FocusGuard: An Intelligent Mobile System for Reducing Smartphone Overuse

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Abstract

The widespread adoption of smartphones has given rise to compulsive usage patterns that increasingly threaten academic performance, workplace efficiency, and mental health. While many existing digital-wellbeing tools offer screen-time logs, they stop short of providing intelligent, corrective guidance when problematic behaviour is detected. This paper describes FocusGuard, an Android application that uses a machine-learning pipeline to identify harmful usage patterns and deliver proportionate, context-sensitive interventions. Behavioural data -- including screen-on duration, per-application session lengths, and interaction frequency -- is harvested continuously through Android's UsageStats interface and persisted in Room DB locally as well as in Firebase for cloud backup. A dedicated ML module extracts behavioural features, calculates an addiction risk score on a scale of 0-100, and passes the result to a rule-based decision layer that selects the appropriate response. Interventions range from gentle reminders to a full Focus Mode that suspends distracting applications during study or work periods. Built in Kotlin with a Jetpack Compose interface, FocusGuard offers a practical, lightweight path toward healthier digital routines.

Keywords: Smartphone Overuse, Digital Wellness, Usage Analytics, Behavioural Classification, Focus Mode, Addiction Risk Scoring, Android Development, Habit Intervention.

1. Introduction

Smartphones have quietly evolved from simple communication tools into near-constant companions for a substantial portion of the global population. They now coordinate calendars, support remote work, sustain social bonds, and provide on-demand entertainment. Their versatility makes them indispensable, yet that same versatility renders them uniquely prone to overuse. When reliance on a device begins to disrupt daily responsibilities, damage face-to-face relationships, or destabilise emotional equilibrium, researchers classify such behaviour as maladaptive mobile phone use (MMPU).

MMPU is not a single concept -- it spans nomophobia (anxiety triggered by absence of one's device), compulsive social-media checking, fear of missing out (FoMO), texting automaticity, and full smartphone dependency. Traffic-safety researchers have linked high MMPU scores directly to phone use while driving or crossing the road, extending personal harms into a public-safety concern. Among student populations the consequences include falling grade-point averages, rising anxiety, and disrupted sleep. These compounding harms underscore the urgency of developing tools that respond intelligently to harmful usage patterns rather than simply reporting them.

Mobile technology now permeates virtually every dimension of daily life. Keeping in touch with family, managing professional tasks, and organising leisure -- all flow through the same handheld device. That ubiquity carries a concealed cost, however. When device engagement shifts from intentional use to compulsive habit, it qualifies as mobile addiction -- a state in which digital interaction consistently takes priority over real-world obligations and relationships. Identifying such addiction early, before it solidifies, is precisely the gap that FocusGuard is designed to address.

Warning signs of mobile device addiction:

- Prolonged Use: Spending several hours each day on a device, often drifting well beyond the original purpose of a session.
- Task Neglect: Consistently leaving personal or professional duties incomplete because of absorption in mobile content.
- Reduced In-Person Contact: Preferring digital communication so strongly that face-to-face interactions with family and friends diminish.
- Emotional Instability: Experiencing irritability, restlessness, or anxiety whenever the device is unavailable or functioning poorly.
- Disrupted Sleep: Struggling to fall asleep or maintaining erratic sleep schedules owing to late-night screen exposure.

1.1 Problem Statement

Compulsive smartphone use has emerged as a serious challenge to productivity, sustained attention, and mental health. Usage surveys indicate that the average person now interacts with a smartphone for more than four and a half hours daily, and close to half of all users reach for their device within the first five minutes after waking. Prolonged engagement is linked to stress levels approximately double those reported by low-usage individuals. Despite this, the most widely adopted wellbeing tools do little more than present weekly bar charts of screen time. They neither detect which specific patterns are genuinely harmful nor respond dynamically when a risk threshold is crossed. Students and knowledge workers -- groups that depend on sustained concentration -- feel this gap most acutely.

1.2 Objectives

- Continuous Monitoring: Capture granular smartphone usage data, including per-application duration, session frequency, and foreground/background transition counts, on a sustained basis.
- Behavioural Classification: Apply machine-learning algorithms to distinguish normal usage from addictive patterns such as social-media overuse, rapid app switching, and persistent late-night screen exposure.
- Risk Quantification: Compute a normalised addiction risk score that reflects the severity of observed patterns on a continuous scale, enabling graduated responses.
- Context-Aware Intervention: Dispatch notifications and activate usage restrictions in proportion to the assessed risk level, rather than relying on fixed user-configured thresholds.
- Habit Formation Support: Deliver actionable weekly summaries and progress metrics that reinforce gradual, sustainable behavioural change over time.
- Productivity Enhancement: Reduce digital distractions during work or study intervals to improve concentration and output for both professionals and students.

