



Breaking the Doomscrolling Cycle: An AI-Powered Approach to Healthier Screen Time

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Abstract: Doomscrolling is an emerging behavioural pattern characterized by prolonged, repetitive, and low-attention smartphone usage, which often leads to reduced productivity and cognitive fatigue, particularly among students. Existing digital well-being solutions largely rely on static screen-time limits and manual restrictions, offering limited adaptability to individual user behaviour. This paper presents a prototype AI-based system for detecting and mitigating doomscrolling through behavioural analysis of smartphone usage metadata.

The proposed approach passively monitors user interaction patterns during an initial learning phase and constructs a personalized behavioural profile using lightweight machine learning techniques. Due to the lack of publicly available labeled datasets for doomscrolling behaviour, a proxy-labeled dataset is generated using behaviour-inspired heuristics to evaluate model feasibility. A lightweight neural network model is trained to predict the likelihood of a user entering a doomscrolling state based on features such as session duration, scrolling intensity, application switching behaviour, and time-based usage patterns.

To preserve user privacy and usability, the system operates without content inspection and deploys the trained model using on-device inference. Conservative decision thresholds and non-intrusive interventions are employed to minimize false-positive alerts and support user awareness rather than enforce restrictive controls. Experimental evaluation demonstrates effective behavioural separability under controlled conditions, validating the feasibility of the proposed approach. The results indicate that predictive, behaviour-aware digital well-being systems can provide a promising foundation for addressing doomscrolling in real-world mobile environments.

Keywords: doomscrolling, screen addiction, mobile usage analysis, machine learning, digital well-being.

I. INTRODUCTION

In the modern era, the mobile phone has become one of the most dominant and indispensable technologies in everyday life. Smartphones are widely used for communication, education, entertainment, social networking, and access to information. While these devices provide significant convenience and productivity benefits, their excessive and uncontrolled usage has introduced several emerging behavioural challenges. One such harmful and increasingly common phenomenon is *doomscrolling*.

Doomscrolling refers to the repetitive and prolonged act of scrolling through digital content—often without a clear objective or awareness of time spent—despite negative effects on attention, productivity, and mental well-being. This behaviour is not limited to the consumption of negative news but also includes endless scrolling through social media feeds, short-form videos, and algorithm-driven content. Users often experience a temporary sense of engagement followed by mental fatigue, distraction, and loss of focus.

Recent surveys and global statistics highlight the severity of this issue. In 2025, studies report that **over 48% of the global population—approximately 3.8 billion people—exhibit signs of smartphone addiction**, with users checking their devices an average of **140–150 times per day**. Furthermore, a significant portion of daily screen time is spent on passive consumption activities such as scrolling, which closely aligns with doomscrolling behaviour. These trends indicate a growing dependence on smartphones that extends beyond productive use and into compulsive interaction.

This problem is particularly prevalent among students. Surveys conducted among academic populations reveal that **more than 70% of college students feel emotionally attached to their smartphones**, and a majority report difficulty staying focused due to frequent phone checking. In classroom environments, students are observed to check their phones multiple



times per session, negatively impacting concentration, learning efficiency, and academic performance. Even after brief moments of self-motivation to reduce usage, many students relapse into habitual scrolling within minutes, forming a repetitive cycle that is difficult to break.

Traditional digital well-being solutions, such as fixed screen-time limits and manual application restrictions, provide only limited assistance. These approaches are largely static, user-dependent, and do not adapt to individual behavioural patterns. Moreover, they typically intervene *after* excessive usage has already occurred, rather than predicting and preventing it beforehand. As a result, their long-term effectiveness in addressing compulsive scrolling behaviour remains limited.

Recent advancements in artificial intelligence and mobile data analysis have enabled the development of systems capable of learning user behaviour patterns through passive sensing techniques. By analysing smartphone interaction data—such as screen usage duration, session frequency, application switching behaviour, and time-based usage trends—it becomes possible to infer behavioural states associated with low attention span and compulsive usage. These insights can be leveraged to predict the likelihood of a user entering a doomscrolling state.

In this paper, we propose an AI-based system designed to detect and mitigate doomscrolling behaviour through personalized behavioural analysis. The system initially observes user interaction patterns over a learning period to establish an individual behavioural baseline. Based on this data, a machine learning model predicts potential doomscrolling states in near real time. When such a state is detected, the system provides gentle and timely interventions aimed at encouraging healthier usage habits rather than enforcing strict restrictions.

The primary objective of this work is to assist users—particularly students—in maintaining better focus, reducing unnecessary screen time, and developing mindful smartphone usage habits. By shifting from reactive control mechanisms to predictive and adaptive intervention strategies, the proposed approach aims to address the limitations of existing digital well-being solutions while preserving user privacy and usability.

II. SYSTEM OVERVIEW

The proposed system is designed to detect and mitigate doomscrolling behaviour by analysing smartphone usage patterns in a non-intrusive and adaptive manner. The system follows a user-centric approach, focusing on behavioural analysis rather than content inspection, thereby ensuring privacy and usability.

