AI-Powered Smart Home Energy Prediction and Recommendations: A Review

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**Abstract.** Residential energy consumption is a major contributor to global energy demand and environmental impact, making smart home energy management a vital area of research. Artificial intelligence (AI) offers powerful tools for enhancing energy prediction and personalized recommendations, aiming to improve efficiency and occupant comfort. This review systematically examines recent advances in AI-driven energy management systems for smart homes, focusing on deep learning models, generative AI techniques, and the integration of enabling technologies such as IoT and blockchain. A systematic literature review was conducted, screening 289 papers from databases including IEEE Xplore, Scopus, and Web of Science. After applying strict inclusion criteria, 34 empirical studies published between 2015 and 2025 were selected for detailed analysis. The incorporation of IoT and blockchain technologies enables real-time responsiveness along with secure control of energy systems. Even with energy savings of about 50% reported, issues concerning privacy of data, processing power requirements, and uniform assessment remain. The combined application of predictive and generative AI is particularly lacking.

# Introduction

AI has quickly transformed smart home energy management by introducing a new era of evolving systems that analyze and optimize energy use, cut down on expenses, and elevate user satisfaction. Deep learning and hybrid models—ConvLSTM, CNN-LSTM, and transformers—have vastly enhanced the accuracy of forecasting residential energy by identifying complex consumption data spatial-temporal patterns [1],[2]. These models aid in accurate demand prediction, which is vital for load-shifting, renewables-sourced energy routing, load leveling, and energy demand-side management [1].

Apart from forecasting, generative data synthesis techniques, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), are applied to create value-added energy consumption recommendations while tackling issues such as scarceness of data and unpredictable user behavior [3]. Systems' ability to change in accordance to real-time conditions and dynamically altering occupant preferences is further tailored by reinforcement learning and sophisticated analytics. In turn, AI-driven recommender systems intelligently allocate energy from solar, batteries, and grid sources to fuel savings while optimizing system performance, achieving enormous savings and maintaining comfort.

Proficient systems incorporate AI with supporting technology like IoT and blockchain. IoT platforms manage a variety of smart appliances and provide real-time data streams which fuel AI models for ongoing optimization [4],[5]. Blockchain technology enables integrity, transparency, and trust in peer-to-peer transactions, allowing mutability-resistant handling of decentralized transactions and management of sensitive information. An example would be deep learning, blockchain, and bidirectional geoenergy flows frameworks that enable the construction of efficient, secure, and adaptive home energy management systems [5]. Comprehensive case studies show integrated approaches can provide measurable, tangible energy cost savings of up to 20% alongside enhanced grid stability [6].

As AI continues evolving, other areas also face significant gaps. The computational demands of deep learning and blockchain can strain resource-constrained IoT devices, raising concerns about scalability, energy efficiency, and latency. Data privacy and cybersecurity remain critical issues, especially as more granular household data is collected and exchanged. Additionally, the lack of standardized benchmarking frameworks and reliance on publicly available datasets-rather than real-time sensor streams-can limit the practical deployment and validation of AI-driven systems across diverse residential contexts. This paper systematically analyzes state-of-the-art AI methodologies for energy prediction and personalized recommendations in smart homes. The following sections provide a comparative analysis of leading AI models, examine the role of generative AI in enhancing user engagement, and discuss the integration of supporting technologies such as IoT and blockchain. The review concludes by highlighting key challenges and outlining future research directions to inform the practical deployment of intelligent energy management systems.

This review contributes to the research literature by analysing the merging of predictive and generative AI methods in the context of smart home energy management. This is a gap often overlooked in existing literature. In contrast to earlier reviews dealing with predicting and recommendation seperately, this paper discusses the potential integration, evaluates their performance across public datasets, and proposes a conceptual framework for combining AI with enabling technologies like IoT and blockchain. With this integration, the paper intends to provide future research directions and provide a reference for building adaptive, scalable, and user-centric smart energy systems.

# Methodology

This literature review was undertaken to critically evaluate existing research on AI-driven energy prediction and recommendation systems in smart homes. The review addresses the following research questions.

