, 2016; Bellala et al., 2017; Kim et al., 2017).

Overall, the dynamic and often unpredictable nature of occupant presence and behavior directly influences building load and energy consumption, demonstrating a positive correlation between occupancy and total building load (Alfalah et al., 2023; Rafiq et al., 2024). The unmanaged or excessive use of these resources, influenced by occupant behavior and the inherent energy needs of modern educational facilities, leads to notable energy inefficiencies. A lack of understanding or control over building interfaces by occupants can also lead to suboptimal energy use (Day et al., 2020). Addressing these occupant-related inefficiencies is crucial for achieving better energy management and cost reduction (Alfalah et al., 2023; Rafiq et al., 2024).

4.3. Findings on the third question: Categories of challenges induced by occupant activities on energy utilization in higher education buildings

Optimizing energy utilization in higher education buildings faces significant challenges rooted in occupant activities and behaviors. These challenges can be categorized as follows:

Unpredictable and highly variable occupancy:

Occupancy is inherently variant and dynamic, differing greatly over space and time (Ardakanian et al., 2018; Z. Yang et al., 2015). Educational and university buildings (resembling small cities), with their diverse users (teachers, researchers, students) and continually changing activities and population densities, present particularly complex occupancy models (Al-Daraiseh et al., 2015; Leong and Essah, 2017; Safwat et al., 2024; J. Yang et al., 2016). Occupancy levels are dynamic, changing daily and seasonally, such as classrooms being 50% occupied on weekdays but 0% on weekends, or full load during academic terms versus 10% during breaks (Brucal et al., 2025; Safwat et al., 2024). This unpredictability makes it difficult to maintain comfort while optimizing energy over long periods (Z. Yang et al., 2015).

Direct and indirect energy impacts of occupant actions:

Occupant-Driven Internal Heat Gains and Loads: Occupants directly contribute to heat gain through metabolism and activity (influenced by activity levels and clothing), and are associated with the use of building systems like lighting and miscellaneous electric loads (MELs) (Azar and Al Amoodi, 2016; Brucal et al., 2025; Safwat et al., 2024; Taheri et al., 2024; Z. Yang et al., 2015). MELs, though individually small, constitute a substantial 36% of commercial building energy consumption (Rafsanjani et al., 2018). For internally-load dominated buildings like offices and research laboratories, these internal loads, including lighting and receptacle use, are the primary drivers of energy consumption, rather than outdoor conditions (Heidarinejad et al., 2017). The increasing need for energy on campuses is also driven by technology advances and energy-consuming laboratory and computing facilities. A significant challenge is occupant behavior, such as leaving PCs working for extended periods, which substantially increases energy consumption in areas like simulation labs (Taheri et al., 2024). Lighting and plug loads

are also highly influenced by occupant behavior (Alfalah et al., 2023; Rafiq et al., 2024; Safwat et al., 2024; Taheri et al., 2024). The growing reliance on electronic devices and other plug loads, contributing up to 30% of total energy in offices, often leads to unmanaged energy use (Tekler et al., 2022). Furthermore, efforts to manage plug loads face challenges due to user resistance and perceived inconvenience of active management, resulting in low system adoption and limited savings (Tekler et al., 2022).

Lack of real-time occupancy information:

A critical limitation is the absence of real-time and predictive occupant information for Building Management Systems (BMS) (Rajabi et al., 2022; Winkler et al., 2020). Many conventional sensing methods, such as motion sensors, struggle to provide accurate occupant counts (only presence) or differentiate between absence of movement and absence of people (Wilson et al., 2022). This deficiency prevents dynamic adjustment of ventilation rates and optimal thermal conditioning (Winkler et al., 2020). Therefore, accurately learning and defining occupant behavior for energy models becomes challenging. While some studies use Wi-Fi infrastructure or specialized sensors (PIR, CO₂) to detect and track occupants (Bellala et al., 2017; Rafsanjani et al., 2018; Zou et al., 2017), these methods can be costly, intrusive, or limited in granularity and accuracy (Bellala et al., 2017; Kim et al., 2017; Merema et al., 2019; Simma et al., 2019; Wilson et al., 2022). Privacy concerns associated with some data collection methods, such as Wi-Fi MAC addresses, also hinder widespread implementation (Jagadeesh Simma et al., 2019; Simma et al., 2019). Obtaining precise, disaggregated data to link energy consumption to individual occupant behaviors remains a gap (Rafsanjani et al., 2018). Additionally, data-driven models require large quantities of high-quality, high temporal resolution data (Markus et al., 2021), which can be difficult to obtain, especially for new or newly monitored buildings with limited historical data (Khalil et al., 2021).

