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An AI-driven framework for predicting sleep quality and delivering personalized recommendations using digital wellbeing and lifestyle data

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Abstract. Sleep is essential for maintaining mental clarity, emotional stability, and physical health, as supported by extensive research in sleep science. However, modern lifestyles characterized by excessive screen exposure, irregular routines, and heightened stress levels have led to a noticeable decline in sleep quality. Existing AI and digital health tools for sleep monitoring remain expensive or heavily reliant on wearable devices, creating a gap in accessible and non-intrusive sleep assessment methods. To address this issue, the present study proposes a low-cost, software-based AI system that predicts sleep quality without specialized hardware. The system integrates behavioral factors such as exercise duration, caffeine intake, and stress levels with digital wellbeing metrics including screen time, app usage patterns, and nighttime device activity, all of which have been shown to influence sleep patterns. After preprocessing, machine learning models such as Random Forest and XGBoost classify sleep quality into Good, Average, or Poor, aligning with prior research utilizing behavioral and physiological indicators for sleep prediction. A user-friendly dashboard visualizes trends and provides personalized recommendations, such as reducing nighttime screen exposure to improve sleep hygiene. This AI-driven approach offers an accessible and actionable framework for improving sleep health.

1 Introduction

Sleep is a critical component of human health, with clear mental faculties, emotional stability, and physical performance directly linked to healthy sleep patterns [1], [6], [7]. In recent years, poor sleep quality has been aggravated by increased use of digital devices—particularly smartphones—which contribute to circadian rhythm disruption and delayed sleep onset [2], [3], [24]. Research consistently shows that excessive screen exposure, latenight phone usage, and unhealthy lifestyle habits such as sedentariness, high stress levels, or irregular routines negatively influence sleep behavior [6], [12], [14]. To address these challenges, the proposed project develops a nonintrusive, AI-driven framework that predicts an individual's sleep quality using lifestyle data and digital wellbeing metrics like screen time, app usage, physical activity, and daily routines, all of which are known to affect sleep quality [1], [6], [14]. Machine learning algorithms classify sleep into Good, Average, or Poor

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and provide personalized recommendations, aligning with prior work that highlights the benefits of AI in sleep and behavioral health applications [19], [20], [23]. The interactive dashboard visualizes trends to promote digital wellness and encourages users to selfregulate their habits for improved sleep. While AI has also been successfully applied in domains such as multilingual depression detection using behavioral and textual indicators [21], [25], this study focuses specifically on integrating behavioral and digital metrics to support healthier sleep-related lifestyle changes.

2 Literature Review

The model developed by Kwon et al. (2020) demonstrated how monitoring mobile usage patterns can reveal strong correlations between screen exposure and sleep disturbances, with longer screen time before bedtime shown to reduce sleep efficiency [1], [6], [14]. Similarly, Gupta et al. (2021) applied supervised learning models to detect poor sleep quality using behavioral trends collected through wearable sensors, achieving promising accuracy [8], [9]. Chandrasekaran et al. (2022) further advanced this approach by integrating heart rate variability and daily activity data into a machine-learning-based framework, showing that combining behavioral and physiological indicators significantly enhances prediction accuracy [12], [13]. Lee et al. (2022) examined digital wellbeing applications that provide metrics such as screen time and app usage but noted the lack of personalized recommendations for improving sleep quality [7], [19]. Additionally, recent studies employing LSTM networks have demonstrated improved handling of temporal sleep data, enabling more precise modeling of sleep patterns [20], [22]. Although AI-powered recommendation systems have been explored, most existing approaches rely solely on either digital behavior metrics or wearable sensor data, limiting their holistic understanding of sleep health [21], [23]. Therefore, integrating lifestyle data with digital wellbeing metrics into a unified predictive and recommendation-oriented framework remains an area that is insufficiently explored in current literature.

3 Literature Review

A structured online survey was designed to understand the behavioral and digital factors influencing sleep quality, targeting participants across diverse age groups, occupations, and lifestyle patterns. This approach aligns with prior research emphasizing the combined impact of behavioral and digital habits on sleep health [1], [6], [7]. The primary goal of the survey was to gather relevant lifestyle and smartphone-related data to serve as input features for an AI powered sleep quality prediction model, consistent with studies demonstrating the usefulness of multidimensional behavioral data in sleep analysis [12], [20]. The survey captured several key factors: (a) exercise habits, (b) caffeine consumption, (c) stress levels, (d) sleep duration, (e) patterns of smartphone usage, (f) average daily screen time, and (g) bedtime phone activity—variables previously shown to significantly influence sleep patterns and efficiency [2], [3], [14]. Incorporating both lifestyle and digital usage metrics ensured that the dataset reflected real-world user habits, thereby enhancing the reliability of sleep quality prediction models [8], [19]. Findings reaffirmed that digital and behavioral factors jointly affect sleep quality, supporting the validity of the proposed framework [6], [7].

