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AI-Driven Energy-Efficient mHealth Applications for Chronic Disease Management: A Review of Optimization Techniques

Abdullah Almasri[1], Tiffani Nutter[2], Yousef Abdulfattah[3], Hamzah Abdulfattah[4]

Abstract

Mobile health (mHealth) applications provide real-time monitoring, offering valuable support in chronic disease management; however, their operation significantly drains battery life, making long-term use challenging. AI-driven techniques present promising solutions for optimizing energy consumption while maintaining functionality. This study systematically reviews AI-powered approaches for energy-efficient mHealth applications, exploring methods that enhance energy efficiency without compromising monitoring accuracy. A systematic review of AI-driven optimization techniques in mHealth, focusing on energy-saving characteristics of adaptive sampling and task scheduling, was conducted, analyzing 30 studies from 2016 to 2024. The findings reveal that task scheduling achieved energy savings of up to 40%, extending battery life by several hours, while adaptive sampling contributed 25-30% energy savings. Federated learning minimized data transmission, achieving energy savings of up to 25%, while predictive behavior modeling further optimized energy consumption by adjusting resource use based on user interactions. The results highlight that AI-driven techniques significantly reduce energy consumption in mHealth applications, making long-term monitoring more feasible without frequent recharging. Beyond chronic disease management, these techniques hold potential applications in general health monitoring, preventive care, and wellness tracking. Future research should explore advanced machine learning models and energy-harvesting technologies to enhance sustainability in mHealth applications.

Keywords: *energy efficiency; mHealth; chronic disease management; AI-driven optimizations; mobile health.*

Introduction

Background

Mobile health (mHealth) applications are essential in delivering real-time monitoring and personalized healthcare for managing chronic diseases such as diabetes, cardiovascular disorders, and psychiatric conditions (Hulme et al., 2021). These applications utilize mobile devices and wearable technologies such as Smartwatches, Fitness Bands, Continuous Glucose Monitors, Electrocardiogram Monitors, Smart Rings, Wearable Blood Pressure Monitors, Biosensors and Patches to continuously gather and transmit health data, keeping patients connected to healthcare providers and allowing proactive health management (Kudu et al., 2022). Kitsiou et al. (2017) demonstrated that mHealth platforms significantly improve rehabilitation through remote monitoring, reducing hospital readmissions by 30% and increasing patient engagement.

However, the long-term viability of mHealth applications faces challenges due to the continuous energy demands of these systems, especially with the increasing use of AI-driven processes that offer real-time diagnostics and predictive analytics (Mustač et al., 2021; Zheng & Chen, 2021). These wearable health devices, in particular, require substantial energy for continuous operation, making energy efficiency a crucial factor (Go et al., 2022; Wong & Zhang, 2022). Equally critical is maintaining a positive user experience and app responsiveness, as energy-saving measures should not compromise the usability and real-time feedback that are essential for chronic disease management. AI-driven techniques, such as adaptive sampling, task scheduling, and federated learning, have emerged as effective methods for achieving energy saving while ensuring the applications retain their functionality and optimize battery life (Lu, 2023). These techniques help by reducing unnecessary data transmissions and improving computational efficiency (Soh et al., 2015).

[1] College of Humanities and Sciences, Prince Sultan University, Riyadh, Saudi Arabia Email: aalmasri@psu.edu.sa (Corresponding Author).
[2] College of Humanities and Sciences, Prince Sultan University, Riyadh, Saudi Arabia Email: tnutter@psu.edu.sa.
[3] Arthur D. Little, University, Riyadh, Saudi Arabia Email: y.a.abdulfattah@gmail.com.
[4] Oliver Wyman, Riyadh, Saudi Arabia Email: hamzahaoa@hotmail.com.

