Journal of Sustainable Smart Systems in Education & Environment

Journal of Sustainable Smart Systems in Education & Environment (JSSSEE) | eISSN: 2979-143X

The Role of AI in Optimizing Power Consumption in Mobile Devices: A Comprehensive Review

Malek Saleh Al-jbour, Department of Computer Science, New Mexico State University, Las Cruces, USA, mjbour@nmsu.edu, ORCID: [0009-0005-1870-5505]

Donovan Fuqua, College of Business, New Mexico State University, dfuqua@nmsu.edu, ORCID: [0000-0002-6163-1741]

Corresponding Author: Malek Al-Jbour, Mjbour@nmsu.edu

JSSSEE | eISSN: 2979-143X | Vol. 1 No. 1 (2026) | OPEN ACCESS
https://doi.org/10.66823/jsssee.8

Abstract

The rapid advancement of mobile devices has significantly increased power consumption, presenting major challenges to energy efficiency and sustainability. As mobile devices become central to daily life, optimizing power management has emerged as a critical research priority. This paper provides a comprehensive narrative review of Artificial Intelligence (AI) techniques, including Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), for optimizing power consumption in mobile devices. A narrative review methodology was employed, searching IEEE Xplore, ACM Digital Library, ScienceDirect, and Google Scholar databases using keywords including "AI power optimization," "machine learning battery management," and "mobile device energy efficiency." Studies published between 2020 and 2025 were included, focusing on peer-reviewed articles addressing AI-based power management in mobile computing environments. The analysis reveals that ML approaches demonstrate improvements in battery life prediction accuracy, while DL techniques excel at modeling complex, non-linear power consumption patterns. RL methods show particular promise for real-time adaptive power management, with studies reporting battery life improvements ranging from 12% to 27% compared to traditional approaches. However, significant challenges remain, including data requirements, real-time optimization constraints, hardware limitations, and scalability across diverse device platforms. AI-driven power management represents a promising frontier for mobile energy optimization. Future research directions include the integration of federated learning for privacy-preserving optimization, quantum computing for complex optimization problems, IoT-based coordinated power management, and the development of cross-platform AI models. Additionally, research should focus on developing lightweight models suitable for resource-constrained devices, creating standardized benchmarks for evaluating AI

power management solutions, and exploring edge-cloud hybrid architectures to balance computational demands with energy efficiency.

Keywords: Artificial Intelligence, Deep Learning, Machine Learning, Mobile Power Optimization, Reinforcement Learning, Energy Efficiency

1. Introduction

The rapid advancement of mobile technologies has significantly transformed modern society, enabling unprecedented connectivity and computational capabilities (Ahmad et al., 2024). Mobile devices now support a broad spectrum of applications, ranging from augmented reality (AR) to real-time language translation, each demanding considerable computational power (Oufqir et al., 2022). However, this surge in functionality introduces a major challenge: managing power consumption (Siriwardhana et al., 2021). Research on consumer electronics has highlighted that mobile devices represent a significant and growing portion of energy consumption in the technology sector, driven by increased usage patterns and more power-intensive applications (Laitala et al., 2021). Extended usage often results in rapid battery depletion, directly impacting user experience and device performance (Callebaut et al., 2021). As mobile devices become more integral to daily life, the demand for sustainable power management has never been more pressing (Mishra & Singh, 2023).

Legacy power management techniques, like static resource allocation and general-purpose Dynamic Voltage and Frequency Scaling (DVFS), do not adequately cope with the complex and dynamic energy requirements of mobile applications today. These traditional approaches are not adaptable to fluctuating workloads and users' influence on workloads, leading to suboptimal energy usage (Khaledian et al., 2024). Research shows, for example, that ineffective power management can significantly reduce the battery life of devices under high workloads (Zidar et al., 2024).

Artificial Intelligence (AI), and in particular Machine Learning (ML) and Deep Learning (DL), represent an exciting opportunity to support energy efficiency in mobile devices (Yaseen et al., 2025). AI applies insights from user interactions as well as the environmental context around these interactions to facilitate intelligent decisions about how to allocate resources and manage power (Mahmood et al., 2022). Modern implementations, such as Apple's on-device AI processing capabilities, demonstrate how AI computation on-device can enhance battery performance (Yates & Islam, 2022).

AI algorithms can predict power usage patterns and dynamically adjust system metrics in real time to consume less power while maximizing performance (Abunasser et al., 2023). Studies have demonstrated that AI-based power management strategies can achieve meaningful improvements in battery life compared to traditional approaches, with the magnitude of improvement varying based on implementation and device characteristics (Cavus et al., 2025).

