Artificial Intelligence Driven Approaches to Smart Home Security and Efficiency: A Systematic Review

Muhammed Ibrahim[1,2,*], Mohammed A. AI-Sharafi[3], Moamin A Mahmoud[4,5], Gamal Alkawsi[5,6], Abdulnaser A Hagar[7]

[1]College of Graduate Studies, Universiti Tenaga Nasional, Selangor, Malaysia

[2]Department of Information System, Nigerian Army University Biu, Borno Nigeria

[3]Center for Finance and Digital Economy, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia

[4]College of Computing and Informatics, Universiti Tenaga Nasional, Selangor, Malaysia

[5]Institute of Informatics and Computing in Energy, Universiti Tenaga Nasional, Selangor, Malaysia

[6]Faculty of Computer Science and Information Systems, Thamar University, Thamar, Yemen

[7]Faculty of Data Science and Information Technology, INTI International University, Nilai, Malaysia

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Abstract

Artificial intelligence (AI) has emerged as a key technology for improving smart home security and energy efficiency. This study aims to systematically review AI-driven approaches in smart home environments. The review follows the PRISMA 2020 framework and uses the Scopus and Web of Science databases, resulting in 2,429 records, of which 60 studies published between 2021 and 2025 meet the inclusion criteria. The findings indicate that AI significantly enhances smart home performance through automation, energy optimization, anomaly detection, intrusion prevention, and predictive decision-making. Machine learning and deep learning are the most frequently adopted techniques, while reinforcement learning and hybrid AI models demonstrate strong capabilities for adaptive control and energy management. The review also identifies challenges related to data quality, model interpretability, privacy, and real-world implementation. Overall, AI plays a vital role in developing secure, intelligent, and energy-efficient smart home systems that contribute to sustainable urban living and smart city development.

Keywords: smart home, artificial intelligence, machine learning, energy management, security

1. Introduction

The rapid advancement of artificial intelligence (AI) has also extended beyond smart home applications to other critical domains, including cloud-based healthcare cybersecurity and intelligent agricultural monitoring [1-2]. These applications demonstrate the scalability and adaptability of advanced AI techniques for security, automation, and real-time decision support. Smart home technologies have evolved considerably with advancements in AI, the internet of things (IoT), cloud computing, and wireless communication technologies. A smart home refers to a residential environment equipped with interconnected devices and intelligent systems that collect, process, and exchange data to automate household operations and support informed decision-making [3]. These systems facilitate the management of lighting, heating, ventilation, air conditioning, security, and entertainment services while improving user convenience, comfort, and quality of life [4]. Increasing concerns regarding sustainability, energy conservation, and residential security have further accelerated the adoption of smart home technologies, positioning them as a fundamental component of intelligent and sustainable living environments [5].

* Corresponding author. E-mail address: ibrahimcrc321@yahoo.com

Recent developments in IoT infrastructures have transformed conventional homes into intelligent environments capable of real-time monitoring, predictive control, and adaptive automation [6-7]. Smart homes contribute not only to user comfort and convenience but also to enhanced energy efficiency and improved resource utilization. Furthermore, the integration of emerging technologies such as AI, blockchain, augmented reality, and ubiquitous computing has expanded the capabilities of smart home systems beyond traditional automation [8-9]. Among these technologies, AI plays a particularly important role by enabling intelligent decision-making, predictive analytics, behavioral learning, and autonomous system adaptation. Consequently, AI-driven smart home solutions have attracted significant attention from both researchers and practitioners seeking to improve security, operational efficiency, and sustainability [10].

One of the primary objectives of smart home systems is to optimize energy consumption while maintaining user comfort and operational efficiency [11]. As urbanization and energy demands continue to increase, smart homes provide practical solutions through intelligent energy management, predictive control mechanisms, and adaptive automation [12-13]. However, the growing interconnectedness of smart home devices also introduces significant challenges, including cyberattacks, unauthorized access, privacy violations, and communication vulnerabilities [14-15]. Addressing these challenges requires intelligent security mechanisms capable of detecting threats, adapting to changing conditions, and responding autonomously. AI techniques are particularly valuable in this context because of their ability to learn from data, recognize patterns, and make informed decisions with minimal human intervention [16-17].

Several review studies have examined smart home technologies from various perspectives, including IoT-based automation, energy management, security, privacy protection, decision-making algorithms, and user adoption [18-20]. These studies have provided valuable insights into the development of smart home ecosystems and their supporting technologies. Nevertheless, most existing reviews focus on individual application domains or specific technologies without providing a comprehensive assessment of how AI techniques collectively contribute to both smart home security and energy efficiency [21-22]. Furthermore, recent advances involving deep learning (DL), reinforcement learning (RL), artificial neural networks (ANNs), natural language processing (NLP), computer vision (CV), and hybrid AI models remain insufficiently synthesized within a unified smart home context [23-25].

Despite the growing body of literature, several important research gaps remain. Existing studies frequently investigate security enhancement, energy management, or individual AI techniques independently, resulting in limited understanding of how multiple AI approaches can be integrated to address security and efficiency challenges [25-28]. In addition, many review studies do not clearly distinguish AI-driven solutions from conventional automation systems, thereby limiting an understanding of the unique contributions of intelligent technologies. Emerging approaches such as hybrid AI models, explainable AI, NLP, and CV also remain insufficiently explored in smart home environments [29-31]. Consequently, there is a need for a comprehensive and up-to-date synthesis of AI-driven approaches for enhancing smart home security and energy efficiency.

To address these research gaps, this study conducts a systematic literature review (SLR) following the PRISMA 2020 framework to examine the application of AI techniques in smart home environments. Specifically, the review investigates the use of ML, DL, RL, ANNs, NLP, CV, and hybrid AI models for improving smart home security and energy efficiency. The review further identifies emerging research trends, technological challenges, and future research opportunities while ensuring methodological rigor through a structured and transparent review process.

Unlike previous review studies, this review provides a unified synthesis of AI-driven approaches that address smart home security and energy efficiency rather than treating these domains independently. Furthermore, the review systematically compares the capabilities, strengths, limitations, application scenarios, and practical suitability of ML, DL, RL, NLP, CV, and hybrid AI models within a single analytical framework. In addition, this study synthesizes recent evidence published between 2021 and 2025 using the PRISMA 2020 methodology to identify emerging technological trends, research gaps, implementation challenges, and future research priorities. Consequently, the review extends beyond descriptive summaries by providing an integrated perspective that supports researchers and practitioners in selecting appropriate AI techniques for secure, intelligent, and energy-efficient smart home systems [17]. The study is guided by the following research questions:

RQ1. What specific AI techniques are applied to enhance security and energy efficiency in smart homes?

RQ2. How are AI techniques evaluated in smart home environments, and to what extent do they improve security and operational efficiency?

RQ3. What are the current research trends, existing gaps, and future directions for AI applications in smart home security and energy efficiency?

This study makes four main contributions. First, it provides a systematic review of recent studies published between 2021 and 2025 on AI applications in smart home security and energy efficiency. Second, it categorizes and synthesizes the use of ML, DL, RL, ANNs, NLP, CV, and hybrid AI models within smart home environments. Third, it identifies current research trends, technological challenges, and limitations associated with AI-enabled smart home systems. Finally, it identifies future research directions and provides practical recommendations to support the development of secure, intelligent, and energy-efficient smart homes.

The remainder of this paper is organized as follows. Section 2 presents the related work. Section 3 describes the research methodology and review protocol adopted in this study. Section 4 presents and discusses the review findings regarding AI techniques used in smart home security and energy efficiency. Section 5 outlines the future research agenda. Finally, Section 6 presents the conclusions, implications, limitations, and future research directions.

2. Related Work

2.1 Artificial intelligence in smart homes

AI has emerged as a fundamental technology for developing intelligent, adaptive, and autonomous smart home systems. AI enables smart homes to process large volumes of data generated by interconnected devices, learn from user behaviors, and make intelligent decisions with minimal human intervention [32-34]. Common AI technologies applied in smart home environments include ML, DL, ANN, RL, NLP, and CV [32].

The integration of AI within smart homes has enhanced system capabilities in areas such as energy management, security monitoring, activity recognition, predictive maintenance, and personalized automation [35-36]. Machine learning algorithms are widely used for energy consumption forecasting, anomaly detection, and behavioral analysis, while deep learning techniques support advanced surveillance, activity recognition, and intrusion detection [37]. Reinforcement learning enables adaptive decision-making and intelligent control of household resources, whereas NLP and computer vision facilitate natural human-smart home interaction through voice assistants, facial recognition, and visual monitoring systems [20, 23, 26].