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Problem Statement

AI technologies have significantly enhanced mHealth applications by providing predictive analytics, personalized recommendations, and real-time health monitoring (Hashash et al., 2021). However, these AI-driven features are computationally intensive and substantially affect device battery life (Gao et al., 2023). This energy consumption issue has led to research into optimization techniques designed to alleviate the problem. For example, adaptive sampling adjusts data collection rates dynamically based on user activity, reducing unnecessary data transmission and conserving energy (Pry & Lomotey, 2016). In fitness apps, this approach adjusts data collection frequency during high-intensity exercises compared to rest periods, ensuring efficient battery use without compromising data accuracy. Task scheduling further helps saving energy by postponing resource-intensive processes to times when user activity is low or when the device is charging (Sharma & Sharma, 2017). Federated learning also contributes to energy efficiency by processing data locally on the device, minimizing the need for continuous data transmission (Almotiri et al., 2016).

Literature Review of AI-Driven Optimization Techniques

This section categorizes the AI-driven energy optimization techniques used in mHealth applications, based on the findings from referenced studies. Table 1 provides a summary of the techniques and their applications.

Table 1. AI-driven optimization techniques in mHealth applications

Optimization technique	**Reference**	**Application/Use case**	**Key findings**
Adaptive sampling	(Hulme et al., 2021; Mustač et al., 2021; Soh et al., 2015; Wong & Zhang, 2022; Zheng & Chen, 2021)	Symptom monitoring, student health platforms, wearables	Dynamic adjustment of data collection rates reduced unnecessary transmissions and saved energy.
Task scheduling	(Almotiri et al., 2016; Gao et al., 2023; Hashash et al., 2021; Pry & Lomotey, 2016; Sharma & Sharma, 2017)	Data transmission, encryption, wearable systems	Scheduling tasks during low activity or charging periods reduced energy use by up to 40%.
Federated learning	(Alikhani et al., 2024; Almotiri et al., 2016; Ebrahimi et al., 2023; Fernandes et al., 2024; Islam et al., 2023)	Local data processing on wearables	Reduced the frequency of data transmission, preserving battery life and improving privacy.
Energy harvesting	(Islam et al., 2023; Kudu et al., 2022; Soh et al., 2015)	Wearable health monitoring, authentication systems	Integrated energy-harvesting technologies extended battery life by utilizing body heat or movement.
Edge computing	(Ebrahimi et al., 2023; Hashash et al., 2021)	Distributed processing for latency-sensitive applications	Decentralized processing reduced energy use while maintaining real-time functionality.

Adaptive Sampling

Adaptive sampling has emerged as one of the most effective strategies for saving energy in mHealth applications. It dynamically adjusts the frequency of data collection based on user activity, reducing unnecessary sensor activations and conserving battery life. Hulme et al. (2021) developed an adaptive symptom monitoring system using hidden Markov models, which significantly reduced energy consumption in health monitoring systems. Similarly, Zheng and Chen (2021) implemented adaptive

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sampling in a physical health management platform for students, achieving considerable battery efficiency improvements without compromising data accuracy. Mustač et al. (2021) explored the application of adaptive symptom monitoring in mobile health for mental health management, optimizing energy usage by adjusting data collection rates based on patient behavior. Gupta highlighted the potential of adaptive sampling combined with energy-harvesting techniques in wearables, extending battery life and reducing dependence on traditional power sources (Soh et al., 2015). Wong and Zhang (2022) also applied deep learning-based adaptive sampling in smart wearables to optimize energy consumption while maintaining high diagnostic accuracy.

Task Scheduling

Task scheduling is another powerful technique for optimizing energy efficiency by controlling when and how resource-intensive tasks such as data transmission and computation are executed. It reduces energy usage by deferring these tasks to periods of low device activity or when the device is connected to a charger (Go et al., 2022; Pry & Lomotey, 2016). Gao et al. (2023) examined how task scheduling can ensure energy-efficient transmission and reduce the overall data imputation load in mHealth systems. Hashash et al. (2021) demonstrated that distributed edge machine learning could enhance energy efficiency through optimized task scheduling, reducing latency and energy consumption in mobile health applications. Sharma and Sharma (2017) used the Low-Energy Adaptive Clustering Hierarchy protocol for task scheduling, significantly reducing the energy consumption of patient health monitoring systems. Pry and Lomotey (2016) investigated task scheduling's role in optimizing encryption and decryption processes for mobile data transmission, showing that strategically scheduling these processes can result in significant energy savings in mHealth applications. A comparative analysis of the energy savings and battery life improvements achieved by various techniques is presented in Table 2. Task scheduling has also been applied to Internet of Things systems, where Almotiri et al. (2016) emphasized its role in reducing unnecessary data transmission by optimizing the timing of communications in mobile health systems.