Building-specific factors and inflexibility:

The multifunctional nature of educational and institutional buildings, with varying schedules for teaching, research, and administration, adds complexity to energy management (Gui et al., 2021). Building design can also create issues; for example, increased insulation levels, while beneficial, can raise the risk of overheating if not coupled with adaptive controls (Merema et al., 2022). Lastly, a disconnection often exists between occupants and building interfaces, with users being unaware of optimal operational practices or lacking direct control over comfort settings (Day et al., 2020).

Over-provisioning and static scheduling:

A primary challenge stems from over-provisioning of services based on static, predetermined schedules, which assume maximum occupancy irrespective of actual building usage (Kula et al., 2023; Wilson et al., 2022). This leads to unnecessary energy consumption from HVAC and lighting systems, which account for a significant portion of a building's total energy use (Kula

et al., 2023; Simma et al., 2019). For instance, buildings are often over-ventilated because real-time Air Handling Unit (AHU) data is not adequately assessed (Matthew et al., 2021), and spaces are conditioned even when unoccupied (Rajabi et al., 2022; Winkler et al., 2020). Conventional pre-timed HVAC scheduling often leads to wasted energy during unoccupied periods. Furthermore, traditional occupancy sensors can misdetect seated individuals, falsely identifying rooms as unoccupied and leading to unnecessary cooling reductions (Brucal et al., 2025).

Complexity of occupant-centric control implementation:

Integrating occupant behavior into HVAC control strategies is challenging. Implementing real-time, adaptive control systems that account for variable occupancies can lead to a high computational burden due to large rule sets, resulting in extended processing times and reduced efficiency. Scaling such systems, especially those relying on wearable sensors, is also difficult for large populations. Many existing demand control strategies also fail to consider the influence of occupancy, focusing only on indoor temperatures (Brucal et al., 2025).

Lack of Incentive: In commercial and institutional settings, occupants often lack a direct financial incentive to conserve energy, as they are not personally liable for the energy consumed, leading to unnoticed inefficiencies (Wei et al., 2018). These occupant-induced factors underscore the need for sophisticated data collection and management to inform energy-saving measures (Safwat et al., 2024).

4.4. Findings on the first question: How energy-efficient practices are promoted in higher educational institutions?

Energy-efficient practices can significantly be promoted through occupant engagement and awareness programmes, although challenges related to user burden and the "rebound effect" necessitate thoughtful implementation. Occupant activities and behaviors are crucial factors influencing energy consumption in buildings, impacting everything from HVAC systems to lighting and plug loads. Key ways in which occupant engagement programmes promote energy efficiency include:

Increasing awareness and understanding:

Initiatives like the "Green School Initiative" explicitly aim to promote sustainable practices, including energy efficiency, by providing training and support to teachers and staff to implement energy-efficient measures. A broader building energy efficiency roadmap for Egypt also emphasizes the need for "training and awareness, incentives and penalties" to encourage the adoption of energy-efficient practices. It is directly stated that "Educational building staff and students should practice energy saving operation" (Azar and Al Amoodi, 2016; Safwat et al., 2024). This is because occupants tend to behave more efficiently when informed about their energy consumption and the savings achieved (Utami et al., 2018). Educational workshops and real-time data visualization tools can effectively enhance occupants' understanding of invisible thermal data and their environmental impact, fostering a more positive perception of

sustainability. For instance, at the University of Westminster, educational workshops leveraging IoT sensors and BEMS successfully raised students' awareness of environmental and behavioral influences on energy saving (Azar and Al Amoodi, 2016; Hossain et al., 2020). Similarly, at Najran University, suggestions from building users for energy efficiency included "continuous awareness of the importance of practicing energy conservation" and converting control systems to "intelligent operation systems" that offer individual adjustment options (Elbellahy et al., 2024).