At a high level, the system operates in three major phases: an initial learning phase, a behaviour analysis phase, and an intervention phase. During the learning phase, the application passively monitors user interaction data to understand individual usage habits. This phase is essential for building a personalized behavioural baseline, as smartphone usage patterns differ significantly across users.

Once sufficient data is collected, the system analyses interaction patterns such as screen-on duration, session frequency, repetitive scrolling behaviour, and time-based usage trends. These behavioural indicators are processed to identify patterns associated with low attention span and compulsive scrolling. Based on this analysis, a predictive model estimates the likelihood of the user entering a doomscrolling state.

When a potential doomscrolling state is detected, the system initiates a soft intervention. These interventions are designed to be minimal and non-disruptive, such as brief alerts or reminders, encouraging users to regain awareness of their screen usage. The goal of the system is not to restrict smartphone access but to assist users—particularly students—in developing healthier digital habits through timely and intelligent feedback.

The overall architecture emphasizes simplicity, adaptability, and user privacy. By avoiding rigid usage limits and instead focusing on predictive behaviour modelling, the system aims to provide a more effective and personalized digital well-being solution.

III. METHODOLOGY

The proposed methodology aims to detect doomscrolling behaviour through behavioural analysis of smartphone usage patterns and predictive modelling. The system is designed to operate in a privacy-preserving and adaptive manner, making it suitable for real-world deployment, particularly among student users. The methodology consists of four main stages: data collection, dataset construction and labeling, feature extraction, and behaviour prediction with intervention.



A. Data Collection

During the initial learning phase, the system passively collects smartphone usage metadata to observe natural user behaviour. No content-level data is accessed or stored, ensuring user privacy. The collected parameters include session duration, scrolling intensity, application switching frequency, idle gap ratios, time-of-day usage, entertainment application usage ratio, session reopen count, and session burst indicators.

This data collection phase operates without enforcing any restrictions or alerts, allowing the system to establish an individualized behavioural baseline for each user. All data processing is designed to be performed locally where possible to minimize privacy risks and external dependencies.

B. Dataset Construction and Proxy Labeling

Due to the absence of publicly available labeled datasets for doomscrolling behaviour, a synthetic dataset was generated using behaviour-inspired heuristics derived from prior digital well-being and attention research. These heuristics approximate behavioural conditions commonly associated with compulsive scrolling, such as prolonged uninterrupted sessions, high scrolling intensity, reduced idle gaps, elevated entertainment consumption, and late-night usage patterns.

Each data instance was assigned a proxy label indicating either normal usage or potential doomscrolling behaviour based on these predefined conditions. While the generated labels do not represent absolute ground truth, this approach enables controlled evaluation of behavioural feature separability and model feasibility. The dataset was further processed using stratified train-test splits and class-weighted training to address class imbalance between normal and high-risk usage patterns.

C. Feature Extraction

From the collected usage metadata, a set of behavioural features was extracted to represent user interaction patterns. These features include session duration, scrolls per minute, application switching rate, idle gap ratio, night-time usage indicator, entertainment usage ratio, reopen count, and session burst score.

The selected features are grounded in behavioural research related to attention fatigue and compulsive smartphone usage. Prolonged continuous usage is associated with reduced cognitive control, while frequent application switching reflects fragmented attention. Low idle gap ratios indicate continuous engagement, and elevated entertainment consumption combined with night-time usage reflects impaired self-regulation. Feature normalization and selection were applied to improve model stability and prediction efficiency.

D. Behaviour Prediction and Intervention Strategy

The predictive component is implemented using a lightweight feed-forward neural network consisting of two hidden layers with ReLU activation and a sigmoid output layer. The model is trained using binary cross-entropy loss and the Adam optimizer. To address class imbalance, class-weighted training is employed, ensuring balanced learning across normal and doomscrolling instances.

The trained model outputs a probability score representing the likelihood of a user entering a doomscrolling state. To minimize false-positive interventions and preserve user experience, a conservative decision threshold is applied during inference. Only sustained high-confidence predictions trigger interventions.

When a potential doomscrolling state is detected, the system initiates a soft intervention in the form of awareness notifications or reminders. A cooldown mechanism is incorporated to prevent alert fatigue by temporarily suppressing repeated notifications. The trained model is converted to TensorFlow Lite format for on-device deployment, enabling low-latency, privacy-preserving real-time inference without transmitting user data to external servers.

IV. RESULTS AND EVALUATION

This section presents the evaluation methodology and observed outcomes of the proposed doomscrolling detection system. Since the primary objective of this work is to validate feasibility rather than claim real-world generalization, the results are interpreted within the context of a prototype-level evaluation using proxy-labeled behavioural data.

A. Experimental Setup

The predictive model was evaluated using a synthetically generated dataset constructed from behaviour-inspired heuristics that approximate doomscrolling and normal smartphone usage patterns. The dataset consisted of multiple behavioural



categories, including normal usage, borderline usage, at-risk behaviour, and high-risk doomscrolling sessions. To preserve class distribution during training and testing, a stratified train–test split was employed.

