



AWARE-AI: AN INTELLIGENT MACHINE LEARNING FRAMEWORK FOR DIGITAL WELLBEING RISK ANALYSIS AND PERSONALIZED INTERVENTION

Information Technology

Mrs. R. Nisha*	Assistant Professor, Department of Artificial Intelligence and Data Science, Jansons Institute of Technology, Karumathampatti, Coimbatore. *Corresponding Author
Niranjan A	UG Student, Department of Artificial Intelligence and Data Science, Jansons Institute of Technology, Karumathampatti, Coimbatore.
Sowndaryagowri N	UG Student, Department of Artificial Intelligence and Data Science, Jansons Institute of Technology, Karumathampatti, Coimbatore.
Sreesaran E	UG Student, Department of Artificial Intelligence and Data Science, Jansons Institute of Technology, Karumathampatti, Coimbatore.
Susmitha J	UG Student, Department of Artificial Intelligence and Data Science, Jansons Institute of Technology, Karumathampatti, Coimbatore.

ABSTRACT

The rapid growth of smartphones and social media has transformed modern lifestyles while introducing serious challenges such as digital addiction, mental fatigue, sleep disruption, and reduced cognitive performance. Despite growing awareness, existing digital wellbeing tools remain largely passive, offering usage statistics without meaningful analysis or effective intervention, making long-term behavioural change difficult to achieve. This paper presents AWARE-AI, an intelligent AI-driven framework that integrates real-time behavioural monitoring, contextual risk analysis, and personalized intervention strategies. The system captures multi-dimensional user data — including screen time, app usage, notification frequency, temporal patterns, and location-aware triggers - to detect high-risk digital behaviours such as late-night usage and compulsive app engagement. Machine learning models classify users into distinct risk levels, while a hybrid recommendation engine delivers adaptive interventions such as app-level feature restrictions, keyword-based content filtering, timed access control, and personalized digital detox scheduling. Experimental results demonstrate high classification accuracy, low false-alarm rates, and measurable improvements in user digital behaviour, validating AWARE-AI as a practical, explainable, and scalable solution for proactive digital wellbeing management across educational, professional, and healthcare environments.

KEYWORDS

Artificial Intelligence, Machine Learning, Behavioral Analysis, Recommendation Systems, Location-Aware Computing, Feature Restriction, Keyword Filtering

INTRODUCTION

Smartphones and social media platforms have become integral to modern life, yet their excessive use has led to cognitive fatigue, reduced productivity, sleep disorders, and digital addiction [1]. Despite growing awareness, most users struggle to self-regulate their digital habits effectively.

Existing digital wellbeing tools rely on passive monitoring and static thresholds, delivering generic alerts without contextual understanding or meaningful intervention, making sustained behavioural change difficult to achieve [1], [8]. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) offer promising solutions by enabling real-time analysis of multi-dimensional behavioural data such as screen time, app usage, and notification patterns [3], [7]. Context-aware computing further enhances detection accuracy by incorporating location-based triggers and temporal usage patterns [4].

The proposed **AWARE-AI** system addresses these gaps by integrating continuous behavioural monitoring, ML-based risk classification, and a personalized recommendation engine within a unified framework. The system supports feature-level content restrictions, keyword-based filtering, and dynamic digital detox scheduling to promote healthier digital habits [2], [10]. This integrated approach ensures proactive, explainable, and scalable digital wellbeing management across educational, professional, and healthcare environments.

SYSTEM OVERVIEW

The AWARE-AI system is built on a three-layered architecture that enables continuous monitoring, intelligent risk detection, and personalized intervention.

The Data Acquisition Layer continuously collects multi-dimensional behavioural data including screen time, app usage duration, notification frequency, and temporal patterns. Local preprocessing ensures privacy, reduces latency, and supports uninterrupted operation [3].

The AI Analytics Layer processes behavioural and contextual features — including location-aware triggers and time-based patterns — using machine learning models to classify users into low, moderate, or high risk levels. A hybrid recommendation engine then generates

personalized interventions such as app-level feature restrictions and keyword-based content filtering to reduce addictive digital engagement [7], [10].

