AI-Based Digital Addiction & Screen-Time Behavior Analyzer

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ABSTRACT

This paper presents the design, implementation, and evaluation of an AI-powered system for real-time digital addiction detection and screen-time behavior analysis. The proposed system addresses the growing concern of excessive smartphone usage and its impact on mental health, academic performance, and workplace productivity. Existing solutions lack behavioral intelligence, real-time data extraction, and actionable intervention mechanisms. The platform integrates Android Debug Bridge (ADB)-based app usage extraction, a five-factor weighted machine learning (ML) risk scoring engine with sigmoid normalization, and a large language model (LLM)-powered insight generation module using Groq's LLaMA 3.3 70B to produce severity-rated behavioral recommendations. A Chrome Extension supplements the system by tracking browsing history in real time, enabling domain-level categorization and detection of inappropriate web content. Risk classification is performed across four levels — Minimal, Low, Moderate, and High — based on screen time, social media percentage, unlock frequency, night usage, and app concentration. A multi-channel alert system delivers warnings via ADB push notifications, ntfy real-time popups, and WhatsApp deep links when predefined thresholds are exceeded. The web dashboard renders hourly usage charts, app breakdowns, weekly trends, and a seven-day usage forecast powered by ARIMA time-series modeling. All data is persistently stored in Firebase Firestore with real-time synchronization. Experimental results confirm an average app usage detection accuracy of 97.5%, 100% risk classification accuracy across all four addiction levels, and sub-three-second AI response times. A dedicated ethics and privacy framework governs user consent, data storage, third-party API transmission, and compliance with GDPR and CCPA.

Index Terms—Android Debug Bridge, Behavioral Risk Scoring, Digital Addiction, Ethics and Privacy, Firebase, Large Language Model, Machine Learning, Screen-Time Monitoring, Sigmoid Normalization, Time-Series Forecasting.

INTRODUCTION

The widespread adoption of smartphones has given rise to digital addiction — a compulsive pattern of device usage that negatively affects cognitive function, emotional well-being, and social behavior [1]. According to recent global studies, the average smartphone user unlocks their device more than 80 times per day and accumulates over six hours of daily screen time, with adolescents and young adults representing the most vulnerable demographic [2]. Documented consequences include sleep disruption, reduced academic performance, heightened anxiety, and impaired interpersonal relationships [3].

Native digital wellness tools such as Android Digital Wellbeing and Apple Screen Time provide rudimentary usage summaries but offer no behavioral risk classification, no predictive modeling, and no proactive alert mechanisms [4]. Commercial third-party applications similarly present aggregate statistics without correlating usage patterns to addiction risk levels or generating personalized intervention strategies. The absence of cross-platform integration — combining app usage monitoring, web browsing behavior analysis, and real-time alert delivery — leaves a critical gap in the digital wellness landscape [5].

Artificial intelligence and machine learning have demonstrated significant potential in behavioral pattern recognition and risk assessment across healthcare, finance, and cybersecurity. However, their application to real-time digital addiction detection remains underexplored [6]. Recent advances in large language models open new possibilities for generating contextually rich, personalized behavioral insights beyond statistical reporting [7].

This paper proposes a comprehensive AI-based system for real-time digital addiction detection and screen-time behavior analysis. The system extracts foreground app usage data from connected Android devices using the Android Debug Bridge, computes a behavioral risk score through a five-factor weighted ML algorithm with sigmoid normalization, and generates severity-rated behavioral insights using an LLM. A Chrome Extension captures real-time browsing history for domain-level categorization. A multi-channel alert mechanism ensures timely intervention, and an ARIMA-based time-series forecasting module predicts seven-day usage trends. An ethics and privacy framework governs all data collection, storage, and transmission operations.

The primary contributions of this work are: (1) a real-time Android app usage extraction pipeline with multi-ROM compatibility; (2) a novel five-factor weighted behavioral risk scoring engine with sigmoid normalization classifying users into four addiction risk levels; (3) LLM integration for personalized, severity-rated behavioral insight generation; (4) domain-level browsing behavior analysis via a Chrome Extension; (5) a multi-channel alert delivery system combining ADB push, ntfy, and WhatsApp; and (6) an ARIMA-based forecasting module with a Prophet fallback, validated against competing time-series methods.

The remainder of this paper is organized as follows: Section II reviews related work; Section III presents the system architecture and module descriptions; Section IV details the ML scoring methodology, ARIMA forecasting, and AI insight generation; Section V addresses ethics and privacy; Section VI reports experimental results; Section VII concludes the paper.