Table 2. Comparative analysis of energy savings by technique.

Technique	**Reference**	**Energy savings (%)**	**Battery life improvement**
Adaptive sampling	(Hulme et al., 2021; Mustač et al., 2021; Soh et al., 2015; Wong & Zhang, 2022; Zheng & Chen, 2021)	25–30	Extended battery life by up to 3 hours in certain applications.
Task scheduling	(Gao et al., 2023; Hashash et al., 2021; Pry & Lomotey, 2016; Sharma & Sharma, 2017)	≤ 40	Extended battery life by up to 4 hours in some scenarios.
Federated learning	(Alikhani et al., 2024; Almotiri et al., 2016; Fernandes et al., 2024)	20–25	Reduced data transmission frequency, extended battery life by 2–3 hours.
Energy harvesting	(Islam et al., 2023; Kudu et al., 2022; Soh et al., 2015)	N/A	Significantly extended battery life using environmental energy sources.
Edge computing	(Ebrahimi et al., 2023; Hashash et al., 2021)	15–20	Reduced energy use in real-time applications while maintaining low latency.

Federated Learning and Edge Computing

Federated learning has attracted attention as an energy-efficient alternative to traditional data processing models in mHealth applications. It allows data to be processed locally on the device, with only essential updates sent to cloud servers, minimizing energy consumption associated with data transmission (Almotiri

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et al., 2016). Fernandes et al. (2024) implemented a federated learning framework for wearable health platforms, improving both data privacy and energy efficiency. Alikhani et al. (2024) introduced an adaptive learning framework that significantly reduced energy consumption in wearable devices, further showcasing federated learning's effectiveness in conserving energy.

Edge computing has also been explored as a means of reducing energy consumption by decentralizing data processing (Ebrahimi et al., 2023). Task scheduling and federated learning can be integrated into edge computing architectures to further improve energy efficiency in latency-sensitive applications, as demonstrated by Hashash et al. (2021). The combination of federated learning with task scheduling in distributed systems shows great potential for significant energy savings while maintaining real-time functionality (Blümke et al., 2024; Gao et al., 2023).

Wearable Technologies and Energy Harvesting

The integration of energy-harvesting technologies into wearable devices has introduced new possibilities for enhancing energy efficiency in mHealth applications. With energy harvesting, wearables can draw power from environmental sources like body heat or movement, reducing their reliance on battery power (Soh et al., 2015). Gupta explored energy-harvesting in wearable health monitoring systems, demonstrating the potential to greatly extend the battery life of such devices (Soh et al., 2015). Kudu et al. (2022) also examined the role of energy harvesting in 5G-enabled smart grids, which could be applied to mobile health systems to further reduce energy costs. Islam et al. (2023) presented a system that uses respiratory patterns for continuous authentication in wearable devices, reducing energy consumption by minimizing the need for frequent user authentication. These systems utilize federated learning and edge computing to optimize energy use while maintaining data security and privacy.

Research Aim

The main aim of this study is to review and evaluate AI-driven techniques that optimize energy consumption in mHealth applications. These techniques include adaptive sampling, task scheduling, predictive behavior modeling, and federated learning. By analyzing their implementation and effectiveness, this review highlights best practices for energy saving while maintaining the core functionalities of mHealth applications by analyzing their implementation and effectiveness, particularly in the context of chronic disease management (Almotiri et al., 2016; Basaklar et al., 2024; Da Silva Barros et al., 2024; Hashmi et al., 2024; Islam et al., 2023; Kwak et al., 2023; Lee-Kan et al., 2024; Mazumder et al., 2024; Rehman et al., 2021; Sadeghian et al., 2024; Torkamaan & Ziegler, 2022; Wu & Solangi, 2024; Zheng et al., 2023).