Recent advances in AI have further evolved smart homes beyond rule-based automation toward intelligent environments capable of learning user preferences, adapting to changing conditions, and autonomously optimizing operational performance [38-39]. Consequently, AI has become a key enabler of secure, efficient, and sustainable smart home ecosystems, supporting both enhanced user experiences and improved resource utilization [40-41].

2.2 Analysis of existing review studies

Several review studies have examined smart home technologies from diverse perspectives, including IoT-enabled automation, energy management, security, privacy preservation, blockchain integration, and user adoption. While these reviews provide valuable insights into the evolution of smart home systems, their scope is generally restricted to specific technologies, application domains, or user-related factors. Table 1 summarizes representative review studies, their primary focus and limitations, and their key distinctions from the present review. Existing reviews have investigated topics such as IoT-enabled automation, decision-making algorithms, sensor-based monitoring, blockchain security, and AI-driven cybersecurity solutions [17, 29, 42].

Table 1 Comparison of existing review studies

Source	Type	Aim/Focus	Identified Limitations	Key Distinction of the Current Study
[29]	Review	Examines the role of IoT in enabling device connectivity and automation across multiple domains.	Focuses primarily on IoT technologies with limited discussion of AI techniques; does not examine the relationship between security and energy efficiency.	Provides an integrated analysis of AI-driven approaches and their contributions to both smart home security and energy efficiency.
[17]	Systematic Literature Review	Reviews decision-making algorithms used in smart home environments.	Restricted to decision-making methods and lacks coverage of emerging AI approaches such as deep learning (DL), reinforcement learning (RL), and hybrid models.	Evaluates a broader spectrum of AI techniques, including ML, DL, RL, ANNs, NLP, CV, and hybrid models.
[30]	Review	Investigates passive infrared (PIR) sensor applications in smart buildings.	Limited to a single sensing technology and does not provide comparative analysis of AI techniques or system-level applications.	Examines multiple AI approaches across diverse smart home applications and operational domains.
[10]	Scientometric Analysis	Maps research trends and publication patterns in smart home studies.	Provides bibliometric insights but lacks technical evaluation of AI techniques and their practical applications.	Offers qualitative, comparative, and application-oriented analysis of AI methods in smart homes.
[43]	Literature Review	Examines blockchain-based approaches for securing IoT-enabled smart homes.	Primarily focuses on blockchain technologies with limited integration of AI methods.	Investigates AI-driven solutions and the role of hybrid approaches in smart home applications.
[42]	Systematic Literature Review	Reviews smart home services, adoption factors, and user perspectives.	Emphasizes user perception and adoption while providing limited technical analysis of AI models.	Focuses on the technical application and effectiveness of AI techniques for security and energy management.
[44]	Systematic Literature Review	Reviews AI applications in system security assurance.	Addresses general cybersecurity contexts without focusing on smart homes or energy efficiency applications.	Specifically investigates AI applications within smart home environments, integrating security and efficiency perspectives.
[45]	Systematic Review / Meta-study	Explores smart home security, IoT technologies, and user perception.	Limited technical comparison of AI approaches and insufficient evaluation of their effectiveness.	Provides a detailed comparison of AI techniques, their applications, strengths, limitations, and performance outcomes.
[46]	Systematic Literature Review	Reviews AI-driven home security systems and IoT integration.	Concentrates mainly on security applications and provides limited discussion of energy efficiency and comparative AI analysis.	Integrates both security and energy efficiency dimensions while identifying emerging trends, challenges, and future research directions.

However, most focus primarily on either security or energy management, with limited attention to how different AI techniques collectively support both objectives. Moreover, emerging AI approaches, including hybrid AI models, explainable AI, federated learning, natural language processing (NLP), and computer vision, remain insufficiently explored in previous reviews. Existing studies also provide limited comparative evaluations of AI techniques based on their strengths, limitations, real-world applicability, and deployment challenges. Consequently, a comprehensive and up-to-date synthesis is needed to critically compare AI techniques and provide a holistic understanding of their contributions to enhancing smart home security and energy efficiency.

Although several previous reviews have discussed smart home technologies, closer examination reveals important differences from the present study. Reviews such as [45] primarily emphasize smart home security and user-related perspectives, whereas [46] focuses predominantly on AI-enabled security systems and IoT integration. In contrast, the present review synthesizes AI applications for both security and energy efficiency while providing a comparative evaluation of different AI techniques, including ML, DL, RL, NLP, CV, and hybrid models. Furthermore, this review extends previous work by examining emerging research trends, implementation challenges, and future research priorities based exclusively on recent studies published between 2021 and 2025.

2.3 Research gap summary

Based on the analysis of existing review studies, several research gaps emerge. First, previous reviews generally focus on individual technologies, application domains, or user-centric perspectives rather than providing a holistic evaluation of AI techniques for both security and energy efficiency. Second, limited attention has been given to the integration of multiple AI approaches within a unified smart home framework. Third, emerging techniques such as hybrid AI models, NLP, Computer Vision, federated learning, and explainable AI remain insufficiently explored. Finally, there is a lack of recent systematic reviews that comprehensively synthesize developments published between 2021 and 2025.

To address these limitations, the present study provides a systematic and up-to-date review of AI-driven approaches for enhancing smart home security and energy efficiency. By examining a broad range of AI techniques and comparing their applications, strengths, limitations, and emerging trends, this study contributes a comprehensive understanding of the current state of research and identifies future directions for AI-enabled smart home systems.

3. Methodology

In accordance with the PRISMA 2020 guidelines [47], this study conducts a systematic literature review (SLR). The main objective of the review protocol is to minimize potential bias and ensure the reliability and accuracy of the study as shown in the study of [48]. Systematic reviews serve a vital role by performing several key functions. They can address gaps that individual studies may overlook, identify limitations in existing research that require attention in future investigations, help develop or test theories explaining phenomena, and provide comprehensive summaries of the current knowledge in a given field to inform future research [47].

3.1 Search strategy

A comprehensive literature review was conducted in the article titles, abstracts, and keywords across two major databases: Web of Science and Scopus. These databases were chosen because of their broad coverage of high-impact and high-quality scholarly articles [49], with many top-tier publications from other sources also available within them. Specific keywords were strategically chosen to identify relevant publications on the application of AI techniques in smart home environments in accordance with the study objectives. The search used the following combinations of terms: (“smart home” OR “intelligent home” OR “home automation” OR “smart building”) AND (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural network” OR “reinforcement learning” OR “fuzzy logic” OR “computer vision”) AND (“energy efficiency” OR “home efficiency” OR “energy management” OR “resource optimization” OR “performance improvement” OR “sustainability” OR “security” OR “cybersecurity” OR “intrusion detection” OR “data privacy” OR “access control”).

3.2 Study selection process

To identify studies relevant to the research objectives, the screening process was conducted independently by two authors. Any disagreements regarding study eligibility were resolved through discussion with the third author until consensus was reached. The initial search identified 2,429 records, including 2,193 records from Scopus and 236 records from Web of Science.

After removing 59 duplicate records, 2,370 studies remained for title and abstract screening. Subsequently, 1,995 records were excluded, leaving 375 studies for full-text assessment. However, five articles could not be retrieved, leaving 370 studies for further evaluation. Following a detailed eligibility review, 307 studies were excluded because they did not satisfy the inclusion criteria. This process yielded 63 potentially relevant studies. Finally, three studies were excluded because they did not apply any AI techniques, resulting in a final sample of 60 eligible studies included in the review, as illustrated in Fig. 1.