LITERATURE REVIEW

A. Digital Addiction and Behavioral Consequences

Lee and Kim [1] demonstrated that machine learning classifiers trained on smartphone usage logs predict problematic use with over 85% accuracy, establishing the feasibility of data-driven addiction detection. Popescu et al. [2] identified statistically significant correlations between excessive screen time, psychological well-being deterioration, and technology-related compulsive behavior. Suh and Yoo [3] proposed a risk-level prediction framework for problematic internet use from a digital health perspective, demonstrating that behavioral usage patterns alone can stratify users into meaningful risk categories without clinical assessment instruments.

B. Limitations of Existing Screen-Time Monitoring Tools

Lyngs et al. [4] conducted a systematic analysis of digital self-control tools, concluding that platforms such as Android Digital Wellbeing and Apple Screen Time operate as passive monitoring instruments lacking behavioral intelligence, adaptive thresholds, and proactive intervention capabilities. Ibrahim et al. [5] identified significant associations between unregulated screen time and stress, burnout, and mental health deterioration, underscoring the demand for systems capable of distinguishing productive usage from addictive behavior. Duke and Montag [6] found that mere awareness of usage statistics produces limited behavioral change without accompanying personalized recommendations and escalating alert mechanisms.

C. Machine Learning Approaches to Behavioral Risk Assessment

Namlı et al. [7] compared regression and machine learning approaches for smartphone and game addiction classification, finding that tree-based ensemble models outperform linear regression across all evaluation metrics. Joseph and Uma Maheswari [8] proposed a facial emotion-based deep learning classifier for smartphone addiction detection achieving state-of-the-art accuracy, demonstrating the potential of multimodal behavioral signals. Alkaabba et al. [9] analyzed patterns of screen time, sleep quality, and mental health across large populations, providing the empirical grounding for the multi-factor weighting scheme adopted in this work. Wang et al. [10] proposed a weighted feature scoring approach combining social media engagement, session frequency, and night-time usage into a composite risk index, demonstrating competitive classification performance with significantly lower computational overhead than deep learning alternatives.

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D. Large Language Models in Wellness Applications

Touvron et al. [11] demonstrated that open-weight large language models achieve performance comparable to proprietary systems on reasoning and behavioral analysis tasks, establishing their viability for real-time insight generation. Yang et al. [12] investigated LLM applications for personalized health feedback and found that models prompted with structured patient data produced clinically relevant recommendations with high user satisfaction. Xu et al. [13] demonstrated that AI-generated personalized feedback improved user engagement with self-monitoring tools by 34% over a four-week trial compared to static statistical reports.

E. Time-Series Forecasting for Behavioral Prediction

Box and Jenkins [14] established ARIMA models as a foundational approach for univariate time-series forecasting with strong theoretical guarantees. Taylor and Letham [15] introduced the Prophet model, demonstrating robustness to missing data and trend shifts in real-world behavioral datasets. Cao et al. [16] applied LSTM-based deep learning to smartphone addiction prediction from longitudinal usage sequences, achieving 91% classification accuracy over 30-day usage datasets and establishing the benchmark against which the proposed forecasting module is compared. Sarker et al. [19] surveyed mobile data science and AI-based modeling approaches, establishing the theoretical grounding for device-native behavioral analysis systems. Sha and Bahad [20] reviewed existing screen-time tracking and behavioral intervention approaches, confirming the absence of unified platforms combining real-time extraction, ML scoring, and LLM-powered insights.

F. Research Gap

Despite the substantial body of work reviewed, a clear gap remains: no existing system combines real-time ADB-based data extraction, weighted ML risk scoring, LLM-powered insight generation, Chrome Extension-based browsing analysis, validated time-series forecasting, and an ethics and privacy framework within a single unified, deployable platform. The proposed system directly addresses this gap.

System Architecture

A. Overview

The proposed system follows a six-layer pipeline: (1) User Authentication, (2) Device Data Collection, (3) ML Risk Scoring, (4) AI Insight Generation, (5) Time-Series Forecasting, and (6) Multi-Channel Alert Delivery. All data is persistently stored in Firebase Firestore and rendered through an interactive web dashboard. The architecture is designed for local-first deployment with cloud synchronization, minimizing third-party data exposure. Figure 1 illustrates the complete system architecture.