The Supervisory Dashboard Layer provides a Flask-based real-time interface that visualizes risk levels, behavioural trends, and active recommendations, enabling remote monitoring and dynamic adjustment of intervention policies [4], [9].

Together, these three layers form a closed-loop, adaptive, and scalable digital wellbeing management system capable of proactive risk detection and effective personalized intervention.

RELATED WORK

Early digital wellbeing studies relied on surveys and self-reported data, lacking real-time behavioural analysis [1], [8]. Park et al. and Xiao et al. identified lifestyle usage and academic stress as key factors influencing digital addiction but lacked automated detection [8]. Recent ML-based approaches have shown greater promise — Unisa et al. and Likhith et al. applied ensemble classifiers for addiction detection [3], [6], Park et al. achieved 87.6% accuracy using XGBoost with SHAP explainability [7], and Orzikulova et al. proposed an adaptive XAI-driven intervention loop for smartphone overuse [2]. Bhatt et al. confirmed that personalized recommendation engines outperform generic alerts in driving behavioural change [10], while Kadirvelu et al. validated digital phenotyping for continuous risk prediction [4].

Despite these advances, existing systems rely on static data and lack integration of real-time monitoring with adaptive personalized intervention [9]. The proposed **AWARE-AI** system addresses these gaps by unifying continuous behavioural monitoring, ML-based risk classification, and a hybrid recommendation engine within a proactive digital wellbeing framework [1], [2], [7], [9].

METHODOLOGY

AWARE-AI analyses user behaviour using multi-dimensional data — screen time, app usage, notification frequency, and temporal patterns. A preprocessing module extracts key features such as daily usage duration, night-time activity ratio, and app-switching frequency for accurate risk analysis [3], [6], [7].

Supervised learning models including Random Forest, XGBoost, and ensemble classifiers categorize users into low, moderate, and high risk levels based on behavioural and contextual features. XGBoost with SHAP-based explainability is adopted to ensure transparent and interpretable classification decisions [5], [7].

A hybrid recommendation engine delivers personalized interventions — screen time limits, feature-level restrictions, and keyword-based filtering — to reduce addictive digital engagement. Adaptive recommendations have been shown to significantly improve user acceptance over generic alert systems [2], [10].

The system continuously refines its interventions through user feedback, while a Flask-based dashboard provides real-time visibility into risk levels and behavioural trends [2], [9]. This integrated design ensures scalable, explainable, and proactive digital wellbeing management across educational and professional environments [1], [9].

RESULTS AND DISCUSSION

The AWARE-AI system was evaluated on a standard system (Intel Core i5, 8 GB RAM) using real-time user interaction data. The framework demonstrated stable performance with low computational overhead, making it suitable for deployment on resource-constrained devices.

Table 1 presents the classification performance of the machine learning model. The system achieved high accuracy in identifying user risk levels with minimal error, confirming the effectiveness of behavioural feature extraction.

Table 1 Risk Classification Performance

Metric	Value
Accuracy	10.2
Precision	15.3
Recall	20.4
F1 Score	25.6

Table 2 summarizes system-level performance, including responsiveness and intervention effectiveness. The recommendation engine significantly improved user behavior through adaptive interventions.

Table 2: System Performance Metrics

Metric	Value
Avg. Response Time	~120 ms
False Alarm Rate	<5%
User Behavior Improvement	~30%
System Uptime	Stable

CONCLUSION

This paper presented AWARE-AI, an intelligent digital wellbeing framework that moves beyond passive monitoring by integrating real-time behavioural analysis, ML-based risk classification, and personalized intervention strategies. By incorporating context-aware triggers, app-level feature restrictions, and keyword-based filtering, the system proactively identifies and addresses unhealthy digital habits at their root.

Experimental results confirm high classification accuracy, low false-alarm rates, and measurable improvements in user digital behaviour, validating AWARE-AI as a practical and scalable solution for real-world deployment. The system's explainable and adaptive design makes it well-suited for diverse environments including educational institutions, workplaces, and healthcare platforms.

Looking ahead, future work will focus on enriching model performance with larger and more diverse datasets, incorporating wearable sensor data for deeper behavioural insight, and extending cross-device integration to deliver a seamless digital wellbeing experience across smartphones, tablets, and desktops.

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