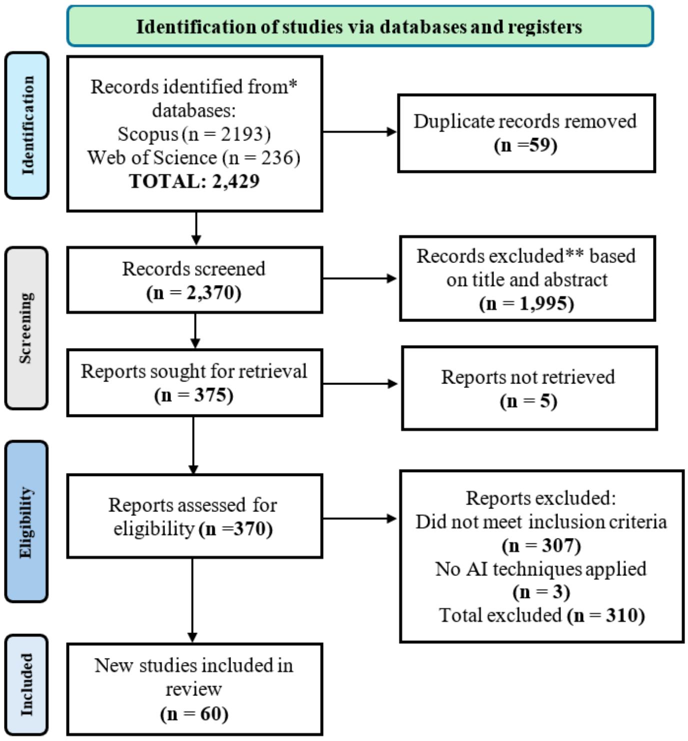

Fig. 1 PRISMA flowchart of the detailed screening strategy for identified studies

3.3 Inclusion and exclusion criteria

In order to ensure the relevance, consistency, and quality of the selected studies, predefined inclusion and exclusion criteria were developed and consistently applied throughout the screening process. Only peer-reviewed studies that met the objectives of this review were considered. The inclusion criteria were as follows: (i) Within the past 5 years, i.e., between 2021 and 2025, to ensure that the studies are as recent as possible; (ii) The studies are written in English; (iii) The studies apply artificial intelligence techniques directly to smart home environments; (iv) The studies present original research findings, which are published in journals or conference proceedings; and (v) the full text of the study is accessible. The exclusion criteria were used at various levels of the screening.

The exclusion criteria included: (i) the studies were not in English; (ii) the studies were published before 2021; (iii) the studies did not involve AI-based methods; (iv) the studies were not related to smart homes; (v) the studies were found in both databases; (vi) the studies are review papers, short papers, or editorials; or (vii) the full text could not be accessed. These criteria were applied during the identification, screening, and eligibility phases of the PRISMA process. Table 2 represents a summary of the inclusion and exclusion results.

Table 2 Study inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
Published in English	Not published in English
Published between 2021-2025	Published before 2021
Based on AI techniques in smart home	Without AI technique; duplicate and review studies
Answers one of the research questions	Short article
Journal, conference paper	Book chapter, review and editorial notes

3.4 Data extraction

To minimize bias and ensure consistency, data extraction was performed independently by two researchers after the final study selection. A structured Microsoft Excel spreadsheet was developed to systematically code and manage the extracted information from each study. The spreadsheet captured key information, including author(s), publication year, study title, AI techniques applied, application domain, country of study, main findings, and identified limitations. All selected studies were carefully reviewed, and relevant data were recorded in a standardized manner to ensure accuracy and completeness. The extracted information was subsequently analyzed and synthesized to address the research questions and identify patterns, trends, challenges, and future research opportunities. This systematic data extraction process enhanced the reliability, transparency, and reproducibility of the review while maintaining consistency with established systematic review practices.

3.5 Quality assessment

To ensure the credibility, relevance, and methodological rigor of the included studies, a structured qualitative quality assessment was conducted following established systematic literature review guidelines [48]. The assessment aimed to evaluate the suitability of each study for addressing the research objectives while minimizing the inclusion of low-quality or irrelevant evidence, as summarized in Table 3. Five quality criteria were applied: (i) clarity of research objectives, (ii) relevance to artificial intelligence applications in smart homes, (iii) appropriateness of the research methodology, (iv) adequacy of validation or evaluation procedures, and (v) transparency in reporting results and findings. Each criterion was scored as 1 if fully satisfied and 0 otherwise, yielding a maximum score of 5 per study. Only studies scoring 3 or above were retained for the final synthesis. The assessment emphasized the description of AI techniques, dataset suitability, robustness of validation methods, reproducibility of the research, and the practical implications for smart home security and energy efficiency. Greater weight was given to studies validated through simulations, experimental evaluations, real-world implementations, or benchmark datasets, which provide stronger empirical evidence than studies with limited validation. Reproducibility was further assessed by examining the clarity of algorithm descriptions, experimental procedures, and performance metrics.

Table 3 Quality assessment criteria

Criterion	Description	Score
QA1	Research objectives are clearly stated	1 = Yes, 0 = No
QA2	Study directly applies AI techniques in smart home environments	1 = Yes, 0 = No
QA3	Research methodology is appropriate and clearly described	1 = Yes, 0 = No
QA4	Validation or evaluation methods are adequately reported	1 = Yes, 0 = No
QA5	Results and findings are clearly presented and discussed	1 = Yes, 0 = No

Since all included publications were peer-reviewed journal articles or conference papers, the overall quality of the evidence base was considered satisfactory. Using the five predefined criteria in Table 3, each of the 60 included studies received a quality score ranging from 3 to 5. All studies achieved the minimum threshold score of 3, confirming that the synthesized evidence was methodologically sound and suitable for inclusion in the review. This quality assessment strengthened the reliability and credibility of the review findings by ensuring that only relevant, rigorous, and high-quality studies informed the analysis. The detailed quality assessment results for all included studies are presented in Appendix A.

4. Results and Discussion

This section provides an overview of the key characteristics of the included studies, focusing on their distribution by year of publication and country of origin.

4.1 Study characteristics

4.1.1 Annual trend

Fig. 2 illustrates the annual distribution of publications from 2021 to 2025 (n = 60), revealing a fluctuating publication trend with a notable increase in 2024. The number of publications remained stable at 13 studies in both 2021 and 2022, indicating sustained scholarly interest and the gradual consolidation of research in this area. A noticeable decline was observed in 2023, with only 8 publications. However, this reduction may reflect a transitional phase characterized by methodological refinement, critical evaluation, or interdisciplinary integration rather than a decline in research interest. Research output increased substantially in 2024, reaching a peak of 18 publications. This surge suggests renewed academic attention and may indicate the growing maturity of the field, driven by technological advancements, increased research funding, and rising practical demand for intelligent smart home solutions. Preliminary data for 2025 show 8 publications, although this figure may increase as additional studies are published throughout the year. Overall, the findings indicate that research activity in this field has experienced periodic fluctuations, with 2024 representing a notable peak, rather than demonstrating a consistent year-on-year increase. This pattern reflects the evolving nature of research in a rapidly developing technological domain.

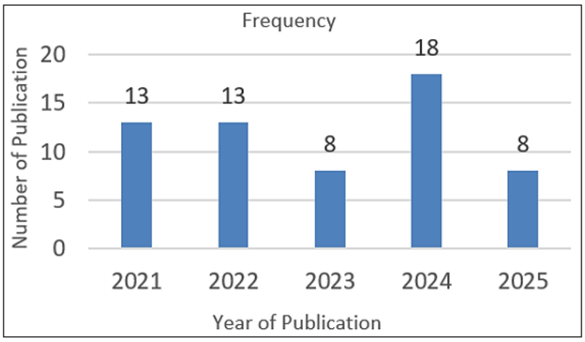

Fig. 2 Annual publications

4.1.2 Geographical characteristics

The geographical distribution of the reviewed studies reveals a concentrated yet globally dispersed research landscape, as illustrated in Fig. 3. India (10 publications) and China (9 publications) emerged as the leading contributors, reflecting the growing research interest in rapidly developing and highly populated economies where smart home technologies are increasingly integrated with urbanization and digital infrastructure initiatives. The United States (6 publications) and the United Kingdom (4 publications) also demonstrated notable contributions. Moderate contributions from countries across Europe, the Middle East, and Asia further highlight the expanding global interest in artificial intelligence-driven smart home technologies. This distribution suggests that research extends across diverse geographical regions rather than being concentrated exclusively in a small number of countries. The participation of multiple countries reflects the growing recognition of smart home technologies as a means of addressing challenges related to security, energy efficiency, automation, and quality of life. Overall, the findings indicate a shift toward a more geographically diversified research landscape, driven by factors such as technological innovation, urban development, population growth, and increasing demand for intelligent and sustainable residential environments.