* RQ1. What are the current state-of-the-art AI models used for energy consumption prediction in smart homes, and how do they compare in terms of accuracy and real-time applicability?
* RQ2. How can generative AI models be leveraged to provide personalized energy-saving recommendations in smart homes, and what advantages do they offer over traditional rule-based or discriminative AI approaches?
* RQ3. What is the impact of integrating AI-driven prediction and generative recommendation systems on overall energy efficiency, cost reduction, and occupant comfort in smart homes?
* RQ4. What are the key challenges in deploying generative AI for energy recommendations in smart homes, particularly regarding data privacy, model interpretability, and real-time decision-making?
* RQ5. How does the integration of supporting technologies (IoT, edge computing, blockchain) enhance the performance and scalability of AI-powered energy prediction and generative recommendation systems in smart homes?
* RQ6. What evaluation metrics and validation methodologies are most effective for benchmarking the performance of AI-based energy prediction and generative recommendation systems in smart home environments?

To address these questions, the review aims to identify prevalent methods, assess their strengths and limitations, highlight existing research gaps, and establish how this study builds upon or diverges from prior work. A systematic approach was employed, comprising a structured search strategy, clearly defined inclusion and exclusion criteria, and a rigorous selection process to ensure the relevance and quality of the synthesized literature.

## Search Strategy

To identify high-quality studies on AI in smart home energy management, we conducted a systematic search across major databases including IEEE Xplore, Scopus, Web of Science, and the ACM Digital Library. These platforms were selected for their extensive collections of peer-reviewed literature in computer science, engineering, and energy systems.

The search strategy was built around key themes such as AI, machine learning, energy prediction, and smart home technologies. We developed a tailored set of keywords, for example “AI for energy management,” “deep learning energy prediction,” “generative AI energy recommendation,” and “IoT and energy management” to capture both predictive and generative AI applications [4],[5],[6].

This iterative process involved refining keyword combinations and incorporating emerging terms from initial results. After screening titles and abstracts, full-text reviews were conducted to ensure studies met inclusion criteria which are peer-reviewed, published between 2015–2025, focused on residential energy management, and empirically validated.

To supplement the database search, we manually reviewed reference lists of key articles to identify additional relevant studies. This comprehensive approach ensured a robust and transparent foundation for synthesizing state-of-the-art AI methods in smart home energy systems.

## Inclusion and Exclusion Criteria

To make sure the relevance and quality of studies included in this review, we instilled a clear set of inclusion and exclusion criteria. We selected only peer-reviewed journal articles and conference papers published between 2015 and 2025, focusing on empirical research related to energy management in residential settings such as smart homes [3]. Conversely, we excluded opinion pieces, editorials, non-peer-reviewed works, and patents to maintain scientific rigor and focus on validated research [3]. Studies centered on industrial or commercial energy management, as well as purely theoretical or simulation-based works lacking empirical validation, were also omitted. This selection process ensured that the reviewed literature is high-quality, relevant, and grounded in practical, data-driven research. It supports a strong analysis of AI-based energy management systems in smart homes.

## Selection Process

Figure 1 shows the selection process flow. Initially, we retrieved 289 studies related to AI technologies in smart home energy management. To refine this set, we applied a multiple step screening process. First, we read through titles and abstracts to remove papers unrelated to AI-powered smart home energy systems. Next, we assessed the remaining studies using inclusion and exclusion criteria, focusing on those addressing residential energy management, employing empirical methods, and published in peer-reviewed journals within a timeframe. Then, we performed a detailed evaluation of each study’s methodology, examining the AI models used, datasets, and evaluation metrics. This revealed a gap, which is limited integration of predictive machine learning with generative AI for personalized energy recommendations. Most studies addressed prediction or recommendation separately, lacking a holistic approach. Finally, we incorporate the findings, categorised themes, and resolved conflicting results. This process led to the selection of 34 high-quality papers that offered methodological rigor and novel insights into AI-driven energy systems. Our review highlights critical gaps, especially in integrating predictive and generative AI. It also lays the groundwork for developing smarter, user-centric energy management solutions.

A diagram of a process

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**FIGURE 1.** The selection process flow

## Quality Assessment and Review Rigor

To improve the transparency and quality of the review, a framework for the structured assessment of quality was applied during the process of full-text analysis. Each paper that had pass the initial cut was graded on a four-point quality checklist measuring methodological reproducibility and clarity of AI model, use of real-world or public data, comparative benchmarking versus other models, and discussion of real-world deployment applicability. Only those studies that satisfied at least three of the four above criteria were selected for synthesis to guarantee a high degree of methodological quality. To lessen selection bias, title-abstract screening and quality scoring were performed independently. Differences were resolved by discussion. The final set of 34 papers has balance between empirical strength and thematic richness, which allows this review to determine dominant trends and gaps in predictive and generative AI approaches to smart home energy management.

