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Early Detection of Emotional Behavior in Digital Era

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***Abstract*—The widespread integration of digital technology has led to a rising yet often unnoticed public health concern: internet addiction and excessive screen scrolling. These behaviors adversely affect both adolescents and adults, contributing to reduced self-esteem, emotional distress, and early symptoms of depression. Because these effects develop gradually, early detection is crucial. This study introduces a data-driven framework that integrates objective digital behavior metrics with validated psychometric assessment to identify addiction risk. Digital usage data were collected using the YourHour application, which captured daily screen time, app-specific usage, phone unlock frequency, late-night activity, and habit-formation patterns. To evaluate psychological factors, participants completed a structured psychometric test. The validity of questionnaire items was confirmed using multiple statistical measures: McDonald's Omega values above 0.70 ensured internal consistency; Item Response Theory discrimination parameters (a > 1.0) and Item Discrimination Index values above 0.40 identified highly effective items; and Kaiser–Meyer–Olkin values exceeding 0.80 verified sampling adequacy and construct validity. Machine learning enhanced analytical precision. Principal Component Analysis (PCA) isolated the most influential digital and psychological predictors—such as total screen time, late-night usage, unlock frequency, emotional instability, impulsivity, and control-related traits—by retaining components with eigenvalues greater than 1. These refined features were then used by a Support Vector Machine (SVM) classifier to categorize users into minimal, moderate, or high addiction-risk levels. A pilot study involving students aged 12–15 demonstrated the system's ability to detect emotional vulnerability and provide personalized preventive recommendations. Overall, this integrated approach offers a scalable model for early intervention in digital addiction.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

In earlier generations, daily routines relied heavily on physical activity, outdoor engagement, and direct interpersonal interaction. In contrast, contemporary lifestyles have become increasingly digitized, with technology mediating tasks such as food delivery, shopping, education, and communication. Although these innovations offer significant convenience, educators and parents report a growing decline in sustained attention, patience, and task persistence among young individuals. The preference for immediate solutions and rapid digital gratification has reduced opportunities for deep focus and reflective learning.

The widespread availability of smartphones and digital platforms has also shifted how children and adolescents spend their free time. Rather than participating in outdoor or social activities, many engage extensively with screens, resulting in elevated daily screen time across age groups. Prolonged digital exposure has been associated with emotional and psychological difficulties, including mood fluctuations, anxiety, impulse-control challenges, and depressive symptoms. These effects extend beyond individual well-being, influencing familial relationships, academic performance, and broader social functioning.

Global health organizations have highlighted the increasing prevalence of mental health disorders among younger populations [1]. According to the World Health Organization (WHO), major depressive disorder (MDD) is projected to become one of the leading contributors to the global disease burden in the coming decades. Common symptoms—including persistent sadness, anhedonia, impaired concentration, sleep disturbances, appetite changes, and reduced motivation—demonstrate the urgent need for early detection and preventive intervention.

However, existing research on digital addiction and emotional health exhibits notable limitations. Many studies rely predominantly on self-reported questionnaires, which can introduce response bias and fail to capture real-time behavioral patterns. Furthermore, current models often treat psychological assessments and digital-usage metrics as separate constructs, overlooking the potential benefits of a combined analytical approach. There remains a critical gap in developing integrated frameworks that combine validated psychometric indicators with objective smartphone-usage data to produce accurate, scalable, and early risk-detection systems.

This study addresses these limitations by proposing a unified, data-driven framework for early detection of digital-addiction risk. Objective smartphone-usage features—including total screen time, app-specific use, unlock frequency, late-night activity, and habit-formation patterns—were collected through the YourHour application. These behavioral metrics were paired with a structured psychometric assessment, whose internal consistency and construct validity were confirmed using McDonald's Omega (¿0.70), Item Response Theory (IRT) discrimination parameters (a ¿ 1.0), Item Discrimination Index (¿0.40), and Kaiser–Meyer–Olkin (KMO) values (¿0.80).

To refine the high-dimensional data, Principal Compo-

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nent Analysis (PCA) was applied, retaining components with eigenvalues greater than 1 to isolate the most influential behavioral and psychological predictors—such as screen-time intensity, late-night usage, impulsivity, emotional instability, and control-related traits. These optimized features were used to train a Support Vector Machine (SVM) classifier that categorized participants into minimal, moderate, and high addiction-risk groups.