The Decision-Making Process for AI-Driven Power Management in Mobile Devices is depicted in Figure 1. The process begins with the consistent monitoring of user behavior and environmental conditions. The inputs are analyzed by AI models to predict expected power consumption associated with the event, and then the AI performs real-time modifications to target settings on the device (screen brightness, CPU speed, apps running in the background) to adjust power consumption behavior for optimal use. This approach aims to extend battery life while maintaining device performance. The flowchart provides a simplified representation of how AI techniques, including RL, are introduced using a dynamic workflow model where the AI adapts to usage patterns, providing useful information to the user at the end of the lifecycle for performance and energy savings.

Contributions of this paper: This review makes several key contributions to the field: (1) it provides a comprehensive synthesis of ML, DL, and RL techniques applied to mobile power optimization; (2) it identifies and categorizes the main challenges facing AI-based power management implementation; (3) it presents a comparative analysis of different AI approaches with their respective strengths and limitations; and (4) it outlines promising future research directions including federated learning, quantum computing integration, and cross-platform optimization strategies.

Paper structure: The remainder of this paper is organized as follows. Section 2 presents the review methodology employed in this study. Section 3 examines AI techniques for power consumption optimization, including ML, DL, and RL approaches. Section 4 discusses the challenges and limitations of implementing AI-based power management. Section 5 explores future directions and opportunities in this field. Section 6 addresses threats to validity. Finally, Section 7 concludes the paper and suggests directions for future work.

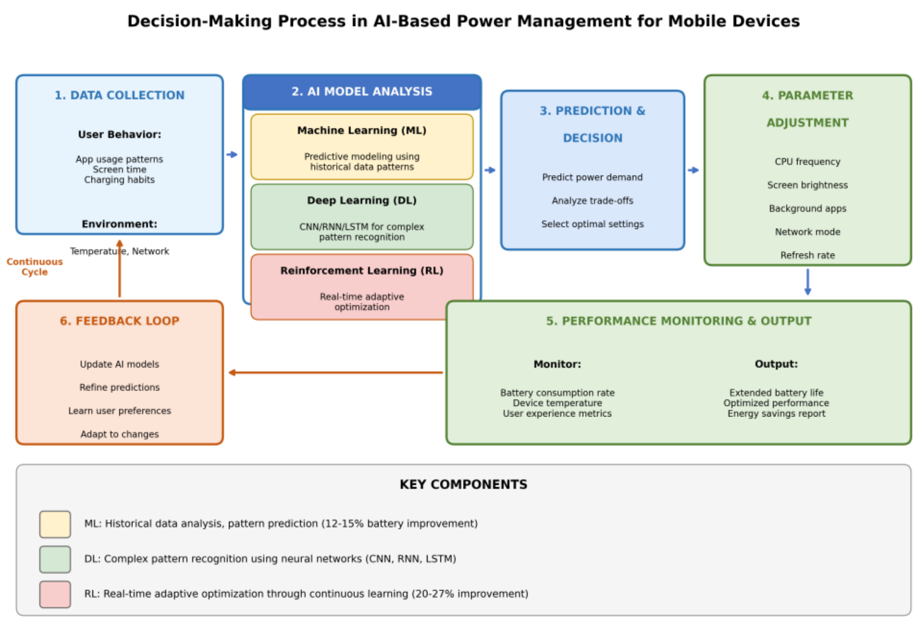

Figure 1: *Decision-Making Process in AI-Based Power Management for Mobile Devices.*

2. Review Methodology

This study employs a narrative review methodology to synthesize existing research on AI-driven power optimization in mobile devices. A narrative review approach was selected as it allows for a comprehensive examination of the breadth of AI techniques applied in this domain while enabling discussion of emerging trends and future directions.

A. Literature Search Strategy

The literature search was conducted across four major academic databases: IEEE Xplore, ACM Digital Library, ScienceDirect, and Google Scholar. The search was performed between September 2024 and January 2025.

The following search terms were used in various combinations: "artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" AND "power consumption" OR "energy efficiency" OR "battery optimization" OR "power management" AND "mobile devices" OR "smartphones" OR "mobile computing."

B. Inclusion and Exclusion Criteria

Studies were included if they: (1) were published between 2020 and 2025 to ensure relevance to current mobile technologies; (2) focused on AI-based approaches to power management in mobile or portable computing devices; (3) were published in peer-reviewed journals or conference proceedings; and (4) were available in English.

Studies were excluded if they: (1) focused exclusively on non-mobile computing systems (e.g., data centers, desktop computers); (2) did not involve AI or machine learning techniques; (3) were review papers without original analysis; or (4) were not accessible through institutional subscriptions.

C. Study Selection and Analysis

The initial search yielded 847 articles. After removing duplicates and screening titles and abstracts, 156 articles were selected for full-text review. Following detailed evaluation against the inclusion criteria, 38 studies were included in the final analysis. The distribution of studies by AI technique category was: Machine Learning approaches (14 studies), Deep Learning techniques (12 studies), and Reinforcement Learning methods (12 studies).