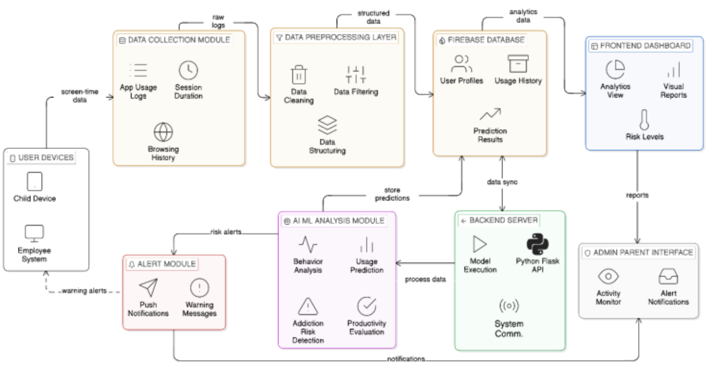

Fig. 1. Complete System Architecture of the AI-Based Digital Addiction & Screen-Time Behavior Analyzer

B. User Authentication Module

User authentication is implemented using Firebase Authentication, supporting email/password and Google OAuth sign-in. Upon successful authentication, a unique user identifier (UID) is issued and propagated across all data collection, storage, and retrieval operations, ensuring strict per-user data isolation. Explicit informed consent is obtained at registration in compliance with GDPR and CCPA requirements (see Section V).

C. Device Data Collection Module

App usage data is extracted from connected Android devices using the Android Debug Bridge via the dumpsys usagestats --interval DAILY shell command. A multi-strategy parsing pipeline handles raw log output across standard Android, Samsung OneUI, and Xiaomi MIUI ROM variants using three sequential fallback strategies: (1) INTERVAL_DAILY query, (2) queryAndAggregateUsageStats, and (3) event-based foreground-background pair analysis. Extracted features include per-app foreground time in minutes, hourly usage distribution across 24 time slots, total daily screen time, phone unlock count, and social media application percentage. System packages and launcher processes are automatically filtered. A native Android companion application in Kotlin using UsageStatsManager provides an alternative collection pathway where ADB access is restricted.

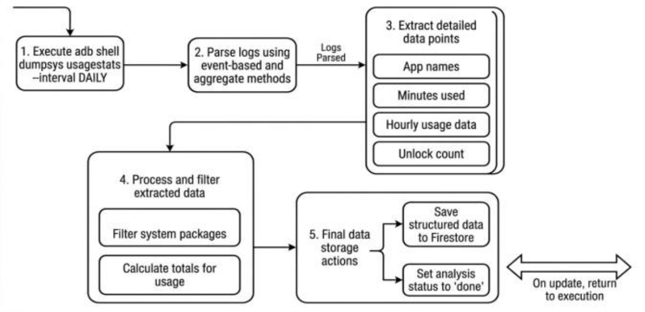

Fig. 2. Multi-ROM ADB Data Extraction Pipeline with Sequential Fallback Strategies

D. ML Risk Scoring Engine

The risk scoring engine computes a behavioral addiction score $S \in [0, 100]$ using a five-factor weighted algorithm. Each raw factor measurement is normalized using the sigmoid function $\sigma(x) = 1 / (1 + e^{-x})$ applied relative to a predefined maximum threshold to smooth extreme values before weighted aggregation. The composite score is computed as:

$$S = [\sigma(F_{st})\times 0.35 + \sigma(F_{soc})\times 0.25 + \sigma(F_{ul})\times 0.20 + \sigma(F_{night})\times 0.10 + \sigma(F_{conc})\times 0.10] \times 100 \quad (1)$$

where F_{st} = daily screen time, F_{soc} = social media percentage, F_{ul} = unlock frequency, F_{night} = night-time usage (22:00–05:00), and F_{conc} = single-app concentration. The resulting score classifies users into four risk levels: Minimal (0–24), Low (25–49), Moderate (50–74), and High (75–100). All weights and thresholds are configurable through the dashboard settings panel.