# results AND discussion

## Predictive AI Models: Performance, Trade-offs, and Trends

Recent advances in AI for smart home energy forecasting have focused on deep learning and hybrid models capable of capturing complex spatial-temporal dependencies. Notably, ConvLSTM and CNN-LSTM architectures combine convolutional layers with LSTM units to effectively model both spatial and temporal patterns in energy consumption data [1],[2],[3]. Empirical studies using real smart home datasets demonstrate that ConvLSTM outperforms other models, achieving mean absolute percentage error (MAPE) improvements of up to 10.53% for multi-day ahead predictions, with CNN-LSTM also showing strong performance [4],[5]. Additionally, Random Forest models have shown high accuracy (up to 99.7%) in predicting appliance-level energy consumption by capturing nonlinear relationships in high-dimensional data. Ensemble learning techniques augmented with explainable AI further improve forecasting accuracy and interpretability by leveraging decision tree bagging and boosting methods. Table 1. summarizes the AI Models for Energy Prediction. These models vary in their real-time applicability; while deep learning models offer superior accuracy, their computational demands may limit deployment on resource-constrained edge devices, whereas tree-based models like Random Forest offer a balance between accuracy and efficiency [3],[4],[5].

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| TABLE 1. AI models for energy prediction | | | |
| Model | **Key Features** | **Performance Metrics** | **Notes on Real-Time Applicability** |
| ConvLSTM | Combines convolutional layers with LSTM units to capture spatial-temporal patterns | MAPE as low as 18.48% (1-day ahead), improves up to 10.53% over baselines for multi-day forecasts | Highest accuracy but computationally intensive; may challenge edge deployment. |
| CNN-LSTM | Synergizes CNN feature extraction with LSTM temporal modeling (spatial feature extraction) and LSTM (temporal modeling). | MAPE ~18.59% (1-day ahead), 22.65% (3-day), 25.20% (6-day) | Strong performance, slightly less accurate than ConvLSTM; moderate computational cost. |
| Random Forest | Tree-based ensemble learning capturing nonlinearities in high-dimensional data | Accuracy up to 99.7% in appliance-level prediction. | More efficient, suitable for resource-constrained environments; balance between accuracy and speed. |
| Ensemble Learning + Explainable AI | Combines multiple models with interpretability techniques | Improved accuracy and model transparency. | Enhances trust and understanding; computational cost varies with ensemble size. |

## Generative AI Approaches: Personalization and Responsiveness

Models like GANs and VAEs are making strides in the generation of synthetic data and crafting personalized, energy-saving recommendations to fit the behavior and preferences of individual users. Unlike discriminative or rule-based conventional models, generative AI incorporates the variability and heterogeneity of users and s enables a context-aware and adaptive energy management, which provides flexibility in scenario evaluation and user variability modeling [6]. Energy-efficient recommendations are also tailored to require dynamically changing feedback from the occupants through the reinforcement learning paradigm, thereby enabling personalization [6],[7],[8]. Such approaches improve user interaction and adherence by integrating fallback customizable recommendations based on personal routines for effortless energy-saving measures as effortless energy-saving measures [6]. Table 2. summarizes the AI Models for Generated Recommendations.

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| TABLE 2. AI models for generated recommendations | | | |
| Feature | **GANs** | **VAEs** | **Traditional Recommenders** |
| Output Quality | High realism | Average/blurry | Rule-based / heuristic |
| Training Stability | Unstable (risk of collapse) | More stable | Stable |
| Personalization Potential | High (with RL feedback loop) | Moderate | Low to Moderate |
| Computational Cost | High | Moderate | Low |
| Adaptability | High (with user feedback) | Medium | Low |
| Real-World Use Cases | Limited in energy domain | Moderate | Widely used but static |

## Impact of Integrating AI-Driven Prediction and Generative Recommendation Systems

The fusion of generative recommendation systems and predictive AI models results in increased performance synergies with respect to overall energy efficiency, cost, and occupant comfort [3],[4],[5]. Predictive models renew energy demand to the precise level such that resources like solar panels, batteries, and grid supply can be controlled in a proactive manner [6],[7],. Generative models enhance this outcome by providing personalization that maximizes energy utilization within the parameters of comfort [9],[10]. Integrated system case studies demonstrate energy cost reductions in the order of 20% alongside enhanced grid stability [11][12]. This provides the framework for real-time responsive human interaction and control, thus enabling the vision of sustainable and user-friendly smart home energy management [11].