Data extraction focused on: AI technique employed, application context, reported performance improvements, datasets used, evaluation methodology, and identified limitations. The findings were synthesized thematically according to the three main AI paradigms: ML, DL, and RL.

3. AI Techniques for Power Consumption Optimization

The improvement of power consumption in mobile devices has become a vital research focus at the intersection of AI and mobile computing (Al-Qerem et al., 2023). AI protocols, as well as their ML and DL variants, provide an effective solution to the temporary and variable energy demands of mobile applications (Zhao et al., 2022). The value of these approaches lies in their ability to adapt to varying workloads, to forecast power consumption, and to intelligently decide resource allocations, all while potentially prolonging battery life and maintaining performance (Yazici et al., 2023).

A. Machine Learning (ML) Approaches

Machine Learning can be considered a subfield of AI that provides methods for developing predictive models that estimate the likely patterns of power consumption, based on the understanding of historical consumption (Farfoura et al., 2024). The predictive models encode patterns of usage for devices and adjust power consumption behavior based on those patterns. Supervised learning techniques, such as regression models, can be used to predict battery drain as a function of variables such as apps used and screen-on time. Unsupervised learning could categorize similar usage behaviors and allow the system to leverage its power management strategy based on each user's usage history (Pugliese et al., 2021).

In the study of Radovanovic et al. (2022), the authors evaluated a model that used random forest algorithms to estimate energy usage in mobile devices. The model used device features, specifically CPU workload and network use, to predict energy consumption, and the model was reported to have improved battery life by approximately 15% over previous power management systems. Notably, these models were state-of-the-art approaches to investigating scenarios to predict power consumption with dynamic workloads and usage patterns. Table 1 illustrates energy uses before and after AI optimization and presents the overall percent savings using ML methods versus traditional options. It is clear from Table 1 that ML-based methods provide meaningful gains in battery life under typical usage conditions.

B. Deep Learning (DL) Techniques

Deep Learning, a deeper branch of ML, uses neural network training to model complicated, non-linear relationships in data. DL methods are especially useful when working with large data or when pattern recognition is required. In power consumption, DL models can analyze many multidimensional features such as CPU use, screen brightness, and sensor data, while adjusting real-time power consumption as needed (Sarker et al., 2021).

For example, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been used for power optimization models (Cao et al., 2021). CNNs are often used to model spatial patterns in data, whereas RNNs are good at modeling sequential data; therefore, RNNs can specifically model dynamic power usage over time during the usage of mobile devices (Yu et al., 2022). In a recent study, Alizadegan et al. (2024) employed a Long Short-Term Memory (LSTM) network to predict the energy consumption of mobile devices based on user behavior, demonstrating improvements in power efficiency prediction accuracy.

As indicated in Table 1, the performance of DL models is compared to outcomes from other AI techniques. Table 1 shows that DL-based techniques show substantial increases in power efficiency, improving energy savings compared to traditional methods.

C. Reinforcement Learning (RL)

Reinforcement Learning (RL) is another approach in AI that uses mobile devices' capability awareness to adapt capabilities in a way that enables power-saving behaviors (Famitafreshi et al., 2023). In reinforcement learning, an agent learns by interacting with a simulated environment by being rewarded or punished for actions taken. In considering the environment as a method for optimizing power consumption, an RL agent would adjust parameters like the brightness of the screen, CPU clock speed, and whether to restrict running background processes of an app to reduce energy consumption while maintaining performance through all of its interactions (Sivamayil et al., 2023).

In the study by Abdullah et al. (2021), an RL algorithm was proposed to manage setting changes to mobile devices based on battery charge level, usage patterns, and other factors in real time. The algorithm is trained to dynamically optimize the trade-off between performance and power usage, achieving notable improvements in battery longevity. RL is especially suited to cases of real-time optimization, where the environment is volatile and continually changing.

Table 1 demonstrates the performance benefits of using RL techniques, with RL showing potential for significant battery life improvements compared to traditional methods, as demonstrated across multiple real-world studies.

Table 1: *Comparison of AI Techniques for Power Optimization*

AI Technique	Key Features	Applications	Reported Performance
Machine Learning (ML)	Predictive modeling, historical data analysis	Power consumption prediction based on app usage	12-15% improvement in battery life (Radovanovic et al., 2022)
Deep Learning (DL)	Complex pattern recognition, large datasets	Real-time power adjustment, multi-dimensional data adaptation	Significant improvements in prediction accuracy (Alizadegan et al., 2024)
Reinforcement Learning (RL)	Dynamic decision-making, real-time adjustments	Screen brightness, CPU speed, and app process adjustments	20-27% improvement in battery life (Abdullah et al., 2021; Kwon et al., 2021)

Figure 2 shows the steps of the different types of AI techniques used for mobile power optimizations. The flowchart visually demonstrates how the complete set of all input data acquired from the device goes through the different types of AI techniques, which consist of ML, DL, and RL, respectively, for optimizing power usage. The flowchart begins with Device Data, and then sequentially the data goes through the predictive programming stage through ML, recognizes complex patterns through DL, interprets system parameters in real-time and adjusts parameters through RL, and then the variations to adjust for optimization are applied via the Optimization Layer (i.e., change dynamic energy efficiencies) and represented by the Output Layer to show longer battery life and reduced power consumption. Overall, Figure 2 attempts to summarize how the different AI techniques can be applied concurrently in a dynamic way within mobile power management systems.