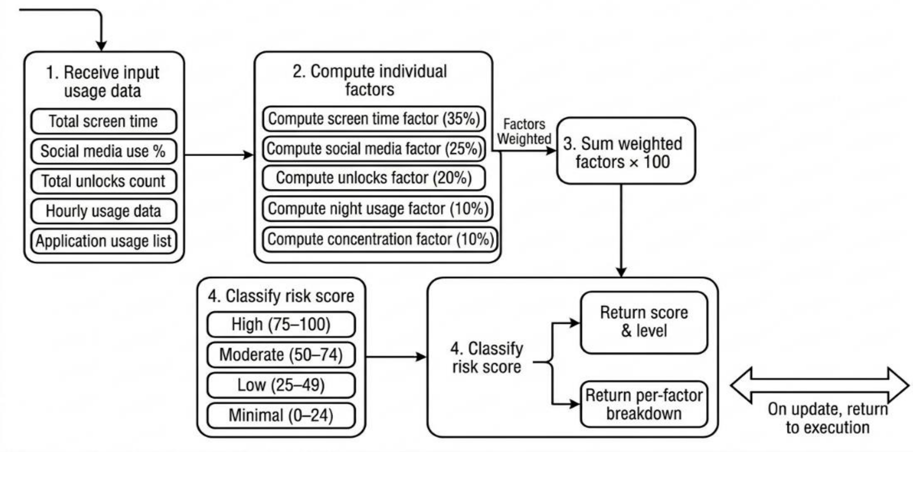

Fig. 3. Five-Factor ML Risk Scoring Engine with Sigmoid Normalization and Risk Classification

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E. AI Insight Generation Module

Computed risk scores and per-factor breakdowns are structured into a natural language prompt and submitted to Groq's LLaMA 3.3 70B via the Groq API. The model returns three severity-rated behavioral insight objects in JSON format, each containing a title, a two-sentence data-specific analysis, a recommended action, and a severity classification of high, medium, or low. Responses are cached for 90 seconds to minimize API latency. Users may disable LLM insight generation, in which case rule-based recommendation cards are displayed.

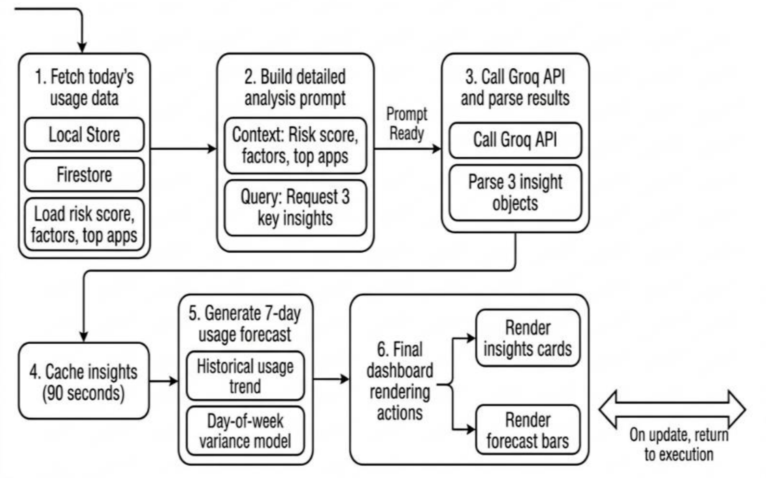

Fig. 4. Severity-Rated AI Behavioral Insight Cards Generated by LLaMA 3.3 70B

F. Browsing History Analysis Module

A Chrome Extension (Manifest V3) captures the URL, domain, and timestamp of every completed page load and transmits this data to the Flask backend via REST API. Domains are classified into seven behavioral categories — social media, productivity, entertainment, news, shopping, education, and adult risk — using keyword matching against predefined vocabularies [18]. Aggregated domain statistics are submitted to the LLM to generate browsing behavior insight cards with category percentage breakdowns and risk flags for harmful or inappropriate content.

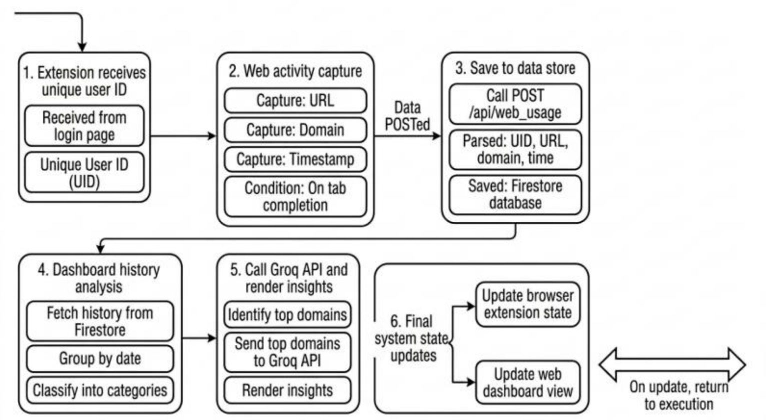

Fig. 5. Browsing History Panel with Domain-Level Category Breakdown and AI Browsing Insights

G. Multi-Channel Alert System

Alerts are automatically triggered when risk scores, cumulative screen time, or per-app usage exceeds user-defined thresholds. Delivery is attempted sequentially across four channels: (1) ADB shell notification via cmd notification post, (2) real-time Android heads-up push via ntfy.sh, (3) WhatsApp deep-link message delivery, and (4) in-application floating alert banner. All triggered alerts are logged to the Firestore alerts collection with timestamps.