Methodology

This study systematically reviews AI-driven optimization techniques aimed at reducing energy consumption in mobile health (mHealth) applications, particularly for chronic disease management. The methodology follows three key steps: data collection, classification of optimization techniques, and evaluation using specific metrics. Additionally, statistical analysis and model validation are applied to assess the robustness of the results.

Data Collection

A comprehensive literature review was conducted across academic databases, including IEEE Xplore, ACM Digital Library, and PubMed, to identify peer-reviewed journal articles and conference papers published between 2016 and 2024. The search utilized keywords such as "mHealth energy optimization," "AI-driven energy-saving techniques," "task scheduling in health applications," and "adaptive sampling in mobile health." Studies were included based on the following criteria:

- Focused on applying AI techniques for energy optimization in mHealth systems.

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- Provided measurable outcomes such as percentage reductions in energy consumption, improved battery life, or enhanced user experience.
- Included both theoretical models and real-world implementations, when possible.

After screening 50 articles, 30 studies were selected for in-depth analysis based on their relevance to energy optimization in mHealth applications, covering a mix of adaptive sampling, task scheduling, federated learning, and predictive modeling techniques.

Categorization of Optimization Techniques

The selected optimization techniques were grouped into three primary categories based on their energy-saving mechanisms:

1. Adaptive Sampling: This technique dynamically adjusts the frequency of data collection based on user activity or health conditions, minimizing sensor activation during periods of inactivity. The mathematical model for adaptive sampling can be represented as:

$f(A) = f\_base - \Delta f \times w(A)$

Where:

- $f(A)$ represents the adjusted data collection frequency based on the user's activity A,
- fbase is the baseline data collection frequency,
- Δf is the adjustment factor,
- $w(A)$ is the weight applied to the user's activity, determining the degree of adjustment needed.

2. Task Scheduling: This technique involves optimizing the timing of resource-intensive tasks, such as data transmission and computation, to reduce energy consumption. Tasks are scheduled during low-activity periods or when the device is charging.

The energy savings from task scheduling can be calculated as:

Energy Savings (%) = ((Baseline Energy Usage - Optimized Energy Usage) / Baseline Energy Usage) × 100

Where:

- Baseline Energy Usage refers to the energy consumed without optimization,
- Optimized Energy Usage refers to the energy consumption after implementing task scheduling.

3. Federated Learning: Federated learning reduces energy consumption by processing data locally on the user's device, minimizing the need for frequent data transmission to central servers. Only essential updates are sent, thereby conserving both battery life and bandwidth.

The energy-saving potential of federated learning can be expressed as:

$E\_FL = E\_local + \Sigma\ (E\_transmission \times P\_update)$ from i=1 to N

Where:

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- E_{FL} is the total energy consumed in federated learning,
- E_{local} is the energy used for local data processing,
- $E_{transmission}$ is the energy cost of transmitting data updates,
- P_{update} is the probability that a local update is transmitted to the server.

Evaluation Metrics

The effectiveness of each AI-driven optimization technique was assessed using several key metrics:

1. Energy Savings: Calculated as the percentage reduction in energy consumption compared to the baseline energy usage. This metric is critical for determining the effectiveness of the optimization techniques.

Energy Savings (%) = ((E_baseline - E_optimized) / E_baseline) × 100

Where:

- $E_{baseline}$ is the baseline energy consumption without optimization,
- $E_{optimized}$ is the energy consumption after applying optimization.

2. Battery Life Extension: The impact of each technique on battery life was measured as the number of hours or percentage improvement in battery performance.