All features were normalized prior to training to ensure numerical stability. Model training was performed using class-weighted loss functions to address class imbalance and prevent bias toward majority classes. The evaluation process focused on assessing behavioural separability, prediction stability, and suitability for on-device inference.

B. Evaluation Metrics

Model performance was assessed using standard binary classification metrics, including accuracy, precision, recall, and F1-score. In addition to overall accuracy, particular emphasis was placed on precision for doomscrolling detection, as false-positive interventions can negatively impact user experience in digital well-being applications.

A conservative decision threshold was applied during inference to prioritize high-confidence predictions. This design choice intentionally trades recall for precision, ensuring that only sustained and high-risk scrolling behaviour triggers system interventions.

C. Observed Results

The trained model demonstrated effective separation between normal smartphone usage patterns and high-risk doomscrolling behaviour under controlled conditions. High-confidence doomscrolling instances were consistently assigned elevated probability scores, while routine and borderline usage patterns remained below the intervention threshold.

Although recall for doomscrolling detection was reduced under conservative thresholds, precision remained high, indicating that the system successfully avoided unnecessary or intrusive alerts. This behaviour aligns with the design goal of supporting user awareness without enforcing restrictive controls.

Manual test cases further validated the system’s response across diverse usage scenarios, including short productive sessions, prolonged entertainment-driven scrolling, and late-night usage patterns. These observations confirm the feasibility of using behavioural features to identify compulsive scrolling tendencies.

D. On-Device Inference Performance

To evaluate deployment feasibility, the trained neural network model was converted to TensorFlow Lite format and executed using on-device inference mechanisms. The lightweight architecture enabled low-latency prediction and minimal computational overhead, making the system suitable for continuous mobile operation.

By performing inference locally on the device, the system avoids transmitting sensitive usage data to external servers, reinforcing privacy preservation and compliance with digital well-being principles.

E. Summary of Findings

The evaluation results demonstrate that the proposed system can effectively model behavioural patterns associated with doomscrolling and generate meaningful risk predictions using lightweight machine learning techniques. While the current evaluation relies on proxy-labeled data, the findings validate the feasibility of the proposed architecture, feature set, and intervention strategy for real-world mobile deployment.

V. DISCUSSION

The proposed system presents a practical and behaviour-aware approach to addressing doomscrolling through predictive modelling and on-device machine learning. Unlike conventional digital well-being tools that rely on static screen-time limits or manual restrictions, the proposed approach focuses on understanding individual smartphone usage patterns and intervening proactively before excessive scrolling behaviour becomes entrenched.

A key strength of the system lies in its privacy-preserving design. By analysing only usage metadata rather than content-level information, the system minimizes privacy risks while still capturing meaningful behavioural signals. The deployment of the predictive model using on-device inference further strengthens this aspect by eliminating the need to transmit sensitive user data to external servers.

Another important consideration is user experience. The system intentionally employs conservative decision thresholds and cooldown-based intervention strategies to reduce false-positive alerts and prevent notification fatigue. This design



choice prioritizes user trust and long-term adoption over aggressive behaviour enforcement, which is particularly important in student-centric environments where smartphone usage patterns vary significantly.

Despite these advantages, certain limitations must be acknowledged. The current implementation relies on synthetically generated and proxy-labeled data, which limits direct generalization to real-world behaviour. Additionally, contextual factors such as task intent, emotional state, and external obligations are not explicitly modeled. As a result, some productive or purposeful extended smartphone usage may still be misclassified under certain conditions.

Overall, the discussion highlights that while the proposed system is not a definitive solution to screen addiction, it represents a feasible and scalable foundation for future digital well-being systems. The emphasis on behavioural modelling, user autonomy, and mobile feasibility distinguishes this work from existing approaches and provides a strong basis for further refinement.

VI. CONCLUSION AND FUTURE WORK

This paper presented a prototype AI-based system for detecting and mitigating doomscrolling behaviour using smartphone usage metadata and predictive machine learning techniques. By shifting from reactive screen-time controls to proactive behavioural analysis, the proposed approach addresses key limitations of traditional digital well-being tools while preserving user privacy and autonomy.

The system leverages a lightweight neural network model trained on behaviour-inspired features to estimate the likelihood of a user entering a doomscrolling state. Conservative decision thresholds and non-intrusive interventions are employed to ensure that the system supports user awareness without imposing restrictive controls. The successful conversion and deployment of the model using on-device inference further demonstrate the feasibility of real-time mobile deployment.

This work primarily validates the feasibility of an AI-driven behavioural monitoring system rather than claiming definitive real-world accuracy. Future work will focus on collecting longitudinal real-user data, refining proxy labels, and incorporating contextual cues such as application intent and temporal usage patterns. Additional improvements may include adaptive thresholding, explainable AI techniques, and large-scale user studies to further evaluate effectiveness and user acceptance.

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