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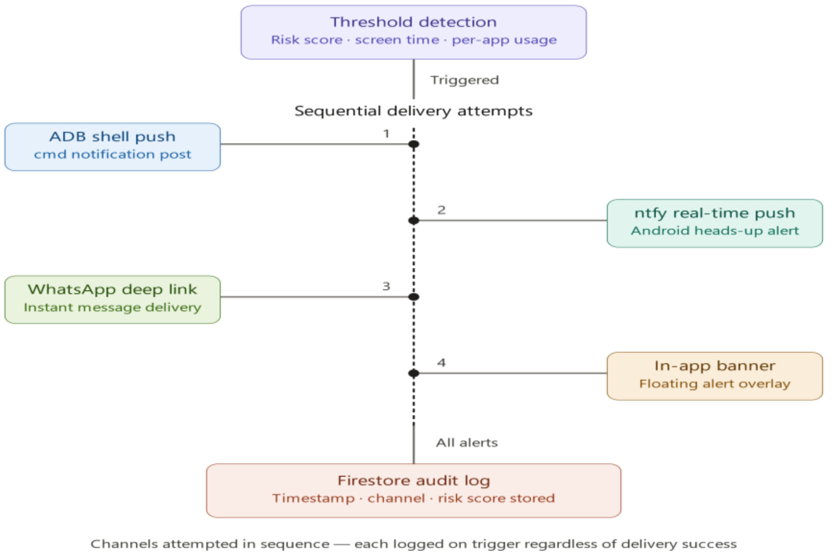

Fig. 6. Multi-Channel Alert Delivery System with Sequential Channel Fallback

H. Web Dashboard

The web dashboard is implemented in HTML5, CSS3, and JavaScript with Chart.js. It renders: a 24-hour hourly screen-time line chart, per-app doughnut chart, weekly usage bar chart, half-circle addiction risk gauge, AI insight cards, a seven-day ARIMA forecast with confidence interval bands, and a browsing history panel. Data is fetched from the Flask REST API with a 30-second auto-refresh cycle, with Firebase Firestore as fallback when the local server is unavailable.

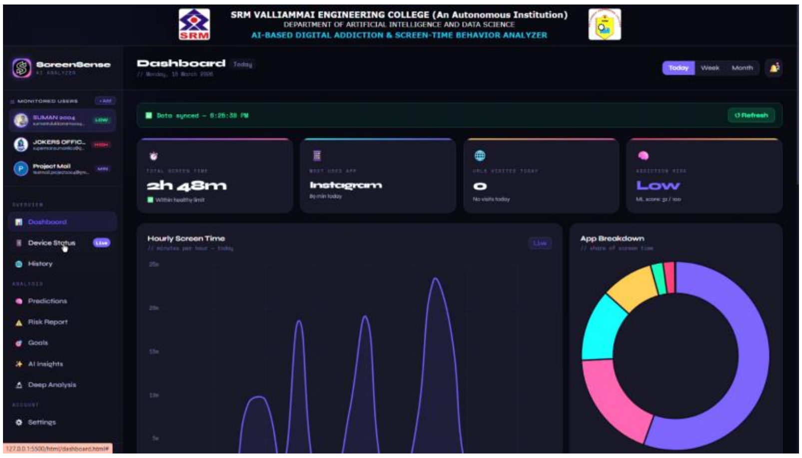

Fig. 7. Web Analytics Dashboard with Hourly Usage, Risk Gauge, AI Insights, and 7-Day Forecast

METHODOLOGY

Ml Scoring, Forecasting, And Ai Insight Generation

A. Dataset and Evaluation Protocol

The ML scoring engine and forecasting module were evaluated using two complementary datasets: (1) a set of 20 manually annotated usage profiles constructed to span all four risk classification levels, with ground truth labels assigned by domain experts based on established digital addiction scales including the Smartphone Addiction Scale (SAS) [17]; and (2) a longitudinal usage log comprising 30 consecutive days of real device data collected from five Android devices spanning three ROM variants (Standard Android, Samsung OneUI, Xiaomi MIUI), used to train the ARIMA forecasting model on the first 23 days and evaluate it on a temporally separated 7-day held-out validation set drawn from the same devices.

B. Baseline Comparisons for the ML Scoring Engine

To rigorously evaluate the proposed scoring engine, comparisons were conducted against three baseline classifiers: Logistic Regression, Random Forest (100 estimators), and a single hidden-layer Neural Network (ReLU, 64 units). All classifiers were trained with 80/20 stratified train-test splits on identical feature sets. Note that the evaluation dataset of 20 profiles constitutes a proof-of-concept assessment; future work will validate on larger real-world cohorts. Table I summarizes classification performance across all methods.