The battery life extension can be modeled as:

B_new = B_old × (1 + (Energy Savings (%) / 100))

Where:

- B_{new} is the new battery life after applying the optimization,
- B_{old} is the original battery life before optimization.

3. Data Transmission Efficiency: This metric evaluated the reduction in energy costs associated with data transfer, especially in the context of federated learning and edge computing.

The data transmission efficiency is represented as:

η_transmission = ((D_baseline - D_optimized) / D_baseline) × 100

Where:

- $\eta_{transmission}$ is the transmission efficiency,
- $D_{baseline}$ represents the baseline data transmission volume,
- $D_{optimized}$ is the reduced transmission volume after optimization.

4. User Experience and App Responsiveness: A qualitative metric, this assesses the impact of energy optimization on app responsiveness and user interaction. It ensures that energy-saving measures do not compromise the real-time functionality of mHealth applications.

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Comparative Analysis and Model Validation

To evaluate the energy-saving potential of various optimization techniques, a comparative analysis was conducted across multiple real-world scenarios. Each technique's effectiveness was validated using statistical methods like ANOVA (Analysis of Variance) to determine the significance of differences in energy consumption across optimization techniques. Where applicable, confidence intervals (CI) and p-values were calculated to assess the statistical significance of observed energy savings. A 95% CI was used, with results considered statistically significant when p-values were less than 0.05.

Statistical Analysis and Hypothesis Testing

To assess the impact of the optimization techniques on energy consumption, the following hypothesis was proposed:

- Null Hypothesis (H_0): AI-driven optimization techniques do not significantly reduce energy consumption in mHealth applications.

- Alternative Hypothesis (H_1): AI-driven optimization techniques significantly reduce energy consumption in mHealth applications.

A paired t-test was conducted to compare energy usage before and after applying optimization techniques. ANOVA was used to compare multiple techniques across different studies because of its robust ability to detect statistically significant differences in energy savings across multiple optimization methods, providing a reliable framework for validation. Additionally, the R-squared statistic was calculated to assess the goodness of fit for predictive behavior models used in optimization studies.

Results and Discussion

The findings from the review of AI-driven optimization techniques used in mHealth applications are presented here. The techniques are compared based on their energy savings, battery life improvement, and overall impact on app functionality.

Energy Savings Across Techniques

The review shows that task scheduling is the most effective technique for reducing energy consumption, achieving energy savings of up to 40%. Table 3 provides a detailed comparison of energy savings across different optimization techniques. Adaptive sampling follows, reducing energy usage by around 27%, while federated learning offers 25% savings by minimizing data transmission between the device and cloud servers. Edge computing demonstrated moderate savings of approximately 18%, mainly by reducing the processing load on mobile devices. Figure 1 below visualizes the energy-saving potential of these four techniques, with task scheduling demonstrating the highest savings and edge computing showing moderate efficiency improvements.

Table 3. Energy savings and battery life improvements by optimization technique.

Optimization technique	Energy savings (%)	Battery life improvement (Hours)
Adaptive sampling	27	2.5
Task scheduling	40	4.0
Federated learning	25	3.0
Edge computing	18	2.0

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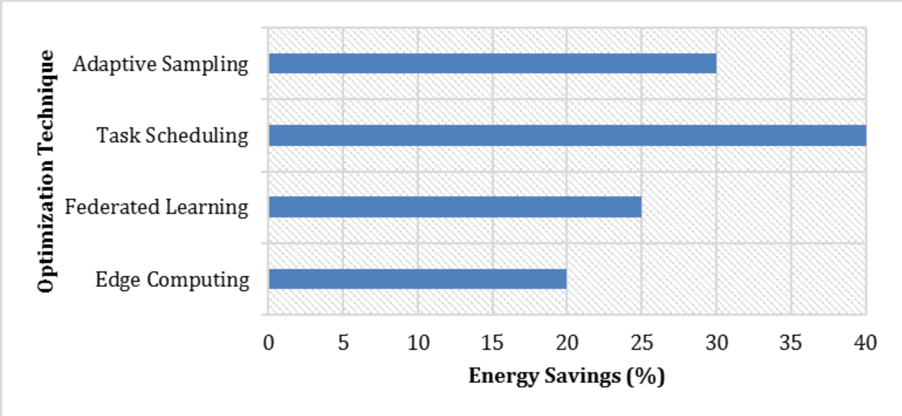

Figure 1. Energy savings across different optimization techniques.