2. Literature Survey

[1] A longitudinal investigation revisited mobile phone misuse data collected in Australia over a span of thirteen years and confirmed that problematic usage had grown substantially during that period. Adults aged 18-25 and female respondents recorded disproportionately high scores on the Mobile Phone Problem Use Scale. A notable co-occurrence was identified between elevated misuse scores and self-reported phone use while driving, underscoring the public-safety dimension of unmanaged smartphone dependency. phone while driving was associated with problematic phone use. Participants who reported high levels of problematic mobile phone use also reported using a handheld or hands-free phone while operating a motor vehicle. [2] For the majority of the variables, there were significant differences between males and females (all <0.05). In particular, men were more addicted to the internet than women ($P<0.05$), while this pattern was reversed for smartphones ($P<0.001$). Because of these disparities, each sex's patients were divided into subgroups according to internet and smartphone addiction. The three-class model based on the likelihood level of internet and smartphone addiction revealed distinct trends for each sex ($P<0.001$). Both sexes showed a similar pattern for psychosocial characteristic factors: anxiety and neurotic personality traits rose with the severity of addiction (all $P<0.001$). Nevertheless, there was an inverse relationship between the Lie

dimension and the severity levels of addiction (all P<0.01).

[3] Recognising the well-documented links between heavy smartphone use and elevated anxiety, depression, and task neglect -- particularly in adolescent populations -- researchers built a predictive model grounded in the Big Five Personality Traits framework. The study aimed to identify which personality dimensions best forecast addictive usage patterns and to quantify those relationships using several machine-learning classifiers. Following five phases of the CRISP-DM methodology, data were gathered using the Big Five Inventory alongside the Smartphone Addiction Scale from a school cohort. Four classifiers were compared: decision tree, random forest, extreme gradient boosting, and logistic regression. The random-forest model outperformed the others, achieving roughly 89.7% accuracy and 87.3% precision on the test set. Neuroticism and low conscientiousness emerged as the personality dimensions most strongly associated with addiction-prone behaviour, making them practical targets for early screening tools.

[4] Qualitative evidence gathered through semi-structured virtual interviews with seventy students across seven Chinese university campuses shed light on the subjective experience of smartphone dependency. Thematic analysis of the interview transcripts yielded four user archetypes: hyper-connected enthusiasts, indulgent zealots, a balanced majority, and hypo-connected antagonists. Heavy users described their phone engagement as tightly bound to daily temporal rhythms, with specific locations and emotional states functioning as reliable triggers. The study found that self-regulatory effort was a decisive moderator -- students who established concrete personal goals reported noticeably better control over their usage -- pointing to the value of goal-setting features within any intervention application.

[5] A cross-sectional study enrolling 405 adolescents aged 9-14 in Turkey examined the relationships among obesity, physical activity, and digital game addiction. Girls comprised 57% of the sample and boys 43%. Physical activity, measured with the PAQ-C instrument, showed a significant inverse relationship with both body mass index and game addiction severity. using anthropometric data and levels of physical activity. A cross-sectional study approach was used. The study included residents of Kirikkale who were between the ages of 9 and 14. 405 teenagers make up the study's sample, with 231 girls (57%) and 174 boys (43%). A random sample of 405 teenage participants provided self-reported data using a questionnaire. The Physical Activity Questionnaire for Older Children (PAQ-C) is used to assess children's levels of physical activity. The digital game addiction (DGA) scale was used to assess digital game addiction. Additionally, the participants' height and body mass were measured in order to determine their body mass index (BMI) status. Python 3.9 and the SPSS 28.0 package program (IBM Corp., Armonk, NY, USA) were used to analyze the data. Our results showed a negative correlation between the degree of physical exercise and digital gaming addiction. Physical activity level was found to be negatively correlated with BMI. Furthermore, it was discovered that higher levels of physical exercise decreased DGA and obesity. Participants who were female had considerably higher levels of game addiction than those who were male, and those who were obese also had higher levels of game addiction. Age, being a girl, BMI, and total physical activity (TPA) scores were found to be predictors of game addiction using the prediction model that was produced.