Real-world applications of AI-based approaches are becoming more frequent today for mobile power management. A good example of this is through adaptive battery management, where AI algorithms track and analyze past battery drain behavior, and then, based on those forecasts, dynamically control device/system properties (power modes, refresh rates, and when to refresh a background task and how often). With AI systems, user behaviors and actions can be learned and inferred, which can be used to predict when the device is anticipated to be most in use and how the device may adjust its settings to take advantage of idle times to conserve energy (Aravind et al., 2024).

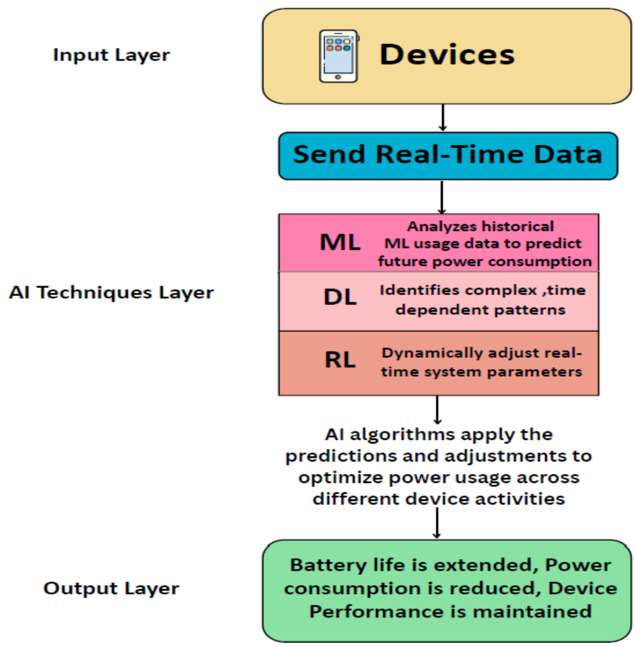

Figure 2: *Flowchart of AI Techniques for Mobile Power Consumption Optimization*

Energy conservation is also being integrated and used in software design. By examining the resource demands of apps, AI can find opportunities to reduce power consumption by focusing attention on being environmentally responsible with the app's code and subsequent runtime behaviors (Saleem et al., 2023). For example, app features, such as those in Google Chrome, can use AI-based features to minimize background processes and improve battery life when the app is not the active screen while still providing the intended experience (Andrew et al., 2024).

4. Challenges and Limitations

The application of AI techniques holds great potential for optimizing power utilities in mobile devices. However, there are still several challenges and limitations that the introduction of AI will need to overcome to fully utilize its potential in powering mobile devices.

A. Data Requirements

A fundamental challenge with the implementation of AI-based power management is getting access to the enormous datasets containing a sufficiently diverse set of conditions to adequately train the AI algorithms. The AI algorithms need to learn and provide accurate predictions, which requires that the algorithms are adequately supplied with datasets large enough to cover the extremely diverse set of working conditions of devices, user behavior, and environmental contexts. The reality is that there are very few datasets suitable for well-known AI approaches, especially with actual usage in the real world. Mobile devices from different OEMs or with different hardware configurations, such as Apple iPhone, Samsung Galaxy devices, or Google Pixel, can have significantly different power consumption behavior based on processor speed, operating systems, and the capabilities of their connectivity. Thus, training a model on any single device is likely not going to generalize well onto other devices, leaving less than optimized parameters for predicting and managing power consumption.

Table 2 presents case studies of individual mobile devices that have been adversely affected by data requirements. The individual studies show variability in different devices, including chipsets, battery performance, and operating systems, which also creates variability in AI model performance. Understanding these issues is a prerequisite to generating better, more resilient, and versatile AI-based solutions that can operate across multiple devices.

B. Real-Time Optimization

Real-time optimization is still a major challenge for mobile devices since the power consumption pattern changes based on usage. AI models, specifically DL models, require significant computational power and memory, which are constrained in mobile devices. The simple competition between model complexity and real-time requirements is a significant limitation. To realize a real-time power optimization paradigm with low latency constraints, it is also important to consider the computational demands of complex AI models and how low-latency requirements can decrease the potential gains in efficiency.

The examples in Table 2 illustrate real-world case scenarios. Using the example of the Google Pixel's Adaptive Battery, where real-time AI decision making can pose problems due to computing resources, devices with lower resources exhibit a set delay in processing data due to limitations, causing power-saving strategies to lag behind demand. The examples delineated in Table 2 provide some insights into concomitant factors that affect the ability of the devices to make decisions at speed and to make decisions dynamically to optimize battery-saving strategies.