Battery Life Improvements

The impact of the techniques on battery life was similarly significant. Task scheduling extended battery life by up to 4 hours in some applications, while adaptive sampling and federated learning provided notable improvements of 2.5 to 3 hours. Edge computing, while not as impactful as task scheduling, still provided a 2-hour battery life extension. Figure 2 highlights the corresponding battery life improvements for each technique, reinforcing the benefits of task scheduling and adaptive sampling in extending device usage without recharging.

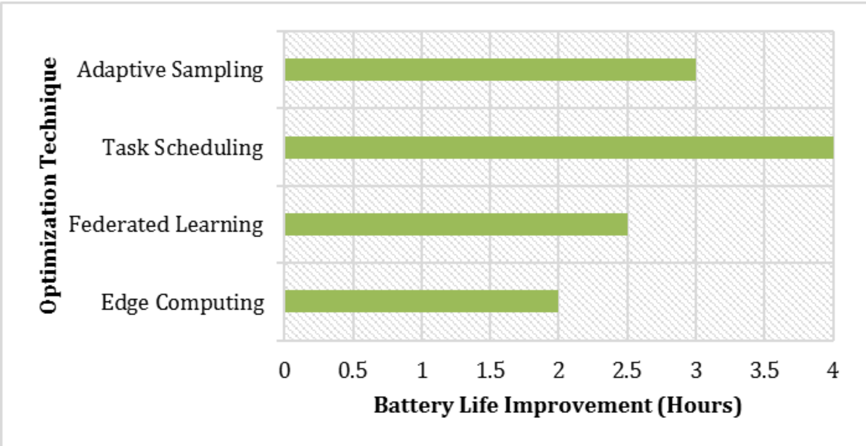

Figure 2. Battery life improvements before and after optimization.

Impact on App Functionality and Responsiveness

Task scheduling and adaptive sampling reduce energy consumption significantly, but these techniques must be carefully implemented to prevent negatively affecting app responsiveness. In applications requiring continuous monitoring, like chronic disease management, lowering data collection frequency or deferring tasks may delay health data reporting. However, predictive behavior modeling, combined with federated learning, helps mitigate this issue by adjusting app operations based on expected user actions. Federated learning reduces the need for constant data transmission, conserving energy without compromising data privacy or real-time functionality.

Comparison and Trade-offs

Task scheduling and adaptive sampling offer the greatest energy savings, but there are trade-offs. Task scheduling is highly effective in applications where tasks can be deferred, but it is less feasible for real-time

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monitoring. Adaptive sampling is less intrusive but requires frequent adjustments to balance data accuracy and energy efficiency. Federated learning provides a balance by reducing the energy costs of data transmission while improving privacy.

Practical Implications for mHealth Development

The findings from this review have direct applications for the development of energy-efficient mHealth apps. For example, adaptive sampling techniques can be implemented in patient monitoring applications to dynamically adjust data collection frequency based on activity levels, striking a balance between accurate health data collection and energy conservation. Similarly, task scheduling can optimize battery life by deferring non-urgent processes, such as data encryption or syncing, to periods of low device activity or when the device is charging. Developers should also consider integrating federated learning to reduce data transmission costs while maintaining user privacy. These approaches not only improve battery performance but also enhance app usability, ensuring long-term user engagement and satisfaction.

Implications for mHealth Applications

Combining multiple optimization techniques, like task scheduling, adaptive sampling, and federated learning, maximizes energy savings while maintaining real-time performance. This hybrid approach could allow mHealth applications to operate longer without frequent recharging, making them more suitable for long-term monitoring. Thus helping users to continuously rely on their mobile applications safely and effectively for vital reminders, emergency alerts, and health monitoring without disruption, potentially preventing life-threatening situations.