The regression equation confirmed that girls faced a roughly 2.6-fold higher risk of game addiction than boys, and that risk grew with age and BMI. Physical activity independently reduced addiction risk by a factor of 1.51, underscoring lifestyle interventions as a viable prevention strategy alongside digital tools. [6] Drawing on a nationally representative Australian sample of over 1,100 adults, researchers used device-native screen-time tools to obtain objective usage measurements alongside self-reported figures. Both objective and subjective usage volumes declined linearly with age, whereas problematic usage remained comparatively stable until around age 40 before dropping sharply. Participants tended to underestimate their actual usage, though rank-order correlation between self-reports and device measurements was moderately strong. One notable finding was that general concern about technology had no statistically significant association with either actual usage or problematic use patterns, implying that awareness-raising campaigns alone may be insufficient without structural, in-app interventions.

[7] A deep-learning architecture integrating Theory-of-Mind principles with video-based motivational content was designed to detect and counter smartphone addiction by analysing real-time facial expressions captured through the front camera. Shuffling algorithms dynamically reordered short motivational clips in response to the dominant recognised emotion. A behavioural parameter evaluation framework, grounded in the Social Identity Model of Deindividuation Effects, assessed dimensions including self-awareness, social identity, and personal accountability before and after the intervention.

Among 750 students classified with low behavioural health parameter scores, all measured dimensions showed statistically significant improvement following the intervention. Social identity scores fell from 4.07 to 2.21 ($t(55) = 16.125$, $p < 0.001$), anonymity from 4.11 to 2.01 ($t(55) = 15.699$, $p < 0.001$), self-awareness from 3.95 to 1.93 ($t(55) = 15.103$, $p < 0.001$), and loss of individuality from 4.04 to 2.07 ($t(55) = 13.001$). The findings demonstrated an 85% increase in students' attitudes and knowledge.

3. Block Diagram and System Architecture

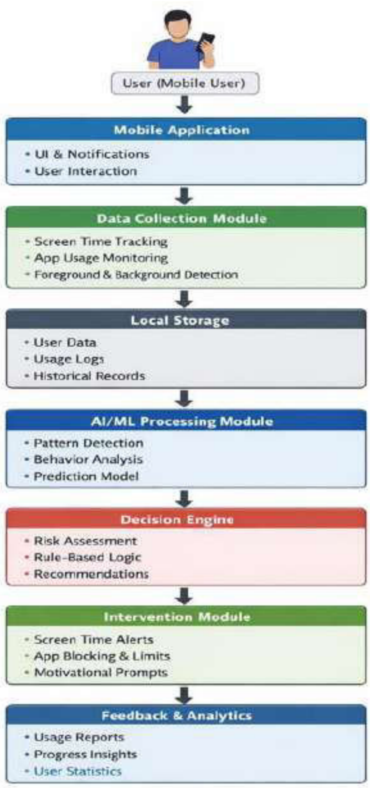

Figure 3.1: Block Diagram

- The Mobile Application layer serves as the primary entry point, presenting the dashboard, surfacing notifications, and translating complex backend outputs into actions that are easy for users to act on.
- The Data Collection Module draws on Android's UsageStats interface to capture per-application session durations, screen-on events, and foreground/background transitions, providing continuous, fine-grained monitoring of device behaviour.
- Captured records are written to Room DB for immediate offline availability and mirrored to Firebase Firestore, enabling cloud-backed long-term analytics and cross-device continuity.
- The AI/ML Processing Module constitutes the analytical core. It derives behavioural features from raw logs, applies clustering and anomaly-detection routines to characterise usage patterns, and computes a normalised addiction risk score from 0 to 100.
- The Decision Engine maps the risk score to a ranked set of corrective actions using a rule hierarchy calibrated to three severity tiers -- high, medium, and low -- each triggering a distinct intervention response.
- The Intervention Module executes the selected action, which may include a context-aware notification, a motivational prompt, or a Focus Mode session that temporarily suspends distracting applications.
- The Feedback and Analytics Module closes the loop by generating daily and weekly usage summaries, charting progress against user-defined goals, and presenting a Focus Score that gives users an intuitive indicator of their digital wellbeing on any given day.