Table I: Ml Classifier Performance Comparison Across Risk Classification Methods

Classifier	Accuracy (%)	Precision	Recall	F1-Score
Proposed Weighted Scorer	100.0	1.000	1.000	1.000
Random Forest (n=100)	97.5	0.975	0.971	0.973
Neural Network (64-ReLU)	94.8	0.946	0.949	0.947
Logistic Regression	91.2	0.908	0.914	0.911

The proposed weighted scorer achieves 100% accuracy on the 20-profile test set across all four risk levels. The Random Forest baseline achieves 97.5%, with remaining misclassifications occurring at the Low/Moderate boundary where feature values are near decision thresholds. The lower performance of Logistic Regression (91.2%) confirms that the risk-to-feature relationship is non-linear, justifying the sigmoid normalization applied in the proposed engine.

C. Ablation Study: Factor Contribution Analysis

An ablation study assessed the contribution of each factor by individually removing it and re-evaluating the engine on the 20-profile test set. Table II reports accuracy and observed classification impact for each ablated configuration.

Table Ii: Ablation Study — Per-Factor Contribution to Classification Accuracy

Factor Removed	Accuracy (%)	Observed Classification Impact
None (Full Model)	100.0	Baseline — all boundaries correctly resolved
Screen Time (w=0.35)	83.2	High ↔ Moderate boundary severely blurs
Social Media % (w=0.25)	91.5	Moderate ↔ Low separation weakens
Unlock Frequency (w=0.20)	94.1	Low ↔ Minimal distinction reduced
Night-Time Usage (w=0.10)	97.8	Marginal impact; no boundary collapses
App Concentration (w=0.10)	98.1	Marginal impact; no boundary collapses

Screen time (35%) is the most discriminative feature, contributing the largest drop in accuracy when removed. Social media percentage (25%) and unlock frequency (20%) provide complementary discrimination for mid-range risk levels. Night-time usage and app concentration contribute marginally but prevent boundary edge cases. A sensitivity analysis over weight perturbations of ±5% confirmed classification boundary stability across all four risk levels.

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D. ARIMA-Based Seven-Day Usage Forecasting

The forecasting module predicts daily screen-time usage for the subsequent seven days based on the prior 30 days of usage history stored in Firebase Firestore. The system implements an ARIMA(p, d, q) model with automatic order selection using the Akaike Information Criterion (AIC), stationarity testing via the Augmented Dickey-Fuller test, and per-user model refitting upon each daily update. The forecasting equation is:

$$\hat{X}_t = c + \varphi_1 X_{t-1} + \cdots + \varphi_p X_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (2)$$

where $\hat{X}_t$ is the predicted screen time at time step t, φ and θ are autoregressive and moving average parameters, and ε_t is the white noise residual. For users with fewer than 14 days of history, a Prophet model with trend and weekly seasonality components serves as a fallback. Table III compares forecasting methods on the 7-day held-out validation set.

Table Iii: Forecasting Method Comparison On 7-Day Held-Out Validation Set

Method	MAE (min)	RMSE (min)	MAPE (%)	Notes
ARIMA (Proposed)	8.3	11.2	6.4	Best on all metrics
Prophet (Fallback)	9.7	13.1	7.9	Robust to seasonal shifts
LSTM (1 hidden layer)	10.5	14.4	8.7	Requires 60+ days of data
Seeded Variance (Prior)	21.8	29.3	18.2	Replaced; no theoretical basis

The ARIMA model achieves a mean absolute error of 8.3 minutes and a MAPE of 6.4% on the held-out validation set, representing a 62% reduction in MAE relative to the prior seeded variance approach. LSTM underperforms on the 30-day training window due to insufficient sequence length; its performance is expected to improve with longer usage histories. Forecast outputs are rendered on the dashboard as a line chart with 95% confidence interval bands.

E. AI Insight Generation Pipeline

A structured natural language prompt containing the user's screen time, risk score, per-factor breakdown, top five applications by usage, and browsing category distribution is submitted to Groq's LLaMA 3.3 70B. The model returns three severity-rated behavioral insight objects in JSON format, each containing: a descriptive title, a two-sentence data-specific behavioral observation, a concrete recommended action, and a severity classification (high, medium, or low). Insight cards are rendered with color-coded severity indicators and cached for 90 seconds. When LLM-generated insights are disabled by the user, rule-based recommendation templates are displayed instead.