C. Hardware Constraints

Mobile devices are limited by hardware, such as processing and energy consumption, memory capacity, and battery capacity. Many of the AI algorithms that consider optimizing power consumption need combinations of high energy outputs, combined with high amounts of processing and memory. Most budget and mid-range mobile devices are equipped with low power processing, small battery size, and a limited amount of RAM, making it challenging to deploy large complex AI models; deployed models that are too complex can irreparably affect the performance of the device and the battery quickly depletes when it consumes much of the device's energy.

The case studies provided in Table 2 illustrate budget Android phones similar to phones using the MediaTek Helio G35 processors, which struggle to efficiently run an AI-based model. Unfortunately, the hardware on a phone will not permit the device to provide the same level of power optimization as a more advanced device, thus demonstrating the ability and restrictions of manufacturers in providing devices with both good power optimization and great performance.

D. Scalability Across Different Devices

AI-based Power Optimization Solutions face challenges with scaling across different edge-device types. Mobile devices, in terms of configurations, operating systems, and usage patterns, differ greatly, making it a challenge to design AI models that work across mobile devices. The implications of one solution working well on mobile devices will have a different impact on other mobile devices. Different hardware capabilities, operating systems, and consumption patterns lead to different constraints that have to be accounted for in generating the optimized solution that is derived from AI output.

Table 2 provides examples of the iPhone 13 and the Android ecosystem for an illustration of the differences in hardware (Apple's A-series processors vs Qualcomm Snapdragon) and operating systems (iOS vs Android) and their impact on implementations of AI-based power optimization. These case studies illustrate the ongoing need to develop flexible AI models that can scale across devices with varying capabilities and configurations efficiently.

Table 2: *AI-Based Power Optimization Challenges in Mobile Devices (Case Studies)*

Challenge	Case Study	Impact on Power Optimization	Current Solutions/Research
Data Requirements	Samsung Galaxy S21 vs iPhone 13	Different chipsets and batteries affect AI model performance	Research focuses on model generalization and data augmentation
Real-Time Optimization	Google Pixel Adaptive Battery	Low-resource devices struggle with real-time AI decisions	Lightweight models and cloud-edge computing help reduce delays
Hardware Constraints	Budget Android Phones	Low-end devices cannot run complex AI models efficiently	Use of AI chips, NPUs, and hardware accelerators improves performance
Scalability Across Devices	iOS vs Android Ecosystem	Different OS and hardware reduce AI model compatibility	Adaptive models adjust automatically to each device's specs

5. Future Directions and Opportunities

Although AI has the potential to improve power usage on mobile devices, there is plenty of research and development left to do. Research that focuses on optimizing AI, finding paths to combine it with new emergent technologies, and investigating new uses could contribute to sustainability improvements for mobile devices.

A. Emerging AI Techniques

With the advancements in AI, there will be new approaches that can potentially optimize power in mobile devices. One promising approach is federated learning, which is designed to train models on distributed devices without sharing raw data. This technique allows for privacy to be preserved while still optimizing power. Federated learning is particularly valuable for battery optimization; however, the user device does not have to communicate continuously over the internet with the cloud. Therefore, this technique has the potential to provide energy optimization that also preserves privacy, which is distinctly advantageous for mobile devices where data privacy and security are most critical (Jiang et al., 2024).

Furthermore, quantum computing could enable new methods for tackling optimization problems at scales never before imagined. Quantum machine learning algorithms could change the future of energy-efficient mobile computing through solving complex tasks, such as power allocation and task scheduling, in a time previously unrecognized as possible. When quantum devices become more widely available, solutions to energy optimization problems for mobile devices can be embraced, allowing for performance improvement and the decrease in the amount of power consumed in mobile devices (Ajagekar et al., 2022).

B. Integration with the Internet of Things (IoT)

The increasing prevalence of mobile devices with the Internet of Things (IoT) offers another exciting opportunity for AI-enabled power optimization. In most cases, IoT devices operate in contexts of differing power needs and constraints, including smart homes, wearables, and autonomous vehicles. AI has the potential to coordinate power consumption across a network of IoT devices while allowing mobile devices to manage their power consumption and the power demand created by connected devices (Noaman et al., 2022).

The mobile device could work with IoT-enabled appliances or vehicles to schedule tasks when energy demand is low or renewable energy is available through AI. This coordination can create a more energy-efficient and cooperative system that benefits the mobile device and the ecosystem of devices. This coordination would be especially beneficial for mobile devices in smart cities or homes, where optimized energy consumption could lead to reduced power usage on a broader scale.