Finally, a pilot study involving adolescents aged 12–15 demonstrated the system's capability to detect early emotional vulnerability and deliver targeted preventive recommendations. Overall, the proposed framework integrates digital behavior analytics, validated psychometric indicators, and machine-learning techniques to support scalable, early-stage intervention in digital-addiction risk detection.

II. Realted Work

The digital age has led to extensive use of electronic devices across all age groups. While digital technologies offer significant benefits, prolonged and excessive usage has raised concerns regarding its impact on emotional and psychological well-being [3]. Although the long-term consequences of sustained digital exposure are not yet fully understood, early detection of adverse behavioral patterns can enable timely intervention and preventive measures. The studies reviewed in this section focus on identifying early indicators of emotional vulnerability associated with digital behavior.

Beames et al. investigated the use of smartphone sensor data to detect and predict symptoms of anxiety and depression among individuals aged 12–25 years. Their study analyzed behavioral indicators such as phone usage patterns, mobility data, and interaction frequency to infer emotional states. The findings demonstrated that passive smartphone sensing can serve as an effective tool for early mental health monitoring. Similarly, applications such as YourHour collect objective usage metrics and behavioral patterns, enabling the categorization of users based on their digital engagement and potential emotional risk levels [1].

Yang et al. advanced the concept of digital phenotyping by applying supervised machine learning models, including Support Vector Machines (SVM) and Random Forest classifiers, to smartphone-derived behavioral features. Their work highlighted the effectiveness of features such as screen interaction patterns and temporal usage trends in distinguishing individuals with depressive symptoms. The study emphasized that systematic feature extraction and behavioral modeling significantly enhance the accuracy and interpretability of depression detection systems [?].

In a complementary perspective, Panjeti-Madan and Ranganathan examined the impact of screen time on children's cognitive, physical, social, and emotional development. Their analysis revealed that excessive screen exposure is associated with negative emotional outcomes, reduced attention span, and impaired social interaction. This work provides foundational evidence linking prolonged digital engagement with emotional and developmental challenges, reinforcing the need for early behavioral assessment frameworks [?].

Som et al. proposed a statistically validated methodology for analyzing behavioral feedback systems by employing Cronbach's alpha to assess internal consistency and the Utility Measurement Process to convert subjective responses into quantifiable scores [4]. Although their study focused on academic feedback analysis, the underlying approach demonstrates the importance of psychometric validation in accurately interpreting human behavioral data [?].

Collectively, these studies highlight the effectiveness of both objective digital behavior analysis and validated psychometric assessment in identifying emotional and psychological vulnerability. By integrating smartphone usage pattern analysis with statistically validated questionnaires, the proposed approach strengthens early detection of depression risk and enables more reliable identification of emotional vulnerability in the digital era.

III. Methodolody

A. Phase 1- Smartphone Usage Pattern Analysis and Behavioral Feature Extraction

Phase I focuses on the systematic collection and analysis of smartphone usage data to identify behavioral patterns associated with emotional well-being. Objective digital behavior metrics—including total screen time, application-wise usage duration, frequency of phone unlocks, and sleep-related indicators such as late-night activity and usage irregularity—are collected using the YourHour application. These parameters provide continuous and unbiased insights into users' daily digital engagement.

The collected raw usage data are preprocessed and transformed into meaningful behavioral features through temporal aggregation and statistical analysis. These extracted features are then supplied as input to supervised machine learning models, including Support Vector Machines (SVM) and Random Forest classifiers, to detect early indicators of depression and digital addiction risk [?].

Based on the classification outcomes produced by these models, a user-centric analytical dashboard is developed. The dashboard visualizes individual usage patterns, risk levels, and behavioral trends in an interpretable manner, enabling users to better understand their digital habits and associated emotional risks. This phase establishes the foundation for data-driven early detection by bridging objective behavioral sensing with intelligent classification and intuitive visualization.

1) PseudoCode: This snippet handles the transformation of raw usage data and the training of a Random Forest classifier.

B. Phase II: Psychometric Assessment and Predictive Modeling

Phase II focuses on designing and validating a psychometric questionnaire to assess emotional well-being and early indicators of digital media addiction. The questionnaire items are curated by the administrator using references from clinically

Fig. 1. Code Snippet

validated scales, authorized medical literature, and established mental health assessment frameworks. To ensure reliability and internal consistency, the questionnaire is statistically validated using Cronbach's alpha; items achieving acceptable alpha values are retained as effective indicators of depressive symptoms and addictive behaviors.