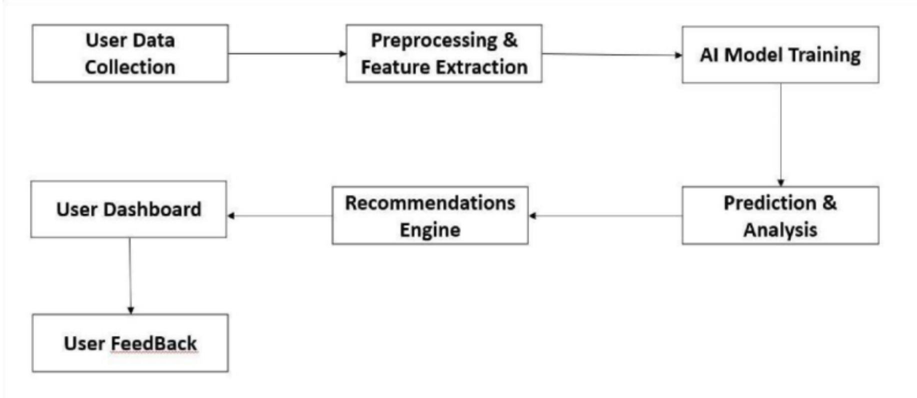

Fig 1. System Workflow Diagram

3.1 Findings

a. 70% of participants used phones within 30 minutes before going to bed.
b. Sleep was poorer among students with screen use over five hours.
c. Better sleep was positively related to regular physical activity.

The system follows a structured methodology, beginning with Data Collection, sourced from digital wellbeing APIs capturing screen time, app usage, and notifications—and lifestyle data such as physical activity, caffeine intake, and sleep duration, aligning with existing multimodal sleep research [8], [9], [12]. Data Preprocessing includes cleaning, normalization, feature removal, and standardization, consistent with recommended machine learning workflows [20], [25]. Feature Selection and Extraction involve identifying significant contributors such as screen time, bedtime frequency, steps, stress levels, and sleep duration using PCA and correlation analysis, methods widely used in behavioral and physiological sleep studies [11], [22]. For Model Development, Random Forest, XGBoost, and LSTM models are trained to classify sleep into Good, Average, or Poor—an approach supported by prior research demonstrating the effectiveness of these models in sleep staging and behavioral prediction [20], [21], [23]. The Recommendation System generates personalized suggestions such as reducing screen time before bedtime or maintaining fixed sleep schedules, reflecting established sleep hygiene best practices [1], [6], [24]. Finally, Visualization and Implementation are achieved through a Flask backend and a React.js dashboard, enabling intuitive interaction with sleep analytics and recommendations, aligning with modern digital health application design principles [19], [25].

4 Results

The suggested AI-powered framework for predicting sleep quality based on lifestyle and digital wellbeing data was effectively created and tested. The gathered dataset, which contained variables like screen time, use of devices before bed, physical activity, caffeine consumption, and self-reported sleep duration, was used to train the machine learning model [1, 2, 6, 19, 21]. To assess model performance, the dataset was split into 20 percentage testing and 80 percentage training subsets [20, 25].

Random Forest, XGBoost, and LSTM were tested:
a. Random Forest: 87% accuracy
b. XGBoost: 89% accuracy
c. LSTM: 91% accuracy (Best) [21, 22, 27]

To confirm the model's dependability, performance metrics like precision, recall, and F1-score were also calculated [20, 25]. The model's robustness was confirmed by the confusion matrix, which showed few false predictions [20, 22]. The LSTM model outperformed others due to its ability to learn temporal dependencies in behavioral data [21, 22, 27]. Performance metrics confirmed its robustness, with low false prediction rates. Visualization: The dashboard effectively displayed daily, weekly, and monthly trends in sleep habits. It also provided actionable insights, helping users visualize how behavior changes improve sleep quality [19, 20].