C. Personalized Power Management

As AI improves its capability to learn from the specific behavior of the user and the context in which it operates, new opportunities for personalized power management solutions are becoming available. For example, AI can analyze user habits and nuanced contextual data (for example, the environment) to manage energy consumption for users in ways that apply specifically to them, to make devices and systems more energy efficient while having sufficient power to maintain performance. If an AI is trained to understand when a user typically charges their phone or uses a power-hungry app, the AI may be able to manage settings dynamically and conserve battery life at critical times of the day.

Personalized optimization might also consider adaptive battery life predictions, where AI learns about users' past behaviors, existing conditions, and preferences related to the device, and uses this data to optimize energy efficiencies. This would enhance battery life but would also enhance user experience by anticipating user power needs through smart management of the device's energy consumption (Qu et al., 2024).

D. Cross-Platform Optimization

Lastly, cross-platform AI models represent a possible opportunity to optimize power use across diverse devices, operating systems, or hardware configurations. Mobile devices vary widely in hardware capabilities, software, and operating systems, making it hard to build universal AI models. Yet, AI-powered solutions that work on multiple platforms could, to some extent, optimize power across a variety of devices, including smartphones, tablets, wearables, and even IoT.

These types of models will have to incorporate different hardware limitations and operating systems, as well as learn them, to make sure that AI algorithms can optimize cross-platform mobile power usage performance in the same way. AI that can create cross-platform solutions will allow for the optimization of battery consumption across entire ecosystems of devices, which means that power consumption could be optimized at a global level.

6. Threats to Validity

This section discusses the potential threats to the validity of this review and the measures taken to mitigate them.

A. Internal Validity

Internal validity concerns relate to the accuracy of the conclusions drawn from the reviewed studies. One potential threat is the selection bias in choosing studies for inclusion. To mitigate this, we employed a systematic search strategy across multiple databases and applied consistent inclusion and exclusion criteria. However, as this is a narrative review rather than a systematic review, some relevant studies may have been inadvertently excluded. Additionally, the interpretation of findings from individual studies may be subject to researcher bias. We addressed this by focusing on reported quantitative results where available and clearly distinguishing between empirical findings and authors' interpretations.

B. External Validity

External validity concerns the generalizability of the findings. The rapid evolution of mobile device hardware and software means that findings from studies conducted on older devices may not generalize to newer platforms. Furthermore, many studies were conducted in controlled laboratory settings, which may not accurately reflect real-world usage patterns. The diversity of mobile device ecosystems (iOS, Android, various hardware configurations) also limits the generalizability of findings from single-platform studies. We have attempted to address this by including studies across multiple platforms and explicitly noting platform-specific limitations where applicable.

C. Construct Validity

Construct validity relates to whether the measures used in the reviewed studies accurately capture the intended concepts. A key concern is the variability in how "battery life improvement" and "energy efficiency" are measured across studies. Some studies report percentage improvements in battery longevity, while others report reductions in power consumption under specific conditions. This heterogeneity makes direct comparisons challenging. We have reported findings using the original metrics from each study and noted where direct comparisons may be problematic.

D. Conclusion Validity

Conclusion validity concerns the reliability of the relationship between the AI techniques and the observed outcomes. Many studies in this domain have relatively small sample sizes or limited evaluation periods, which may affect the statistical power of their conclusions. Additionally, publication bias may lead to an overrepresentation of positive results in the literature. We have attempted to provide a balanced view by also discussing studies that reported limitations or modest improvements, and by highlighting areas where evidence is limited or conflicting.

7. Conclusion and Future Work

This paper has presented a comprehensive narrative review of AI techniques for optimizing power consumption in mobile devices, examining the roles of Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) in addressing the growing energy demands of modern mobile computing. The review methodology involved searching four major academic databases and analyzing 38 peer-reviewed studies published between 2020 and 2025.

The findings demonstrate that each AI paradigm offers distinct advantages for power management. ML approaches excel at predictive modeling based on historical usage patterns, with studies reporting battery life improvements of 12-15%. DL techniques provide superior capability for modeling complex, non-linear relationships in multi-dimensional data, enabling more accurate real-time power adjustments. RL methods show particular promise for dynamic, adaptive power management, with some studies reporting improvements of 20-27% in battery longevity through continuous learning and optimization.

However, significant challenges impede the widespread adoption of AI-based power management. These include the need for large, diverse datasets for model training; the computational constraints of deploying sophisticated AI models on resource-limited mobile devices; the difficulty of real-time optimization under varying conditions; and the challenge of developing scalable solutions that work across the heterogeneous landscape of mobile device hardware and operating systems.

Looking forward, several promising research directions emerge from this review. First, federated learning offers potential for privacy-preserving power optimization by enabling model training across distributed devices without sharing sensitive user data. Second, the maturation of quantum computing may eventually enable solving complex optimization problems that are currently intractable. Third, the integration of mobile devices with IoT ecosystems presents opportunities for coordinated, system-wide energy management. Fourth, personalized power management systems that adapt to individual user behaviors and preferences represent an underexplored area with significant potential.