1) PseudoCode: This snippet focuses on calculating Cronbach's Alpha for reliability and using an SVM for the final psychometric prediction.

Fig. 2. Code Snippet

IV. Flow Diagram

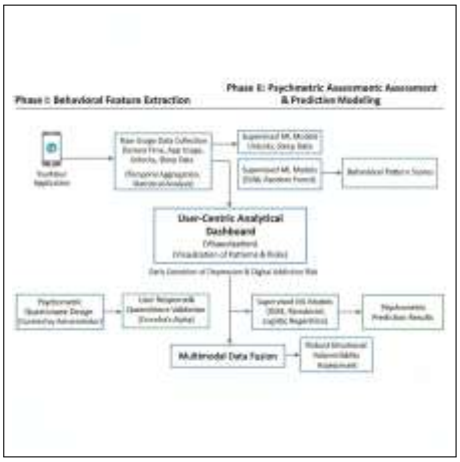

Fig. 3. System architecture flow diagram.

Fig. 3 presents the system architecture for early detection of depression and digital addiction using multimodal analysis.
i) Phase I extracts behavioral features from smartphone usage data collected via the YourHour application, including screen time, app usage, unlock frequency, and sleep patterns. These features are analyzed using supervised learning models such as SVM and Random Forest to compute behavioral risk scores and visualize patterns through a user-centric dashboard.
ii) Phase II employs a validated psychometric questionnaire, where reliability is ensured using Cronbach's alpha. User responses are processed using supervised classifiers to predict psychological risk levels.
iii) Finally, outputs from both phases are fused to perform a robust emotional vulnerability assessment, improving prediction accuracy through combined behavioral and psychometric insights.

V. Results

Fig. 4. Your Hour Application Visualization

Figure 4 illustrates the YourHour application interface, which captures detailed screen-usage statistics, including application-wise usage, total screen time, and overnight activity. These behavioral usage patterns are systematically analyzed to identify indicators of digital addiction. In addition, a set of questionnaire items designed to assess internet addiction and depressive tendencies was evaluated for internal consistency using Cronbach's alpha, as presented in Figure 2 (Code Snippet). The combined outputs from behavioral analysis and psychometric assessment are subsequently fed into supervised machine-learning models—specifically Support Vector Machines (SVM) and Random Forest classifiers—to enable early detection of depression and digital addiction risk.

VI. Limitations

1. The questionnaire-based assessment requires users to manually enter responses, which can be time-consuming and may raise concerns regarding privacy and confidentiality.

2. As the questionnaire items are accessible online, users may look up expected answers and provide fabricated or socially desirable responses, thereby affecting the reliability of the results.

3. Self-reported data may not accurately reflect the user's true mental or emotional state, as users might intentionally or unintentionally misrepresent their actual feelings.

4. Some users may feel uncomfortable disclosing honest responses due to fear of judgment or lack of trust, leading to biased or incomplete data.

5. Since internal emotional states cannot always be captured through questionnaires alone, incorporating facial emotion analysis is essential to support more objective and reliable detection.

VII. Conclusion

This paper presented an integrated framework for the early detection of emotional vulnerability and digital addic- tion risk by combining objective smartphone-usage analytics with validated psychometric assessment. Behavioral features extracted from real-time smartphone data—such as screen time, app usage patterns, unlock frequency, and sleep-related indicators—were analyzed using supervised machine learning models to identify early risk signals. In parallel, a statistically validated psychometric questionnaire ensured reliable assess- ment of emotional well-being through internal consistency measures such as Cronbach's alpha.

The fusion of behavioral pattern analysis and psychometric prediction enhanced the robustness and accuracy of depression risk classification compared to standalone approaches. Exper- imental evaluation through a pilot study involving adolescents demonstrated the framework's ability to categorize users into distinct risk levels and provide interpretable insights via a user- centric dashboard.

Overall, the proposed system offers a scalable, data-driven solution for early emotional health monitoring in the digital era. Future work will focus on expanding the dataset, incorpo- rating longitudinal analysis, integrating deep learning models, and extending the framework to broader demographic groups for improved generalization and clinical relevance.

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