## Challenges in Deploying Generative AI for Energy Recommendations

The use of generative AI in smart homes creates new challenges in data privacy, model explainability, and decision-making in real-time, too. Privacy regulations and user trust are sensitive issues when concerning energy information about the household. While challenges like these can be addressed through federated learning and differential privacy, the techniques must still ensure privacy. Moreover, generative models are intricate and opaque and, therefore, need to be supplemented with explainable AI approaches aimed at improving transparency and user acceptance. Responsiveness to environment and occupant behavior changes is needed in real-time, but this introduces difficulties due to the high resource cost and need for continual learning [13]. Figure 2 shows the challenges and mitigations.

## Integration of Supporting Technologies for Scalable and Responsive AI Energy Systems

The complementarity of Internet of Things (IoT), edge computing, and blockchain technologies is revolutionizing the potential of AI-driven energy forecasting and recommendation systems in intelligent homes. IoT sensor high-resolution, real-time data significantly enhances forecasting accuracy and supports adaptive control techniques [5]. Edge computing also supports localized processing, reducing latency but promoting data privacy by reducing cloud-based communication [5]. Although physical IoT deployment as well as blockchain adoption are not part of this research, blockchain is seen as a prospective integration platform, particularly for managing recommendation logs, ensuring decision making transparency, and enabling secure, tamper-proof peer-to-peer energy transactions. Its distributed and immutable characteristics can help enhance user confidence and enable scalable, autonomous energy systems [6],[7],[8]. All of these supporting technologies provide the basis for safe, efficient, and scalable smart home energy systems based on AI [7].

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**FIGURE 2.** The flowchart of the challenges and mitigations

## Evaluation Metrics and Validation Methodologies

Finding the best combination of quantitative and qualitative metrics which properly benchmark AI models in smart home energy management is no easy task. Using MAE, RMSE, and even MAPE has proven useful in predicting energy consumption, but accuracy is a different matter. In the realm of recommendation systems, we actively focus on user engagement, adherence, and energy savings ratios as key performance indicators. In the name of transparency, explainable AI frameworks justify claims using interpretability metrics such as Shapley additive explanations. When it comes to validating our models, we use cross-validation, hold-out testing with real-world datasets, and scenario-based simulations to balance model robustness with generalizability [6],[7],[8].

## Proposed Integrated Framework

To address the observed gap in existing literature, we propose a unified framework that integrates predictive with generative recommendation capabilities, as shown in Figure 3.

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**FIGURE 3.** The integrated AI-driven framework for smart home energy prediction and personalized recommendations

# Challenges and Research Gaps

By enabling intelligent systems that optimize consumption, lower costs, and improve comfort, artificial intelligence has greatly advanced smart home energy management. By identifying intricate spatial-temporal patterns, deep learning and hybrid models such as transformers, CNN-LSTM, and ConvLSTM have enhanced residential energy forecasting. Precise demand prediction is made possible by these models, which is essential for demand-side management, load balancing, and renewable integration. To address data scarcity and user variability, generative AI techniques like GANs and VAEs create synthetic datasets and offer tailored energy-saving recommendations. Reinforcement learning further enhances adaptability to occupant preferences, optimizing energy allocation among solar, battery, and grid sources with substantial cost savings [6],[7].

Recent advances integrate AI with IoT and blockchain. IoT platforms connect diverse devices, providing real-time data for continuous optimization, while blockchain ensures data integrity and secure peer-to-peer energy trading. Combined frameworks create adaptive, efficient, and secure energy management systems, achieving up to 20% cost reductions and improved grid stability [6],[7],[8]. However, challenges remain. High computational demands strain IoT devices, raising concerns about scalability and latency. Data privacy and cybersecurity are critical as granular household data is collected. The lack of standardized benchmarks and reliance on public datasets limit practical deployment. This review analyzes state-of-the-art AI methods for energy prediction and personalized recommendations, discussing key models, generative AI’s role, and integration with IoT and blockchain, concluding with challenges and future research directions [6],[7],[8].