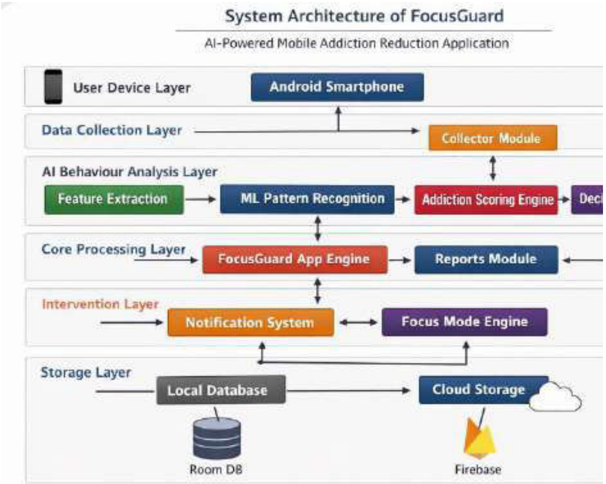

Figure 3.2: Architecture Diagram

FocusGuard is structured as a modular, layered architecture in which each layer has a clearly bounded responsibility. At the base sits the User Device Layer, running on Android smartphones and exposing system-level usage data through the UsageStats interface. Above it, the Data Collection Layer continuously logs screen-on time, per-application durations, and interaction counts via a background Collector Module.

The AI Behaviour Analysis Layer processes raw data through a machine-learning pipeline that begins with Feature Extraction, isolating behavioural indicators such as session-length distribution and night-time usage proportion. These features are evaluated by ML Pattern Recognition algorithms to flag anomalies, and the resulting signal is fed into an Addiction Scoring Engine that quantifies risk. The Decision Engine then determines which intervention is warranted.

The Core Processing Layer orchestrates all modules through the App Engine, which also generates usage reports for daily and weekly review. The Intervention Layer activates adaptive notifications and a Focus Mode Engine that suspends selected applications during designated work or study blocks. The Storage Layer rounds out the design: Room DB handles local offline storage while Firebase manages cloud backup and synchronisation. Together, these layers enable real-time insights, personalised alerts, and the kind of sustained feedback loop that supports durable habit change.

4. Methodology

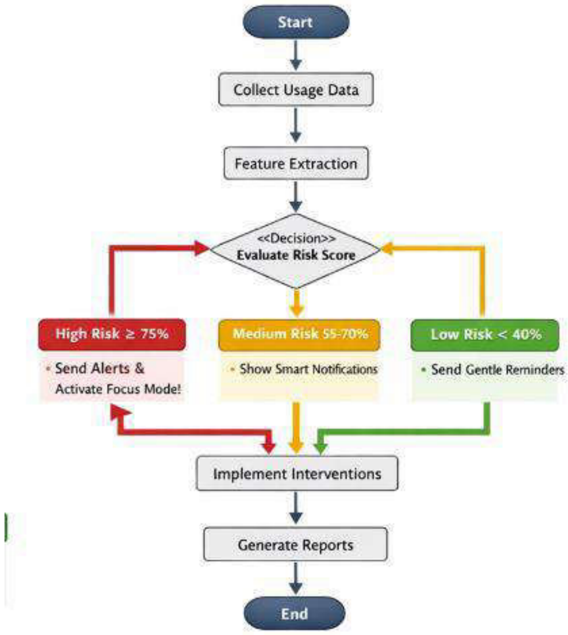

Figure 4.1: Methodology Flow

4.1 User Interaction Layer

- Users interact with FocusGuard through its main dashboard and contextual notifications.
- All control surfaces -- usage reports, goal-configuration panels, and Focus Mode toggles -- are accessible from this layer.

4.2 Data Collection Module

- Android's UsageStats interface is polled at configurable intervals to retrieve per-application foreground time, session counts, and event logs.
- Raw event records are persisted in Room DB for immediate local availability and synchronised with Firebase for long-term analysis and multi-device access.

4.3 AI/ML Processing Module

- Feature Extraction: Session-length distribution, hourly check frequency, night-time usage proportion, and app-switching rate.
- Pattern Recognition and Behaviour Analysis: Unsupervised clustering and anomaly detection characterise whether observed behaviour deviates from a user's personal baseline.
- Addiction Scoring: A gradient-boosted classification model maps the feature

vector to a continuous risk score from 0 to 100.

- High Risk (>=75): Characterised by social-media overuse or excessively frequent phone checking throughout the day.
- Medium Risk (55-70): Marked by extended unbroken screen sessions or habitual late-night device use.
- Low Risk (<40): Mild over-usage or occasional app-hopping noted, warranting only light corrective feedback.