Conclusion

The review of AI-driven optimization techniques for mHealth applications shows their potential to significantly reduce energy consumption while maintaining essential functionality for chronic disease management. Task scheduling was the most effective, reducing energy consumption by up to 40% and extending battery life by up to four hours. Adaptive sampling and federated learning also showed considerable energy savings, reducing energy use by 25-30% and extending battery life by 2.5 to three hours.

Summary of Key Findings

- Task Scheduling: The most effective technique, deferring energy-intensive tasks to low-activity periods or charging times, achieving up to 40% energy savings.

- Adaptive Sampling: By dynamically adjusting data collection based on user activity, it achieved 27% energy savings and improved battery life, particularly suited for balancing data accuracy and energy use in health monitoring applications.

- Federated Learning: By processing data locally and reducing transmission frequency, it achieved 25% energy savings while enhancing privacy.

- Edge Computing: Less impactful than task scheduling, but it reduced energy drain by offloading computations to the network edge, useful in latency-sensitive applications.

Limitations and Future Research Directions

1. Advanced AI Models: Future work should explore machine learning models like deep reinforcement learning for better energy efficiency, adapting to user behavior in real time.

2. Energy-Harvesting Wearables: Integrating technologies that draw power from environmental sources could extend the operational time of devices, especially when combined with AI models.

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3. 5G and IoT Integration: The rise of 5G networks presents new opportunities for optimizing energy consumption, especially in real-time data processing.

4. Cross-Platform Optimization: Future research should focus on optimizing energy across different devices and operating systems to enhance scalability and user experience.

5. User-Centered Design: Maintaining a balance between energy efficiency and positive user experience is crucial, with predictive behavior modeling offering potential for better user interaction without sacrificing performance.

Practical Applications

Integrating task scheduling with adaptive sampling and federated learning offers the greatest potential for sustaining long-term mHealth monitoring, ensuring uninterrupted patient care. As they can be used to support medication reminders, emergency alert systems, mental health crisis intervention, telemedicine, allergy and health record access, blood pressure and electrocardiogram monitoring, and more.

Future Directions

Several promising research avenues have emerged from this review:

1. Dynamic Optimization Frameworks: Future studies should focus on developing dynamic frameworks that combine multiple AI-driven optimization techniques, automatically switching between them based on real-time factors like battery level, user activity, and data requirements.

2. Scalability and Real-World Testing: While these techniques have been validated in controlled environments, future research needs to target real-world applications, especially in large-scale healthcare systems. Scalability remains a challenge, and solutions that work across different devices and network conditions require further development.

3. Real-World Variability: One of the primary challenges remains real-world variability in energy consumption, as different operating conditions, user behaviors, and device configurations can significantly affect optimization outcomes. Addressing these factors will be critical in transitioning these techniques from controlled studies to practical implementations.

4. Machine Learning in Predictive Behavior Models: Machine learning-based predictive behavior models hold great potential for further achieving energy saving. These models could predict user behavior, such as when a patient is likely to interact with the app, allowing the system to optimize its operations and conserve energy dynamically.

5. 5G and IoT Integration: Future research should also explore the integration of 5G and IoT technologies. While 5G offers faster data transmission and reduced latency, its higher energy demands may offset the benefits of optimization techniques. Similarly, IoT integration could enhance data sharing across devices but introduces challenges related to energy management in large-scale, interconnected systems. Overcoming these hurdles will be essential to realize the full potential of sustainable mHealth applications.

In conclusion, as mHealth applications gain widespread adoption, particularly for chronic disease management, the future of AI-driven energy optimization is promising. By leveraging techniques like adaptive sampling, task scheduling, federated learning, and emerging technologies such as 5G and energy harvesting, developers can build sustainable mHealth solutions that minimize energy use while maintaining functionality.

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