Personalized Recommendations: Actively involving occupants through "move recommendations" (suggesting a move to a more energy-efficient space) or "shift schedule recommendations" (adjusting arrival/departure times) can significantly enhance energy savings. These personalized recommendations, derived from historical location data and simulations, can contribute 25% more energy savings than traditional occupancy-based HVAC management alone (Wei et al., 2018).

Providing control and feedback:

- When occupants are given the ability to manually control or override building interfaces (such as blinds, HVAC, windows, thermostats, or electric lighting), they tend to report increased environmental comfort and satisfaction. This sense of control is vital because a disconnection often exists between occupants and building interfaces, where users might be unaware of optimal practices or lack direct control over comfort settings (Day et al., 2020; Elbellahy et al., 2024; Winkler et al., 2020). Systems that integrate "human-in-the-loop" comfort feedback, allowing users to vote on their thermal preferences in real-time, have demonstrated significant reductions in occupant dissatisfaction while also achieving energy cost decreases. For example, the OFFICE framework, which combined real-time and predictive occupancy with human comfort feedback, reduced dissatisfaction from 25% to 0% and decreased energy costs by over 10% in a LEED Gold building (Winkler et al., 2020). Similarly, the Plug-Mate system for plug loads found that the control strategy offering the most user input achieved the highest satisfaction, even with a slight reduction in energy savings compared to full automation. This highlights the need for an optimal balance between automation and user control to encourage long-term engagement and energy savings (Tekler et al., 2022). More so, novel approaches like Non-Intrusive Occupant Load Monitoring (NIOLM) provide granular, occupant-level data, enabling tailored feedback and better evaluation of behavioral interventions (Rafsanjani et al., 2018). This addresses the common issue of occupants lacking direct financial incentive to conserve energy (Wei et al., 2018).
- **Addressing Behavioral Interventions:** While direct behavioral intervention strategies, such as eco-feedback and email reminders aim to encourage energy-saving habits, their long-term effectiveness can be uncertain due to reliance on voluntary change or perceived inconvenience. This highlights the need for intelligent systems that reduce user burden while maintaining user control, striking an "optimal balance between automation and user control" to ensure higher user satisfaction and long-term engagement. The Plug-Mate system, for instance, found that the control strategy offering the most user control had the highest satisfaction score, despite a slight decrease in energy savings (Tekler et al., 2022).

- Thermal comfort surveys actively involve occupants by collecting their subjective feedback on Air Conditioning Unit (ACU) setpoints. This data, combined with objective environmental monitoring, helps refine control strategies to balance occupant comfort with energy efficiency (Brucal et al., 2025). This shows how direct occupant input can lead to more efficient system operation. The integration of occupant behaviors into HVAC control strategies is crucial. Fuzzy logic-based control systems, sometimes augmented by mobile applications and Predicted Mean Vote (PMV)-based feedback, have been developed to enhance user interactions and improve thermal comfort efficiency, leading to energy savings. This demonstrates how technology can facilitate occupant engagement for improved energy performance. Awareness of how these systems work and the importance of adhering to schedules could be part of occupant engagement. Machine Learning models also use "occupancy" as a critical input for energy prediction, underscoring its impact on consumption (Brucal et al., 2025; Ramli et al., 2024).

Analyzing energy use and understanding its characteristics which inherently includes occupant patterns is the foundation for introducing control measures and improving energy efficiency. For instance, studies have identified lighting, air conditioning, and water heating as major energy consumers in schools, areas where targeted occupant awareness campaigns could encourage more efficient practices (Safwat et al., 2024). However, a key challenge remains the "intention gap," where environmental awareness doesn't always translate into action, highlighting a need for further research in this area (Wei et al., 2018). Therefore, by making occupants aware of their energy consumption patterns and providing them with tools or knowledge to influence these patterns, significant progress can be made towards more sustainable and efficient building operations (Safwat et al., 2024).