5 Discussion

Integrating digital wellbeing data with lifestyle metrics significantly enhances prediction accuracy. The system bridges the gap between conventional wearable based monitoring and AI-driven behavioral analytics [8, 9, 19]. A strong negative correlation was found between screen time and sleep duration. Users exceeding 6 hours of screen time daily experienced poor sleep quality. Excessive digital exposure disrupts circadian rhythm and delays sleep onset [1, 2, 6, 7].

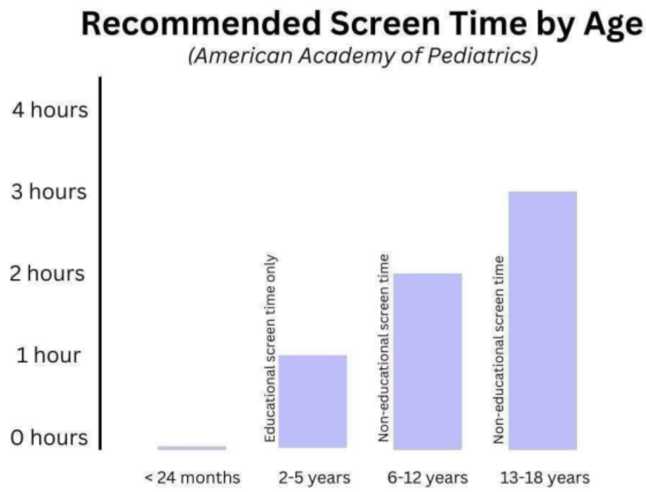

Fig 2. Recommended screen time by age

The framework can evolve with IoT devices for real-time monitoring. The analysis showed a strong negative correlation between daily screen time and duration of sleep. Individuals who used digital devices for more than six hours a day showed shorter and poor-quality sleep compared to their moderate counterparts. In addition, too much exposure to screens disrupts the circadian rhythm, especially at bedtime, which delays falling asleep [1, 2, 7, 19]. Consequently, users with balanced screen habits have continued to keep their sleep patterns consistent and healthy. These findings identify the huge impact of digital behavior on sleep quality and establish the need to monitor screen time [1, 6, 7, 19]. The proposed AI model analyzes such trends in a competent manner to provide personalized recommendations to help improve sleep health [19, 20, 21]. Looking to the future, this underlying framework can be further developed by the incorporation of IoT and wearable sensors to allow real-time monitoring and adaptive feedback [8, 9, 10]. Such future developments could allow continuous learning from user data, offering even more personalized and dynamic recommendations for improving sleep quality and overall wellbeing [19, 20, 21].

6 Future Scope

Although the proposed system has shown promising results, there remains considerable scope for improvement and expansion. Future studies can be conducted in which wearable devices and IoT-based sensors such as Fitbit, Mi Band, or Apple Watch are integrated for the acquisition of real-time physiological data, including heart rate, movement, and sleep cycles [8, 9, 10, 12]. This, in turn, would make it possible for the model to adapt itself continuously and improve its predictions [19, 20, 21]. Increasing the dataset size by incorporating subjects from various age groups, professions, and regions will lead to better generalization and reliability for different populations [1, 2, 6]. Advanced deep learning architectures, such as CNN-LSTM hybrids, can also be explored to better capture temporal and behavioral patterns in user data [21, 22, 27]. In addition, developing a mobile companion app could provide real-time feedback, personalized insights, and digital wellness alerts to foster healthier screen and sleep habits [19, 20]. Hosting the system on cloud platforms such as AWS or Google Cloud would ensure scalability, faster processing, and global accessibility [25]. Finally, data encryption and privacy-preserving AI techniques will further enhance user trust and security, laying a very strong foundation for future AI-driven and personalized health and wellbeing systems [19, 20, 21].

7 Conclusion

This study successfully demonstrates that AI and data analytics can reliably estimate sleep quality using simple, easy to-measure behavioral and digital wellbeing parameters such as screen time, caffeine intake, stress levels, and physical activity . By combining these features, the implemented Random Forest model accurately classifies sleep quality into Good, Average, and Poor, with observed results showing a clear negative correlation between increased screen exposure and total sleep duration consistent with established sleep hygiene research. The complete system integrates a Flask backend for model processing and a React dashboard for visualization, enabling users to view their sleep predictions, track daily trends, and receive personalized recommendations through an intuitive interface These results validate the effectiveness of the proposed approach in making sleep health insights both accessible and actionable. Overall, the project bridges an important gap between advanced technology and everyday health management, emphasizing preventive care, self-awareness, and well-being through AI-driven predictive insights and tailored digital feedback.

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