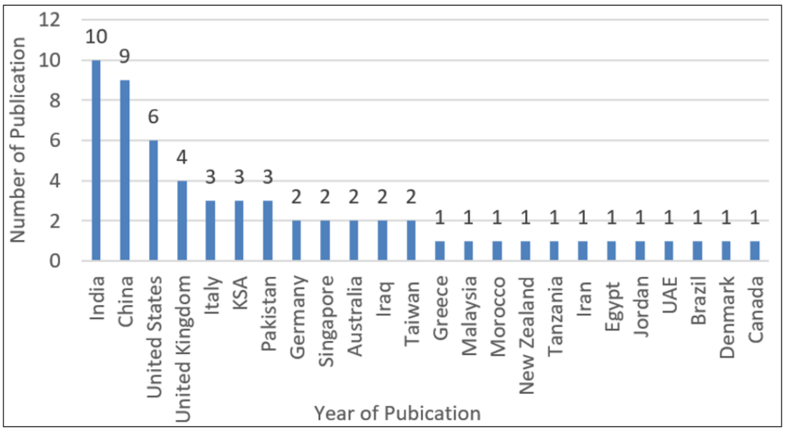

Fig. 3 Countries of the included studies

4.2 Artificial intelligence techniques used in smart home security and efficiency

AI has been widely applied to enhance smart home security and energy efficiency by enabling intelligent automation and data-driven decision-making. The reviewed studies applied various AI techniques, including ML, DL, RL, NLP, CV, and hybrid approaches, to improve security, energy management, predictive analytics, and overall system performance.

Table 4 AI techniques used

Technique	Frequency	Main Applications	Key Strengths	Main Limitations
ML	21	Energy forecasting, anomaly detection, user behavior analysis	Computationally efficient; suitable for real-time prediction	Requires feature engineering; limited for complex data
RL	12	Energy management, adaptive smart control	Learns from dynamic environments; adaptive decision-making	High training complexity; computationally intensive
Hybrid	11	Energy forecasting, security, optimization	High predictive accuracy and robustness	High implementation complexity
DL	12	Surveillance, intrusion detection, activity recognition	Excellent performance on complex and unstructured data	Requires large datasets and high computational resources
NLP	2	Voice interaction, intelligent assistants	Natural and user-friendly interaction	Limited adoption and language dependency
CV	2	Facial recognition, surveillance	Real-time visual monitoring and threat detection	Privacy concerns and sensitivity to environmental conditions

4.2.1 Machine learning (ML)

Machine learning was the most widely adopted AI technique, appearing in 21 of the reviewed studies (Table 4). Its popularity stems from its ability to analyze large volumes of sensor data, identify hidden patterns, and support predictive decision-making for energy management, anomaly detection, intrusion detection, and user behavior analysis [50]. ML has been widely applied to predict energy consumption, forecast demand, detect abnormal appliance activities, and identify potential system failures, thereby improving resource utilization and proactive maintenance [50-52]. For security applications, [53] proposed an ML-based anomaly detection framework that strengthens IoT network protection in resource-constrained smart homes. Similarly, [54] developed a proactive smart home assistant that predicts user preferences based on environmental values, energy costs, and responsibility perceptions, achieving accuracies between 0.67 and 0.82 with F-scores ranging from 0.66 to 0.74. These findings demonstrate that ML effectively balances predictive performance, computational efficiency, and implementation complexity, making it particularly suitable for real-time energy forecasting, anomaly detection, and intelligent automation in smart home environments [55].

4.2.2 Reinforcement learning (RL)

Reinforcement learning was identified in 12 of the reviewed studies (Table 4), reflecting its growing importance in intelligent smart home applications. Unlike supervised learning, RL learns optimal actions through continuous interaction with the environment, making it well-suited for dynamic scenarios involving changing user behavior, energy demand, and environmental conditions [56]. By continuously updating control policies based on real-time feedback, RL supports adaptive decision-making for energy optimization, personalized indoor environments, and autonomous system control [23, 34, 57, 58]. For example, [20] proposed a safe multi-agent RL framework for energy management that improves voltage stability while integrating renewable energy sources. Similarly, [59] introduced MAGPIE, an RL-based intrusion detection system that adapts to dynamic IoT environments using a probabilistic reward mechanism and clustering-based learning. These studies demonstrate that RL is highly effective for adaptive energy management and autonomous control. However, its practical deployment remains constrained by high computational requirements and training complexity.

4.2.3 Hybrid methods

Hybrid AI methods, identified in 11 of the reviewed studies (Table 4), combine two or more AI techniques to improve prediction accuracy, robustness, and adaptability. By leveraging the complementary strengths of different algorithms, hybrid approaches can mitigate the limitations of individual models and support more effective decision-making in smart home applications [60, 61]. For example, [62] proposed an integrated framework combining convolutional neural networks (CNNs), bidirectional long short-term memory (Bi-LSTM), graph neural networks (GNNs), and transformers for energy load forecasting. The model achieved a root mean square error (RMSE) of 5.7532 Wh, a mean absolute percentage error (MAPE) of 3.5%, and an R^2 value of 0.9701, demonstrating the benefits of integrating complementary learning models [63, 64]. Similarly, [65] developed a hybrid framework combining CNNs, LSTMs, Bi-LSTMs, and gated recurrent units (GRUs) for multi-scale energy forecasting, outperforming conventional neural networks with a mean square error of 0.109. These findings indicate that hybrid AI methods generally can improve predictive accuracy and robustness compared to single-model approaches, making them well suited for complex smart home security and energy management tasks. However, their improved performance is often accompanied by greater implementation complexity and computational requirements.

4.2.4 Deep learning (DL)

Deep learning was identified in 12 of the reviewed studies (Table 4), highlighting its growing role in smart home security, automation, and energy management. Built on artificial neural networks (ANNs), DL effectively learns complex patterns from heterogeneous data, including sensor readings, video streams, and user behavior, making it well-suited for surveillance, activity recognition, and intrusion detection [66-69]. For example, [6] proposed a DL-based anomaly detection model that improved intrusion detection by integrating feature selection and hyperparameter optimization. Similarly, [70] developed a CNN-based security system that achieved an accuracy, recall, and F1-score of 98.67% for real-time motion detection, while [71] introduced an ANN-based anomaly detection model that attained 99.51% accuracy on the DS2OS dataset, outperforming traditional methods such as logistic regression and support vector machines. Beyond security, [72] applied an ANN-based framework to improve the quality of energy consumption data by detecting and correcting missing, redundant, and outlier values. These findings suggest that DL can effectively support surveillance, intrusion detection, and intelligent energy management by effectively processing complex and unstructured data. However, its practical deployment remains constrained by high computational requirements and the need for large training datasets.

4.2.5 Natural language processing (NLP)

Although natural language processing was identified in only two of the reviewed studies (Table 4), it plays an important role in enabling intuitive human smart home interaction. Through voice commands and conversational interfaces, NLP allows users to control security systems, lighting, appliances, and other smart home functions more naturally [31]. It also enhances accessibility, personalized interactions, and context-aware responses by adapting to user preferences over time [73]. In addition to improving user experience, NLP supports security through voice-based authentication, intelligent notifications, and alert systems. Although its adoption remains limited, the reviewed studies indicate considerable potential for developing more intelligent, voice-enabled, and context-aware smart home systems, highlighting an important direction for future research.

4.2.6 Computer vision

Computer vision was identified in only two of the reviewed studies (Table 4), indicating that it remains an emerging AI technique for smart home security. By processing visual data from cameras and surveillance devices in real time, CV enables facial recognition, object detection, activity monitoring, and automated threat detection, thereby enhancing situational awareness and access control [74]. For example, [75] developed a smart home security system integrating MediaPipe for face detection and FaceNet for feature extraction, achieving an accuracy of 80.55%. The system combines Android-based monitoring, ESP8266-enabled door control, and intrusion alerts, providing an intelligent alternative to conventional security systems [74]. Although the reviewed studies demonstrate the potential of CV for intelligent surveillance and access control, its wider adoption is constrained by challenges related to privacy, environmental conditions, and computational efficiency.

4.3 Assessment of AI techniques for smart home security and efficiency

The reviewed studies indicate that the effectiveness of AI techniques depends on application requirements, data characteristics, and computational constraints. ML remains the most widely adopted technique because it offers a practical balance between predictive performance and computational efficiency. It is particularly effective for energy forecasting, anomaly detection, and user behavior analysis, making it suitable for resource-constrained IoT environments [30, 53, 76]. However, ML is less effective for processing complex and unstructured data, where advanced feature extraction is required [77]. Hybrid AI approaches combine complementary learning models to improve prediction accuracy, robustness, and adaptability, thereby showing promising results in energy forecasting, anomaly detection, and integrated smart home applications [63, 78]. RL is well suited for adaptive decision-making because it continuously learns from environmental feedback to optimize energy management, climate control, and autonomous system behavior [27, 56]. In contrast, DL is particularly suitable for perception-oriented tasks, including intrusion detection, activity recognition, and intelligent surveillance, owing to its ability to process complex sensor and visual data [70, 79]. However, both RL and DL require substantial computational resources and extensive training, limiting their deployment in resource-constrained smart home environments. Meanwhile, NLP and CV primarily enhance human–home interaction through voice control, facial recognition, and intelligent surveillance [73, 75]. Although these techniques show considerable potential, challenges related to privacy, environmental conditions, and computational efficiency remain.