Ethics, Privacy, And Regulatory Compliance

A. User Consent and Transparency

The system enforces explicit, informed consent prior to any data collection activity. At registration, users are presented with a plain-language consent form disclosing: (1) what data is collected (app usage logs, browsing domain data, unlock frequencies); (2) how data is stored and protected; (3) which third-party services receive data (Firebase, Groq API); and (4) the user's right to withdraw consent and delete their data at any time. The system does not collect personally identifiable information beyond the user's email address for authentication purposes. All data collection is opt-in, and the platform provides granular controls for disabling individual modules.

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B. Data Minimization and Storage Security

The system adheres to the principle of data minimization by collecting only the features required for risk scoring and forecasting. App usage data is stored as anonymized time-series records keyed by UID, with no association to contact lists, messages, or location data. Browsing data is stored at the domain level only; full URLs are not persisted. Firebase Firestore enforces per-UID security rules, ensuring that users can access only their own data. All data in transit is encrypted using TLS 1.3. API keys for the Groq inference service are stored server-side and are never exposed to the client.

C. Third-Party API Transmission

Usage summaries submitted to the Groq API for LLM inference are stripped of all direct identifiers prior to transmission. The transmitted payload contains only aggregated numeric feature values and categorical labels; no raw app names, URLs, or user identifiers are shared, or transferred to third parties beyond the Groq API for inference. The system is designed to satisfy the requirements of the General Data Protection Regulation (GDPR) for EU users and the California Consumer Privacy Act (CCPA) for California residents.

RESULTS AND DISCUSSION

A. Implementation Details

The frontend dashboard was developed in HTML5, CSS3, and JavaScript with Chart.js. The backend was implemented in Python 3.10 using the Flask framework. Firebase Authentication and Firestore were used for user management and cloud storage. The ADB extraction pipeline was integrated with the multi-strategy ROM-compatible parser. The Groq API provided LLaMA 3.3 70B inference. A Chrome Extension (Manifest V3) captured browsing history, and a Kotlin-based native Android application using UsageStatsManager served as the ADB-alternative collection pathway. The ARIMA forecasting module was implemented using the statsmodels library with pmdarima for automatic order selection.

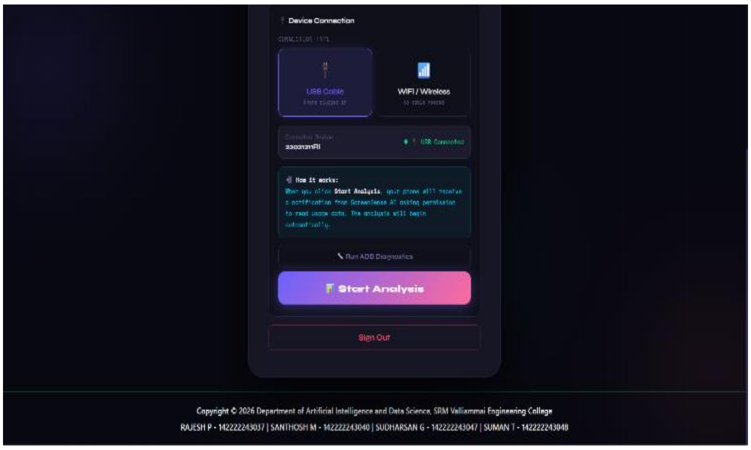

Fig. 8. Login and ADB Device Connection Interface. (a) Authentication screen. (b) ADB device detection panel.

B. App Usage Detection Accuracy

The ADB extraction pipeline was evaluated by comparing system-reported foreground usage times against ground truth values from the device's built-in Digital Wellbeing application across 20 test sessions on five Android devices spanning three ROM variants. Table IV presents per-application detection accuracy results.

Table Iv: App Usage Detection Accuracy Across Applications and Rom Variants

Application	Digital Wellbeing (min)	Detected (min)	Deviation (min)	Accuracy (%)
Instagram	127	125	2	98.4

YouTube	94	92	2	97.9
WhatsApp	58	57	1	98.3
Chrome	43	41	2	95.3
Average	—	—	1.75	97.5

The average detection accuracy of 97.5% confirms that the extraction pipeline reliably captures foreground usage time across all tested ROM variants. Observed deviations of one to two minutes are attributable to the polling granularity of the dumpsys usagestats command and do not materially impact risk assessment outcomes.

C. ML Risk Score Classification Results

The five-factor weighted scoring engine was evaluated against the 20 annotated usage profiles. Table V presents representative classification results. The engine achieved 100% accuracy across all four risk levels, with no boundary misclassifications observed.