5. Discussion

This systematic literature review, encompassing 52 articles, reveals the pivotal role of dynamic occupant behavior in energy consumption within higher education buildings. The review highlights a significant shift towards smart building technologies IoT, BEMS, and advanced machine learning (ML/DL) for understanding and adapting to occupant patterns. Various sensing technologies, from infrared to Wi-Fi infrastructure, are now instrumental in gathering real-time data on occupancy, movement, and activities, enabling more precise HVAC and lighting control. However, the unpredictability of occupant behavior remains a primary challenge, contributing to a persistent "performance gap" between predicted and actual energy use. Human actions like overriding controls or leaving windows open can negate technological efficiencies. Addressing this requires a blend of sophisticated automation and active occupant engagement. Programs promoting awareness, gamification, and incentives, alongside "human-in-the-loop" systems, are crucial for fostering energy-efficient practices and balancing comfort with conservation, ultimately aiming for sustainable building operations.

5.1. Limitations

This study followed the PRISMA framework and applied systematic search and screening procedures. However, certain methodological elements required in systematic reviews remain incomplete. In particular, no formal risk of bias assessment or quality appraisal of included studies was performed, and the synthesis is descriptive in parts. These omissions were due to the large number of heterogeneous studies reviewed. Future systematic

reviews with narrower scope or fewer studies should incorporate these components to provide deeper critical evaluation. Therefore, while our study meets key aspects of a systematic review, the above gaps should be considered as limitations.

6. Conclusion and future agenda

The systematic review underscores the critical role of dynamic occupant behavior in achieving efficient energy utilization in higher education buildings. While significant advancements in sensing technologies (e.g., infrared, Wi-Fi), data analytics (e.g., ML, DL, MPC), and smart building systems have provided powerful tools for understanding and adapting to occupant activities, a substantial "performance gap" persists. This gap is primarily driven by the inherent unpredictability of human behavior, the lack of standardized data collection and analysis methodologies, and challenges related to occupant acceptance and user burden with automated systems. Effective energy management necessitates a holistic approach that not only leverages advanced technologies but also prioritizes active occupant engagement, awareness, and the integration of user feedback into building control strategies. The shift towards "human-in-the-loop" systems and non-intrusive monitoring approaches represents a promising direction for balancing energy efficiency with occupant comfort and satisfaction.

This review also highlighted that occupant activities—particularly HVAC setpoint adjustments, fixed scheduling, and equipment mismanagement—are central drivers of inefficiency. While progress has been made, many studies rely heavily on simulation and short-term data, with little focus on student accommodation, which remains a significant research gap.

6.1. Future agenda

Based on the identified gaps, emerging trends, and methodological considerations, the future agenda for research on energy utilization in higher education buildings should focus on:

- *Standardizing Data Protocols and Addressing Privacy:* Developing standardized methods for occupant data collection and tackling privacy concerns related to sensing technologies in higher education buildings.
- *Advanced Modeling and User Integration:* Advancing AI/ML models for predicting complex occupant behaviors especially in student accommodations and seamlessly integrating occupant feedback into building management systems.
- *Context-Specific Energy Dynamics:* Conducting long-term empirical studies on occupant activities and investigating how academic calendars, seasonal variations, and institutional schedules influence energy consumption patterns in higher education.
- *Cost-Benefit Analysis and Scalability:* Performing detailed cost-benefit analyses of smart building technologies and researching the scalability of solutions across diverse educational settings.
- *Strengthening Methodological Rigor in Reviews:* Future systematic reviews should incorporate formal risk of bias assessment, systematic study quality appraisal, and deeper synthesis of findings. These steps will enhance the reliability, comparability, and generalizability of evidence for policy and practice while also strengthening the systematic review methodology in this field.

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