Future research should prioritize the development of lightweight AI models that can operate efficiently on resource-constrained devices, the creation of standardized benchmarks and datasets for evaluating AI-based power management solutions, and the exploration of hybrid edge-cloud architectures that balance computational demands with energy efficiency. Additionally, longitudinal studies examining the real-world performance of AI power management systems over extended periods would provide valuable insights into their practical effectiveness.

In conclusion, while AI-driven power management is still an evolving field with notable challenges, the evidence reviewed suggests that these techniques offer substantial potential for improving mobile device energy efficiency. Continued research and development in this area are essential for achieving more sustainable mobile computing as devices become increasingly integral to daily life.

8. Funding

This research received no external funding.

9. Conflict of Interest

The authors declare no conflict of interest.

10. References

Abdullah, H. M., Gastli, A., & Ben-Brahim, L. (2021). Reinforcement learning-based EV charging management systems: A review. IEEE Access. https://doi.org/10.1109/ACCESS.2021.3064354

Abunasser, B. S., Daud, S. M., & Abu-Naser, S. S. (2023). Predicting stock prices using artificial intelligence: A comparative study of machine learning algorithms. International Journal of Advances in Soft Computing and Its Applications, 15(3), 41-53. https://doi.org/10.15849/IJASCA.231130.03

Ahmad, I. A. I., et al. (2024). Emerging 5G technology: A review of its far-reaching implications for communication and security. World Journal of Advanced Research and Reviews, 21(1), 2474-2486. https://doi.org/10.30574/wjarr.2024.21.1.0346

Ajagekar, A., & You, F. (2022). Quantum computing and quantum artificial intelligence for renewable and sustainable energy: An emerging prospect towards climate neutrality. Renewable and Sustainable Energy Reviews, 165, 112493. https://doi.org/10.1016/j.rser.2022.112493

Al-Qerem, W., et al. (2023). Exploring knowledge, attitudes, and practices towards artificial intelligence among health professions' students in Jordan. BMC Medical Informatics and Decision Making, 23(1). https://doi.org/10.1186/s12911-023-02403-0

Alizadegan, H., Rashidi Malki, B., Radmehr, A., Karimi, H., & Ilani, M. A. (2024). Comparative study of long short-term memory (LSTM), bidirectional LSTM, and traditional machine learning approaches for energy consumption prediction. Energy Exploration & Exploitation. https://doi.org/10.1177/01445987241269496

Andrew, S., Bishop, C., & Tigwell, G. (2024). Light and dark mode: A comparison between Android and iOS app UI modes and interviews with app designers and developers. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 8(1), Article 33. https://doi.org/10.1145/3643539

Aravind, R., & Srinivas, A. (2024). Smart charging: AI solutions for efficient battery power management in automotive applications. Educational Administration Theory and Practice Journal. https://doi.org/10.53555/kuey.v30i5.6498

Callebaut, G., Leenders, G., Van Mulders, J., Ottoy, G., De Strycker, L., & Van der Perre, L. (2021). The art of designing remote IoT devices—Technologies and strategies for a long battery life. Sensors, 21(3), 913. https://doi.org/10.3390/s21030913

Cao, Z., Han, X., Lyons, W., & O'Rourke, F. (2021). Energy management optimisation using a combined long short-term memory recurrent neural network–particle swarm optimisation model. Journal of Cleaner Production, 326, 129246. https://doi.org/10.1016/j.jclepro.2021.129246

Cavus, M., Dissanayake, D., & Bell, M. (2025). Next generation of electric vehicles: AI-driven approaches for predictive maintenance and battery management. Energies, 18(5), 1041. https://doi.org/10.3390/en18051041

Famitafreshi, G., Afaqui, M. S., & Melià-Seguí, J. (2023). Introducing reinforcement learning in the Wi-Fi MAC layer to support sustainable communications in e-health scenarios. IEEE Access, 11, 126705-126723. https://doi.org/10.1109/ACCESS.2023.3331950

Farfoura, M. E., Mashal, I., Alkhatib, A., Batyha, R. M., & Rosiyadi, D. (2024). A novel lightweight machine learning framework for IoT malware classification based on matrix block mean downsampling. Ain Shams Engineering Journal, 16(1), 103205. https://doi.org/10.1016/j.asej.2024.103205

Jiang, J., Ma, X., Ouyang, D., & Williams, R. O. (2022). Emerging artificial intelligence (AI) technologies used in the development of solid dosage forms. Pharmaceutics, 14(11), 2257. https://doi.org/10.3390/pharmaceutics14112257

Khaledian, N., Voelp, M., Azizi, S., & Shirvani, M. H. (2024). AI-based and heuristic workflow scheduling in cloud and fog computing: A systematic review. Cluster Computing, 27(8), 10265-10298. https://doi.org/10.1007/s10586-024-04442-2