Overall, no single AI technique is universally optimal for all smart home applications. ML is best suited for predictive analytics, DL excels in perception-based applications, RL supports adaptive control, and hybrid approaches generally achieve the highest overall performance by combining multiple AI models. Therefore, selecting an appropriate AI technique should consider application requirements, computational resources, data availability, and deployment constraints. Table 5 summarizes the comparative strengths, limitations, and application areas of the reviewed AI techniques.

Table 5 Comparison of AI technologies used

Technique	Strengths	Limitations	Typical Applications
Machine Learning	Computationally efficient; suitable for real-time prediction	Requires feature engineering; limited for complex data	Energy forecasting, anomaly detection, user behavior analysis
Deep Learning	High predictive accuracy; effective for complex and unstructured data	Requires large datasets and high computational resources	Surveillance, intrusion detection, activity recognition
Reinforcement Learning	Adaptive decision-making in dynamic environments	High training complexity and computational cost	Energy management, autonomous control
Hybrid Methods	High accuracy and robustness through model integration	High implementation complexity	Energy forecasting, security, integrated optimization
Natural Language Processing	Natural human–device interaction	Limited adoption; language dependency	Voice control, intelligent assistants
Computer Vision	Real-time visual monitoring and threat detection	Privacy concerns; sensitive to environmental conditions	Facial recognition, surveillance

4.3.1 Comparative analysis of AI techniques

A cross-study comparison reveals important differences in the suitability of AI techniques for smart home applications. ML remains the most widely adopted approach because it balances predictive performance, computational efficiency, and ease of implementation, making it suitable for energy forecasting, anomaly detection, and resource-constrained IoT environments [48, 53]. In contrast, DL consistently demonstrated superior performance for perception-oriented tasks, including intrusion detection, activity recognition, and surveillance, with several studies reporting accuracies exceeding 98% [4, 68, 69]. However, its practical deployment is constrained by high computational requirements and the need for large training datasets. Reinforcement learning (RL) is particularly suitable for adaptive energy management and autonomous control because it continuously learns from environmental feedback [18, 57]. Nevertheless, RL requires extensive training and considerable computational resources. Hybrid AI approaches often reported improved prediction accuracy and robustness than single-model techniques by integrating complementary learning models, although this comes at the cost of increased implementation complexity [60–63]. Although NLP and CV appeared less frequently, both showed considerable potential for intelligent human-home interaction, surveillance, and access control, while still facing challenges related to privacy, environmental conditions, and computational efficiency [29, 72, 73]. Overall, the findings indicate that the choice of AI technique should be guided by application requirements, data availability, computational resources, and deployment constraints.

5. Future Research Agenda

According to the conclusions of this systematic literature review, there are numerous critical points that should be considered to advance academic research and practical applications in this field, as presented in Table 6. Based on the synthesis of the reviewed studies, future research directions were prioritized according to their expected scientific impact and practical significance. High-priority areas address challenges that directly influence the reliability, trustworthiness, and large-scale deployment of AI-enabled smart home systems, whereas medium-priority areas focus on improving model performance, standardization, and broader applicability across different contexts.

Table 6 Future research agenda

Priority	Research Agenda	Description
High	Empirical Validation of AI Models in Real-World Smart Homes	Future studies should prioritize long-term real-world validation of AI models across diverse residential environments to evaluate robustness, scalability, reliability, and user acceptance beyond controlled experimental settings.
High	Ethical and Privacy-Centered AI Research	Future research should develop privacy-preserving AI techniques, including federated learning, differential privacy, explainable AI, and transparent decision-making frameworks to strengthen user trust and regulatory compliance.
High	Multi-Agent Reinforcement Learning	Future work should advance decentralized and safe multi-agent reinforcement learning for autonomous energy management, renewable energy integration, adaptive control, and dynamic decision-making in complex smart home environments.
Medium	Hybrid AI Methods	Further research is needed to optimize hybrid models combining CNNs, LSTMs, GRUs, Transformers, and GNNs to improve predictive accuracy, computational efficiency, interpretability, and scalability.
Medium	Standardization and Cross-Domain Benchmarks	Developing standardized datasets, evaluation metrics, benchmark protocols, and open-source simulation platforms would improve the reproducibility and comparability of AI models across smart home applications.
Medium	Underexplored Techniques: NLP and Computer Vision	Future studies should investigate multilingual voice assistants, context-aware natural language interaction, and advanced computer vision techniques for real-time surveillance, human activity recognition, and intelligent access control.
Medium	Inclusive and Region-Specific Research	Future research should expand to developing countries and underrepresented regions to examine infrastructure constraints, cultural factors, affordability, and technology adoption, improving the generalizability of AI-enabled smart home solutions.

To further synthesize the findings, Fig 4 presents a conceptual framework linking the reviewed AI techniques with smart home application domains, key implementation challenges, and prioritized future research directions. The framework provides an integrated view of how AI can support secure, energy-efficient, and intelligent smart home systems while addressing current technological and deployment challenges.

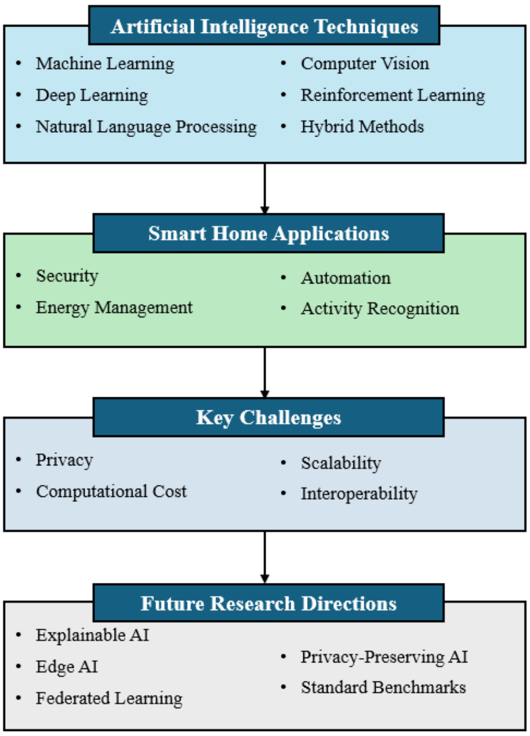

Fig. 4 Conceptual framework of AI-driven approaches for smart home security and energy efficiency

5.1 Practical challenges and future deployment considerations

Despite the promising performance of AI-driven smart home systems reported in the reviewed studies, several practical challenges continue to hinder their large-scale deployment. First, many AI models have been evaluated using benchmark datasets or controlled laboratory environments, with limited validation in real-world residential settings. Consequently, future studies should emphasize long-term field deployments across diverse households, user behaviors, and environmental conditions. Second, privacy and security remain major concerns because smart home applications continuously collect sensitive personal data. Emerging privacy-preserving techniques, including federated learning, differential privacy, and secure edge computing, offer promising solutions by reducing data sharing while maintaining predictive performance. Furthermore, explainable AI should be incorporated to improve transparency, user trust, and regulatory compliance in safety-critical applications. Standardized benchmark datasets, common evaluation metrics, and open-source experimental platforms are also required to improve reproducibility and facilitate fair comparison among AI techniques. Finally, future AI solutions should emphasize computational efficiency, scalability, and interoperability to support deployment on resource-constrained IoT devices while ensuring reliable real-time decision-making in practical smart home environments.

6. Conclusions

This study presented a systematic literature review of research published between 2021 and 2025 on the application of AI in enhancing smart home security, energy efficiency, and operational performance. Following the PRISMA 2020 guidelines, 60 relevant studies were identified and analyzed to examine the role of ML, DL, RL, ANNs, NLP, CV, and hybrid AI approaches in smart home environments. The findings provide a comprehensive overview of current research trends, key achievements, and existing challenges associated with AI-driven smart home systems. The main conclusions of this review are summarized as follows:

(1) Machine learning is the most widely adopted AI technique, while deep learning and reinforcement learning are also frequently applied to support anomaly detection, intrusion detection, energy consumption forecasting, and user behavior analysis.

(2) Deep learning models improve surveillance and security performance by enhancing activity recognition, motion detection, and threat identification while reducing false alarms.