# Conclusion

This literature review highlights the transformative potential of AI, particularly deep learning models like CNN-LSTMs and Transformers, for smart home energy management. These models enhance energy consumption forecasting and enable adaptive, user-centric strategies through generative AI (GANs, LLMs). By synthesizing findings from 34 selected research papers, this review underscores the importance of accurate load forecasting, optimized HVAC control, and personalized recommendations in achieving energy efficiency. Challenges persist in data privacy, model complexity, and the need for standardized validation frameworks. To address these gaps, future research should prioritize the integration of predictive and generative AI with enabling technologies (IoT, blockchain) and the development of XAI solutions. Ultimately, advancements in AI-driven energy management hold promise for creating more sustainable, efficient, and user-friendly smart homes.

# References

1. I.H. Ou Ali, A. Agga, M. Ouassaid, M. Maaroufi, A. Elrashidi, and H. Kotb, “Predicting short-term energy usage in a smart home using hybrid deep learning models,” Front. Energy Res. 12, 1323357 (2024).

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1. B. Dağkurs, and İ. Atacak, “Deep learning-based novel ensemble method with best score transferred-adaptive neuro fuzzy inference system for energy consumption prediction,” PeerJ Computer Science **11**, e2680 (2025).
2. M. Razghandi, H. Zhou, M. Erol-Kantarci, and D. Turgut, “Smart Home Energy Management: VAE-GAN Synthetic Dataset Generator and Q-Learning,” IEEE Trans. Smart Grid **15**(2), 1562–1573 (2024).
3. F. Iqbal, A. Altaf, Z. Waris, D.G. Aray, M.A.L. Flores, I.D.L.T. Díez, and I. Ashraf, “Blockchain-Modeled Edge-Computing-Based Smart Home Monitoring System with Energy Usage Prediction,” Sensors **23**(11), 5263 (2023).
4. E. Jaber Al-Reshidi, R.Α. Ramadan, B.W. Aboshosha, M. Salem, and A.M. Alayba, “Real-Time Home Energy Management with IoT and Blockchain: Balancing Consumption and Peer-to-Peer Trading,” Eng. Technol. Appl. Sci. Res. **14**(3), 14014–14021 (2024).
5. F. Naseer, A. Addas, M. Tahir, M.N. Khan, and N. Sattar, “Integrating generative adversarial networks with IoT for adaptive AI-powered personalized elderly care in smart homes,” Front. Artif. Intell. **8**, 1520592 (2025).
6. W. Zhang, Y. Wu, and J.K. Calautit, “A review on occupancy prediction through machine learning for enhancing energy efficiency, air quality and thermal comfort in the built environment,” Renewable and Sustainable Energy Reviews **167**, 112704 (2022).
7. A. Raza, L. Jingzhao, Y. Ghadi, M. Adnan, and M. Ali, “Smart home energy management systems: Research challenges and survey,” Alexandria Engineering Journal **92**, 117–170 (2024).
8. I. Priyadarshini, S. Sahu, R. Kumar, and D. Taniar, “A machine-learning ensemble model for predicting energy consumption in smart homes,” Internet of Things **20**, 100636 (2022).
9. Z. Severiche-Maury, C.E. Uc-Rios, W. Arrubla-Hoyos, D. Cama-Pinto, J.A. Holgado-Terriza, M. Damas-Hermoso, and A. Cama-Pinto, “Forecasting Residential Energy Consumption with the Use of Long Short-Term Memory Recurrent Neural Networks,” Energies **18**(5), 1247 (2025).
10. M. Beaudin, and H. Zareipour, “Home energy management systems: A review of modelling and complexity,” Renewable and Sustainable Energy Reviews **45**, 318–335 (2015).
11. F. Luo, G. Ranzi, W. Kong, G. Liang, and Z.Y. Dong, “Personalized Residential Energy Usage Recommendation System Based on Load Monitoring and Collaborative Filtering,” IEEE Trans. Ind. Inf. **17**(2), 1253–1262 (2021).
12. N.S. Dasappa, K. Kumar G, and N. Somu, “Multi-sensor data fusion framework for energy optimization in smart homes,” Renewable and Sustainable Energy Reviews **193**, 114235 (2024).