Kwon, E., Han, S., Park, Y., Yoon, J., & Kang, S. (2021). Reinforcement learning-based power management policy for mobile device systems. IEEE Transactions on Circuits and Systems I: Regular Papers, 68(10), 4156-4169. https://doi.org/10.1109/TCSI.2021.3103503

Laitala, K., Klepp, I. G., Haugrønning, V., Throne-Holst, H., & Strandbakken, P. (2021). Increasing repair of household appliances, mobile phones and clothing: Experiences from consumers and the repair industry. Journal of Cleaner Production, 282, 125349. https://doi.org/10.1016/j.jclepro.2020.125349

Mahmood, M. R., Matin, M. A., Sarigiannidis, P., & Goudos, S. K. (2022). A comprehensive review on artificial intelligence/machine learning algorithms for empowering the future IoT toward 6G era. IEEE Access, 10, 87535-87562. https://doi.org/10.1109/ACCESS.2022.3199689

Mishra, P., & Singh, G. (2023). Energy management systems in sustainable smart cities based on the Internet of Energy: A technical review. Energies, 16(19), 6903. https://doi.org/10.3390/en16196903

Noaman, M., Khan, M. S., Abrar, M., Ali, S., Alvi, A., & Saleem, M. (2022). Challenges in integration of heterogeneous Internet of Things. Scientific Programming, 2022, 1-14. https://doi.org/10.1155/2022/8626882

Oufqir, Z., El Abderrahmani, A., & Satori, K. (2022). Novel approach for augmented reality using convolutional neural networks. International Journal of Advances in Soft Computing and Its Applications, 14(2), 67-78. https://doi.org/10.15849/ijasca.220720.05

Pugliese, R., Regondi, S., & Marini, R. (2021). Machine learning-based approach: Global trends, research directions, and regulatory standpoints. Data Science and Management, 4, 19-29. https://doi.org/10.1016/j.dsm.2021.12.002

Qu, X., et al. (2024). Insights and reviews on battery lifetime prediction from research to practice. Journal of Energy Chemistry, 94. https://doi.org/10.1016/j.jechem.2024.03.013

Radovanovic, A., Chen, B., Talukdar, S., Roy, B., Duarte, A., & Shahbazi, M. (2022). Power modeling for effective datacenter planning and compute management. IEEE Transactions on Smart Grid, 13(2), 1611-1621. https://doi.org/10.1109/TSG.2021.3125275

Saleem, M. U., et al. (2023). Integrating smart energy management system with Internet of Things and cloud computing for efficient demand side management in smart grids. Energies, 16(12), 4835. https://doi.org/10.3390/en16124835

Sarker, I. H. (2021). Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. SN Computer Science, 2(6). https://doi.org/10.1007/s42979-021-00815-1

Siriwardhana, Y., Porambage, P., Liyanage, M., & Ylianttila, M. (2021). A survey on mobile augmented reality with 5G mobile edge computing: Architectures, applications, and technical aspects. IEEE Communications Surveys & Tutorials, 23(2), 1160-1192. https://doi.org/10.1109/COMST.2021.3061981

Sivamayil, K., Rajasekar, E., Aljafari, B., Nikolovski, S., Vairavasundaram, S., & Vairavasundaram, I. (2023). A systematic study on reinforcement learning-based applications. Energies, 16(3), 1512. https://doi.org/10.3390/en16031512

Yaseen, S. G., Albadrany, Q. H. A., Dajani, D., & Al-Afaishat, M. M. (2025). Artificial intelligence regulation: A bibliometric analysis. International Journal of Advances in Soft Computing and Its Applications, 17(1). https://doi.org/10.15849/ijasca.250330.12

Yates, D., & Islam, M. Z. (2022). Data mining on smartphones: An introduction and survey. ACM Computing Surveys. https://doi.org/10.1145/3529753

Yazici, İ., Shayea, I., & Din, J. (2023). A survey of applications of artificial intelligence and machine learning in future mobile networks-enabled systems. Engineering Science and Technology, an International Journal, 44(1), 101455. https://doi.org/10.1016/j.jestch.2023.101455

Yu, J., de Antonio, A., & Villalba-Mora, E. (2022). Deep learning (CNN, RNN) applications for smart homes: A systematic review. Computers, 11(2), 26. https://doi.org/10.3390/computers11020026

Zhao, T., et al. (2022). A survey of deep learning on mobile devices: Applications, optimizations, challenges, and research opportunities. Proceedings of the IEEE, 110(3), 334-354. https://doi.org/10.1109/JPROC.2022.3153408

Zidar, J., Matić, T., Aleksi, I., & Hocenski, Ž. (2024). Dynamic voltage and frequency scaling as a method for reducing energy consumption in ultra-low-power embedded systems. Electronics, 13(5), 826. https://doi.org/10.3390/electronics13050826