(3) Reinforcement learning enables adaptive and autonomous decision-making, making it suitable for dynamic energy management, intelligent control systems, and intrusion prevention in complex smart home environments.

(4) Hybrid AI models generally outperform single-model approaches, particularly in energy forecasting, optimization, and security applications, due to their ability to leverage the strengths of multiple techniques.

(5) Natural language processing and computer vision contribute to intelligent human-home interaction, supporting voice-controlled systems, facial recognition, access control, and context-aware automation.

(6) Several challenges remain unresolved, including limited real-world validation, data availability and quality issues, model interpretability, communication reliability, privacy concerns, ethical considerations, and user-centered design requirements.

(7) Future research should focus on large-scale real-world deployment, explainable and privacy-preserving AI models, region-specific studies, edge computing integration, and collaboration with industry partners to improve the practical adoption and long-term sustainability of AI-enabled smart homes.

Overall, the findings demonstrate that AI has significant potential to transform smart homes into secure, intelligent, adaptive, and energy-efficient living environments. Continued research and real-world implementation efforts are essential to fully realize these benefits and address existing limitations.

6.1 Practical and research implications

The findings of this review demonstrate that AI-driven approaches have significant potential to enhance smart home security, energy efficiency, and user experience. Machine learning, deep learning, and reinforcement learning enable intelligent energy management, anomaly detection, adaptive automation, and predictive decision-making. These capabilities can contribute to reduced energy consumption, lower operational costs, improved security, and enhanced user comfort. In addition, AI facilitates the integration of renewable energy sources through adaptive energy management strategies that respond to changing demand and environmental conditions [6, 18, 70, 80]. From a research perspective, the growing adoption of hybrid AI models and advanced reinforcement learning techniques provides opportunities to address complex security and energy management challenges. Future studies should emphasize explainable AI, privacy-preserving mechanisms, and interdisciplinary collaboration among researchers, energy specialists, cybersecurity experts, and industry practitioners. Such efforts can support the development of transparent, secure, and sustainable smart home ecosystems.

6.2 Limitations and future directions

Despite the significant potential of AI to enhance smart home security and energy efficiency, several challenges remain. First, many AI models rely on large volumes of high-quality data, while data scarcity, class imbalance, and limited access to real-world datasets continue to affect model performance and generalizability. Future research should therefore investigate data-efficient learning approaches, standardized benchmark datasets, and open evaluation frameworks to improve the reproducibility and comparability of AI techniques. Second, the limited interpretability of many AI models remains a critical challenge, particularly in security and energy management applications where transparency and user trust are essential. Consequently, greater emphasis should be placed on explainable AI, privacy-preserving techniques such as federated learning and differential privacy, and edge AI to support secure, low-latency, and trustworthy smart home systems. Furthermore, although many studies reported promising results, most evaluations were conducted in simulated or controlled environments. Future research should prioritize long-term real-world deployments involving diverse households to assess scalability, robustness, interoperability, and user acceptance under practical operating conditions.

This review also has several methodological limitations. First, the literature search was restricted to English-language publications, which may have excluded relevant studies published in other languages. Second, only the Scopus and Web of Science databases were considered, potentially omitting relevant studies indexed elsewhere. Third, grey literature, including technical reports, dissertations, preprints, and industry publications, was excluded to maintain a focus on peer-reviewed evidence. Although these selection criteria enhanced the methodological rigor of the review, they may have reduced the comprehensiveness of the evidence base. Future systematic reviews should consider incorporating additional databases, multilingual publications, and carefully selected grey literature to provide a broader understanding of AI-driven smart home security and energy efficiency.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] A. D. Kounoudes, G. M. Kapitsaki, I. Katakis, and M. Milis, "User-Centred Privacy Inference Detection for Smart Home Devices," Proceedings of IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Internet of People and Smart City Innovation (SmartWorld/UIC/ATC/ScalCom/IoP/SCI), pp. 210-218, 2021.

[2] R. S. Dixit, S. L. Choudhary, N. Arya, N. Nathani, C. Bhowmik, V. Roy, et al., "Artificial Intelligence-Powered Cloud Security Strategies for Protecting Critical Clinical Operations in Healthcare Environments," Scientific Reports, 2026.

[3] S. FakhrHosseini, C. Lee, S. H. Lee, and J. Coughlin, "A Taxonomy of Home Automation: Expert Perspectives on the Future of Smarter Homes," Information Systems Frontiers, vol. 27, no. 2, pp. 449-466, 2025.

[4] I. Muhammed, M. A. Al-Sharafi, M. A. Mahmoud, and N. A. Iahad, "Towards Digital Sustainability: Conceptualizing a Model for Smart Home Adoption and Implementation," Proceedings of the 29th Pacific Asia Conference on Information Systems (PACIS), Paper no. 2, 2025.

[5] Z. Xu, D. Zhao, Q. Zou, J. Xiao, Y. Jiang, Z. Yuan, et al., "Synthetic User Behavior Sequence Generation with Large Language Models for Smart Homes," IEEE Internet of Things Magazine, vol. 8, no. 6, pp. 17-23, 2025.

[6] N. Butt, A. Shahid, K. N. Qureshi, S. Haider, A. O. Ibrahim, F. Binzagr, et al., "Intelligent Deep Learning for Anomaly-Based Intrusion Detection in IoT Smart Home Networks," Mathematics, vol. 10, no. 23, article no. 4598, 2022.

[7] B. M. Jalal and R. H. Al-Rubayi, "Energy Management Strategy with Smart Building Control System to Reduction Electrical Load Using ANN," Bulletin of Electrical Engineering and Informatics, vol. 11, no. 6, pp. 3188-3200, 2022.

[8] M. Feyzi and H. Mojallali, "Optimal Placement of Light Sensor for Improving Energy Efficiency and Visual Comfort in Smart Buildings," e-Prime - Advances in Electrical Engineering, Electronics and Energy, vol. 9, article no. 100681, 2024.

[9] A. Yarali, "Wireless Sensors/IoT and Artificial Intelligence for Smart Grid and Smart Home," in Intelligent Connectivity: AI, IoT, and 5G, Hoboken, NJ, USA: John Wiley & Sons, pp. 239-249, 2021.

[10] W. Li, T. Yigitcanlar, A. Liu, and I. Erol, "Mapping Two Decades of Smart Home Research: A Systematic Scientometric Analysis," Technological Forecasting and Social Change, vol. 179, article no. 121676, 2022.

[11] S. Atiewi, A. Al-Rahayfeh, M. Almiani, A. Abuhussein, and S. Yussof, "Ethereum Blockchain-Based Three Factor Authentication and Multi-contract Access Control for Secure Smart Home Environment in 5G Networks," Cluster Computing, vol. 27, no. 4, pp. 4551-4568, 2024.

[12] K. R. Jothi and B. Vaithiyanathan, "Developing a Hybrid Approach with Whale Optimization and Deep Convolutional Neural Networks for Enhancing Security in Smart Home Environments' Sustainability through IoT Devices," Sustainability, vol. 16, no. 24, article no. 11040, 2024.

[13] H. M. Fayez, G. M. Amer, and E. S. F. El Tantawy, "Load Management in Smart Home Using Intelligent Algorithms," Proceedings of the 22nd International Middle East Power Systems Conference (MEPCON), pp. 521-527, 2021.

[14] S. Biswas, K. Sharif, Z. Latif, M. J. F. Alenazi, A. K. Pradhan, and A. K. Bairagi, "Blockchain Controlled Trustworthy Federated Learning Platform for Smart Homes," IET Communications, vol. 18, no. 20, pp. 1840-1852, 2024.

[15] A. R. Dasgupta, P. Kumari, H. Sahu, S. Amarnath, and S. Nanda, "Smart-Home Automation Using AI Assistant and IoT," Proceedings of the 4th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), pp. 329-333, 2022.

[16] Y. Wang and L. Liu, "Research on Sustainable Green Building Space Design Model Integrating IoT Technology," PLOS One, vol. 19, no. 4, article no. e0298982, 2024.