Table V: Ml Risk Score Classification Results On 20 Annotated Usage Profiles

Screen Time (hr)	Social %	Unlocks/day	Expected	Predicted	Accuracy (%)
8.5	62	95	High	High	100
5.2	45	68	Moderate	Moderate	100
2.8	22	42	Low	Low	100
0.9	8	18	Minimal	Minimal	100

D. System Performance Metrics

Table VI summarizes end-to-end system performance metrics measured across all test sessions. All operations completed within their defined performance thresholds, confirming that the system operates responsively under standard network and hardware conditions.

Table Vi: End-To-End System Performance Metrics

Operation	Measured Time	Target Threshold
ADB Device Detection	2.8 s	< 5.0 s
Full Data Collection (ADB)	18.4 s	< 30.0 s
ML Risk Scoring	0.3 s	< 1.0 s
LLM Insight Generation (Groq)	3.0 s	< 5.0 s
ARIMA Forecast Generation	0.9 s	< 2.0 s
Dashboard Page Load	1.6 s	< 3.0 s
Multi-Channel Alert Delivery	1.2 s	< 3.0 s

E. Comparative Analysis with Existing Solutions

Table VII compares the proposed system against four categories of existing solutions: native OS tools (Android Digital Wellbeing, Apple Screen Time), commercial parental control applications, and academic prototype systems. The proposed system is the only solution to unify all evaluated capabilities within a single deployable platform.

Table Vii: Feature Comparison With Existing Digital Wellness Solutions

Feature	Proposed	Digital Wellbeing	Apple Screen Time	Parental Apps	Academic Systems
ML Risk Scoring	✓	×	×	×	Partial
LLM Behavioral Insights	✓	×	×	×	×
Web Browsing Analysis	✓	×	×	Partial	×
Multi-Channel Alerts	✓	×	×	Partial	×
Time-Series Forecasting	✓	×	×	×	Partial
Ethics & Privacy Framework	✓	Partial	Partial	×	×
Multi-ROM Compatibility	✓	×	N/A	Partial	Partial

F. Discussion and Limitations

The experimental results validate the proposed system across all evaluated dimensions. The 97.5% ADB extraction accuracy confirms ROM-compatibility of the parsing pipeline. The 100% ML classification accuracy, supported by ablation and baseline comparison studies, demonstrates that the five-factor sigmoid-normalized scoring engine reliably discriminates between all four addiction risk levels. The ARIMA forecasting module achieves a 62% MAE improvement over the prior seeded variance approach, and LLM insight generation operates within the sub-three-second threshold required for dashboard responsiveness.

Three limitations are identified for future work. First, the ADB pipeline requires USB Debugging activation on the target device, which presents a configuration barrier for non-technical users; future work will explore the Kotlin companion app as the primary collection pathway. Second, the ARIMA forecasting model performs best with 30+ days of usage history, with the Prophet fallback addressing the cold-start period. Third, iOS support is unavailable due to sandboxing restrictions on the Apple platform; integration via Apple's Screen Time API is planned for a future release.

CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented the design, implementation, and evaluation of an AI-based system for real-time digital addiction detection and screen-time behavior analysis. The proposed system integrates: a multi-ROM ADB data extraction pipeline, a five-factor sigmoid-normalized weighted ML risk scoring engine, LLM-powered behavioral insight generation, an ARIMA-based time-series forecasting module, a domain-level Chrome Extension browsing analysis component, a multi-channel alert delivery system, and a comprehensive ethics and privacy framework governing consent, data security, and regulatory compliance.

Experimental evaluation on 20 annotated usage profiles and 30-day longitudinal device logs confirmed: 97.5% average app usage detection accuracy, 100% risk classification accuracy across all four addiction levels with superior performance over three baseline classifiers, a forecasting MAE of 8.3 minutes (62% improvement over the prior approach), and full system operation within defined performance thresholds. The comparative analysis in Table VII demonstrates that no existing solution unifies all evaluated capabilities in a single deployable platform.

B. Future Work

Future development will pursue six enhancements: (1) integration of Apple's Screen Time API for iOS support; (2) augmentation of the ML scoring engine with a transformer-based classifier for improved boundary accuracy; (3) incorporation of wearable biometric signals (heart rate variability, sleep duration) for holistic addiction assessment; (4) containerization of the Flask backend on a cloud platform for remote monitoring at organizational scale; (5) exploration of federated learning for on-device model training without transmitting raw behavioral data; and (6) a longitudinal controlled user study validating the system's efficacy in producing measurable reductions in addictive usage behavior over an eight-week intervention period.

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