[17] L. Jin and A. Boden, “Review on the Application Areas of Decision-Making Algorithms in Smart Homes,” Frontiers in Artificial Intelligence and Applications, vol. 368, pp. 74-92, 2023.
[18] Y. Sun, S. Zhang, M. Liu, R. Zheng, and S. Dong, “Energy Management Based on Safe Multi-agent Reinforcement Learning for Smart Buildings in Distribution Networks,” Energy and Buildings, vol. 318, article no. 114410, 2024.
[19] A. H. Sodhro, A. Gurtov, N. Zahid, S. Pirbhulal, L. Wang, M. M. Ur Rahman, et al., “Toward Convergence of AI and IoT for Energy-Efficient Communication in Smart Homes,” IEEE Internet of Things Journal, vol. 8, no. 12, pp. 9664-9671, 2021.
[20] S. Sohail, Z. Fan, X. Gu, and F. Sabrina, “Multi-tiered Artificial Neural Networks Model for Intrusion Detection in Smart Homes,” Intelligent Systems with Applications, vol. 16, article no. 200152, 2022.
[21] Z. Wu, X. Chen, Y. Lin, J. Wen, and Y. Chen, “A Smart Home Energy Management System Based on Human Activity Recognition and Deep Reinforcement Learning,” Energy and Buildings, vol. 325, article no. 114951, 2024.
[22] F. Meng and X. Wang, “Application of Energy Scheduling Algorithm Based on Energy Consumption Prediction in Smart Home Energy Scheduling,” Renewable Energy, vol. 231, article no. 120620, 2024.
[23] N. S. Dasappa, G. K. Kumar, and N. Somu, “Multi-Sensor Data Fusion Framework for Energy Optimization in Smart Homes,” Renewable and Sustainable Energy Reviews, vol. 193, article no. 114235, 2024.
[24] Z. Cheng and Z. Yao, “A Novel Approach to Predict Buildings Load Based on Deep Learning and Non-Intrusive Load Monitoring Technique, toward Smart Building,” Energy, vol. 312, article no. 133456, 2024.
[25] L. Langer and T. Volling, “A Reinforcement Learning Approach to Home Energy Management for Modulating Heat Pumps and Photovoltaic Systems,” Applied Energy, vol. 327, article no. 120020, 2022.
[26] U. H. Garba, A. N. Toosi, M. F. Pasha, and S. Khan, “SDN-Based Detection and Mitigation of DDoS Attacks on Smart Homes,” Computer Communications, vol. 221, pp. 29-41, 2024.
[27] M. Y. Chen, “Establishing a Cybersecurity Home Monitoring System for the Elderly,” IEEE Transactions on Industrial Informatics, vol. 18, no. 7, pp. 4838-4845, 2022.
[28] R. Singh, K. R. Utkurovich, A. Alkhayyat, G. Saritha, R. Jayadurga, and K. B. Waghulde, “Machine Learning Applications in Energy Management Systems for Smart Buildings,” E3S Web of Conferences, vol. 540, article no. 08002, 2024.
[29] P. Sivagami, D. Jamunarani, P. Abirami, M. Pushpavalli, V. Geetha, and R. Harikrishnan, “Smart Home Automation System Methodologies-A Review,” Proceedings of the International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), pp. 1386-1390, 2021.
[30] A. Shokrollahi, J. A. Persson, R. Malekian, A. Sarkheyli-Hägele, and F. Karlsson, “Passive Infrared Sensor-Based Occupancy Monitoring in Smart Buildings: A Review of Methodologies and Machine Learning Approaches,” Sensors, vol. 24, no. 5, article no. 1533, 2024.
[31] E. Alqahtani, N. Janbi, S. Sharaf, and R. Mehmood, “Smart Homes and Families to Enable Sustainable Societies: A Data-Driven Approach for Multi-Perspective Parameter Discovery Using BERT Modelling,” Sustainability, vol. 14, no. 20, article no. 13534, 2022.
[32] M. A. Siam, K. Y. Lucky, S. N. Hasan, J. Kaur, H. Kaur, M. S. Uddin, et al., “Cybersecure Intelligent Sensor Framework for Smart Buildings: AI-Based Intrusion Detection and Resilience Against IoT Attacks,” Sensors, vol. 25, no. 24, article no. 7680, 2025.
[33] L. Cao, “AI Science and Engineering: A New Field,” IEEE Intelligent Systems, vol. 37, no. 2, pp. 3-13, 2022.
[34] H. R. O. Rocha, I. H. Honorato, R. Fiorotti, W. C. Celeste, L. J. Silvestre, and J. A. L. Silva, “An Artificial Intelligence Based Scheduling Algorithm for Demand-Side Energy Management in Smart Homes,” Applied Energy, vol. 282, part A, article no. 116145, 2021.
[35] H. Ding, Y. Xu, B. Chew Si Hao, Q. Li, and A. Lentzakis, “A Safe Reinforcement Learning Approach for Multi-Energy Management of Smart Home,” Electric Power Systems Research, vol. 210, article no. 108120, 2022.
[36] P. Rajesh, F. H. Shajin, and G. Kannayeram, “A Novel Intelligent Technique for Energy Management in Smart Home Using Internet of Things,” Applied Soft Computing, vol. 128, article no. 109442, 2022.
[37] I. Wachter, P. Rantuch, and T. Štefko, “Smart Buildings,” in Transparent Wood Materials, Springer Series in Materials Science, vol. 330, Cham, Switzerland: Springer, pp. 87-95, 2023.
[38] A. A. Mahmud, “Artificial Intelligence (AI)-Based Identification of Appliances in Households through NILM,” Proceedings of the 4th Global Power, Energy and Communication Conference (GPECOM), pp. 414-426, 2022.
[39] T. Senapati, G. Chen, and W. Pedrycz, “Artificial Intelligence-Driven Energy Optimization in Smart Homes Using Interval-Valued Fermatean Fuzzy Aczel-Alsina Aggregation Operators,” Journal of Building Engineering, vol. 105, article no. 112418, 2025.
[40] M. R. King, “A Conversation on Artificial Intelligence, Chatbots, and Plagiarism in Higher Education,” Cellular and Molecular Bioengineering, vol. 16, no. 1, pp. 1-2, 2023.

[41] M. A. Khan, A. M. Saleh, M. Waseem, and I. A. Sajjad, "Artificial Intelligence Enabled Demand Response: Prospects and Challenges in Smart Grid Environment," IEEE Access, vol. 11, pp. 1477-1505, 2023.

[42] W. Li, T. Yigitcanlar, I. Erol, and A. Liu, "Motivations, Barriers and Risks of Smart Home Adoption: From Systematic Literature Review to Conceptual Framework," Energy Research & Social Science, vol. 80, article no. 102211, 2021.

[43] O. Popoola, M. Rodrigues, J. Marchang, A. Shenfield, A. Ikpehai, and J. Popoola, "A Critical Literature Review of Security and Privacy in Smart Home Healthcare Schemes Adopting IoT & Blockchain: Problems, Challenges and Solutions," Blockchain: Research and Applications, vol. 5, no. 2, article no. 100178, 2024.

[44] S. F. Wen, A. Shukla, and B. Katt, "Artificial Intelligence for System Security Assurance: A Systematic Literature Review," International Journal of Information Security, vol. 24, article no. 43, 2025.

[45] C. M. Torres-Hernandez, M. Garduño-Aparicio, and J. Rodriguez-Resendiz, "Smart Homes: A Meta-Study on Sense of Security and Home Automation," Technologies, vol. 13, no. 8, article no. 320, 2025.

[46] R. Muhammad, M. S. A. Sagara, Y. M. Teluma, and F. A. Wicaksana, "AI as Modern Technology for Home Security Systems: A Systematic Literature Review," Engineering Proceedings, vol. 107, no. 1, article no. 35, 2025.

[47] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, et al., "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews," BMJ, vol. 372, article no. n71, 2021.

[48] M. A. Al-Sharafi, I. Muhammed, S. Alzaeemi, M. A. Albashrawi, I. Chae, and Y. K. Dwivedi, "Factors Shaping FinTech Adoption: A Systematic Review, Key Determinants, Theoretical Insights, Conceptual Framework and Future Research Directions," Information Discovery and Delivery, 2025.

[49] M. Ibrahim, M. A. Mahmoud, N. Islam, and S. S. Gunasekara, "Enhancing Smart Grid Stability Using AI Techniques: A Systematic Literature Review," Proceedings of the 21st IEEE International Colloquium on Signal Processing & Its Applications (CSPA), pp. 50-55, 2025.

[50] C. Zhao, X. Wu, P. Hao, Y. Wang, and X. Zhou, "Machine Learning for Optimal Net-Zero Energy Consumption in Smart Buildings," Sustainable Energy Technologies and Assessments, vol. 64, article no. 103664, 2024.

[51] S. Iram, H. Al-Aqrabi, H. M. Shakeel, H. M. A. Farid, M. Riaz, R. Hill, et al., "An Innovative Machine Learning Technique for the Prediction of Weather Based Smart Home Energy Consumption," IEEE Access, vol. 11, pp. 76300-76320, 2023.

[52] B. Galeb, H. Saad, H. Bashar, K. Al-Majdi, and A. Al-Hilali, "Anomaly Detection in Smart Home Electrical Appliances Using Machine Learning with Statistical Algorithms and Optimized Time Series Algorithms," Journal of Mechanics of Continua and Mathematical Sciences, vol. 19, no. 5, pp. 116-135, 2024.

[53] A. Srinivasan, V. Parmar, T. Oh, J. Ryoo, and M. Viglione, "Anomaly Detection System for Smart Home Using Machine Learning," Proceedings of the International Conference on Software Security and Assurance (ICSSA), pp. 52-55, 2021.

[54] T. He and F. Jazizadeh, "Proactive Smart Home Assistants for Automation—User Characteristic-Based Preference Prediction with Machine Learning Techniques," Proceedings of the ASCE International Conference on Computing in Civil Engineering, pp. 271-278, 2022.

[55] A. Javed, M. N. Awais, A. u. H. Qureshi, M. Jawad, J. Arshad, and H. Larijani, "Embedding Tree-Based Intrusion Detection System in Smart Thermostats for Enhanced IoT Security," Sensors, vol. 24, no. 22, article no. 7320, 2024.

[56] S. Afroosheh, K. Esapour, R. Khorram-Nia, and M. Karimi, "Reinforcement Learning Layout-Based Optimal Energy Management in Smart Home: AI-Based Approach," IET Generation, Transmission & Distribution, vol. 18, no. 15, pp. 2509-2520, 2024.

[57] S. J. Chen, W. Y. Chiu, and W. J. Liu, "User Preference-Based Demand Response for Smart Home Energy Management Using Multiobjective Reinforcement Learning," IEEE Access, vol. 9, pp. 161627-161637, 2021.

[58] X. Ding, A. Cerpa, and W. Du, "Exploring Deep Reinforcement Learning for Holistic Smart Building Control," ACM Transactions on Sensor Networks, vol. 20, no. 3, pp. 1-28, 2024.

[59] R. Heartfield, G. Loukas, A. Bezemskij, and E. Panaousis, "Self-Configurable Cyber-Physical Intrusion Detection for Smart Homes Using Reinforcement Learning," IEEE Transactions on Information Forensics and Security, vol. 16, pp. 1720-1735, 2021.

[60] W. A. Alonazi, H. Hamdi, N. A. Azim, and A. A. A. El-Aziz, "SDN Architecture for Smart Homes Security with Machine Learning and Deep Learning," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 13, no. 10, pp. 917-927, 2022.

[61] M. Razghandi, H. Zhou, M. Erol-Kantarci, and D. Turgut, "Smart Home Energy Management: VAE-GAN Synthetic Dataset Generator and Q-Learning," IEEE Transactions on Smart Grid, vol. 15, no. 2, pp. 1562-1573, 2024.

[62] R. Sunder, S. R, V. Paul, S. K. Punia, B. Konduri, K. V. Nabilal, et al., "An Advanced Hybrid Deep Learning Model for Accurate Energy Load Prediction in Smart Building," Energy Exploration & Exploitation, vol. 42, no. 6, pp. 2241-2269, 2024.

[63] K. Yu, Q. Li, D. Chen, and L. Hu, "Safeguarding User-Centric Privacy in Smart Homes," ACM Transactions on Internet Technology, vol. 24, no. 4, pp. 1-33, 2024.

[64] A. R. Javed, L. G. Fahad, A. A. Farhan, S. Abbas, G. Srivastava, R. M. Parizi, et al., “Automated Cognitive Health Assessment in Smart Homes Using Machine Learning,” Sustainable Cities and Society, vol. 65, article no. 102572, 2021.

[65] F. Ibude, A. Otebolaku, J. E. Ameh, and A. Ikpehai, “Multi-Timescale Energy Consumption Management in Smart Buildings Using Hybrid Deep Artificial Neural Networks,” Journal of Low Power Electronics and Applications, vol. 14, no. 4, article no. 54, 2024.

[66] S. Karamizadeh, M. Moazen, M. Zamani, and A. A. Manaf, “Enhancing IoT-Based Smart Home Security through a Combination of Deep Learning and Self-Attention Mechanism,” Arabian Journal for Science and Engineering, vol. 49, no. 9, pp. 12431-12441, 2024.

[67] R. Sharma, A. Potnis, and V. Chaurasia, “Enhancing Smart Home Security Using Deep Convolutional Neural Networks and Multiple Cameras,” Wireless Personal Communications, vol. 136, no. 4, pp. 2185-2200, 2024.

[68] R. Chambers and M. Fahim, “Healthy Aging: A Proactive Model to Prevent Self-neglecting Behavior in Smart Homes,” Proceedings of the IEEE International Conference on E-Health Networking, Application & Services (HealthCom), pp. 173-178, 2022.

[69] H. Cimen, E. J. Palacios-Garcia, M. Kolaek, N. Cetinkaya, J. C. Vasquez, and J. M. Guerrero, “Smart-Building Applications: Deep Learning-Based, Real-Time Load Monitoring,” IEEE Industrial Electronics Magazine, vol. 15, no. 2, pp. 4-15, 2021.

[70] C. Sanjay, K. Jahnavi, and S. Karanth, “A Secured Deep Learning Based Smart Home Automation System,” International Journal of Information Technology, vol. 16, pp. 5239-5245, 2024.

[71] A. Bajpai, D. Chaurasia, and N. Tiwari, “A Novel Methodology for Anomaly Detection in Smart Home Networks via Fractional Stochastic Gradient Descent,” Computers and Electrical Engineering, vol. 119, part B, article no. 109604, 2024.

[72] K. P. Prakash, Y. V. P. Kumar, K. Ravindranath, G. Pradeep Reddy, M. Amir, and B. Khan, “Artificial Neural Network-Based Data Imputation for Handling Anomalous Energy Consumption Readings in Smart Homes,” Energy Exploration & Exploitation, vol. 42, no. 4, pp. 1432-1449, 2024.

[73] P. Piruthiviraj, P. Pitchandi, S. Sharma, B. Saroja, G. Rajesh, and P. V. Nandankar, “Automatic Access Control Solution in Smart Homes Using IoT and AI,” AIP Conference Proceedings, vol. 2587, no. 1, article no. 080004, 2023.

[74] S. Bhatlawande, S. Shilaskar, T. Gadad, S. Ghulaxe, and R. Gaikwad, “Smart Home Security Monitoring System Based on Face Recognition and Android Application,” Proceedings of the International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), pp. 222-227, 2023.

[75] A. S. Kumar and R. Rekha, “Improving Smart Home Safety with Face Recognition Using Machine Learning,” Proceedings of the International Conference on Intelligent Systems Communication, IoT and Security (ICISCoIS), pp. 478-482, 2023.

[76] I. Priyadarshini, S. Sahu, R. Kumar, and D. Taniar, “A Machine-Learning Ensemble Model for Predicting Energy Consumption in Smart Homes,” Internet of Things, vol. 20, article no. 100636, 2022.

[77] M. A. Khan, Z. Sabahat, M. S. Farooq, M. Saleem, S. Abbas, M. Ahmad, et al., “Optimizing Smart Home Energy Management for Sustainability Using Machine Learning Techniques,” Discover Sustainability, vol. 5, article no. 430, 2024.

[78] S. T. Spantideas, A. E. Giannopoulos, and P. Trakadas, “Autonomous Price-Aware Energy Management System in Smart Homes via Actor-Critic Learning with Predictive Capabilities,” IEEE Transactions on Automation Science and Engineering, vol. 22, pp. 15018-15033, 2025.

[79] A. Hussain, G. Franchini, M. Akram, M. Ehtsham, M. Hashim, L. Fenili, et al., “Hybrid ML/DL Approach to Optimize Mid-Term Electrical Load Forecasting for Smart Buildings,” Applied Sciences, vol. 15, no. 18, article no. 10066, 2025.

[80] A. Vasudevan, S. I. S. Mohammad, A. A. S. Mohammad, K. I. Al-Daoud, R. M. Batyha, A. Y. AlHadid, et al., “Comprehensive Framework that Can Be Used for Successful Internet of Things Deployment in Smart Home Environments,” in Artificial Intelligence for Agile Business Solutions, M. Alsyasneh and J. Masih, Eds., Cham, Switzerland: Springer Nature Switzerland, pp. 203-214, 2026.