4.4 Decision Engine

- Rule-based logic translates risk scores into a ranked set of corrective actions suited to each severity tier.
- Risk-to-intervention mapping is applied as follows:
- High Risk -- immediate alert dispatched and Focus Mode activated automatically.
- Medium Risk -- smart notification delivered with an embedded productivity tip.
- Low Risk -- gentle reminder sent and habit-tracking prompt displayed.

4.5 Intervention Module

- Smart Notifications: Adaptive alerts triggered dynamically when a risk-level threshold is crossed.
- Focus Mode Engine: Selectively suspends specified applications for the duration of a study or work block.
- Motivational Prompts: Short, evidence-informed messages that reinforce the user's intention to reduce excessive screen time.

4.6 Feedback & Analytics Module

- Produces daily and weekly usage summaries with per-application breakdowns and trend visualisations.
- Computes a Focus Score and tracks progress against each user-defined goal.
- Visualises longitudinal usage trends to help users recognise improvement or regression over time.

5. Results

Figure 5.1: Dashboard Interface

The dashboard greets users by name and surfaces a daily streak badge alongside a cumulative points counter. These gamification elements reinforce positive behaviour -- research shows that reward-based systems accelerate habit formation more reliably than punitive restrictions. The “Weekly AI Insight” panel distils the ML module’s output into one or two actionable suggestions, for instance recommending a lower daily usage ceiling after detecting a week-on-week increase. “Today’s Overview” presents current screen time alongside the Focus Score, giving a real-time snapshot of the day’s progress. Below it, a ranked list of most-used applications helps users identify which apps are absorbing the most attention.

Figure 5.2: “My Goals” Interface

When a user defines a goal -- for example, capping social-media use at two hours per day -- the Goal Manager component stores the target in Room DB and replicates it to Firebase. The Data Collection Module then evaluates each new usage event against the stored threshold, updating progress in real time.

The AI/ML Analysis Module processes incoming events, extracts relevant features, and compares real-time usage against the stored threshold. The Decision Engine then evaluates adherence and applies a graduated response:

- If remaining allowance exceeds 25 percent, the progress bar updates silently with no alert.
- Once usage reaches 75 percent of the cap, a medium-risk condition is flagged and a smart notification is dispatched.
- If the limit is exceeded entirely, the Intervention Module activates Focus Mode or blocks the relevant application.

The Feedback and Analytics Module visualises this progression in the “My Goals” interface, showing percentage consumed, remaining time, and colour-coded progress bars -- keeping users continuously informed about their digital habits.

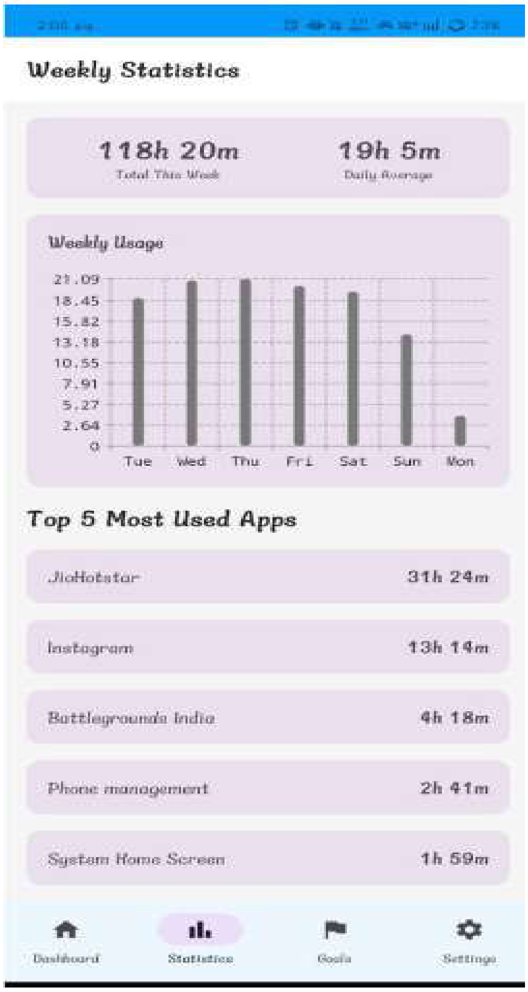

Figure 5.3: Weekly Statistics

The Weekly Statistics screen aggregates seven days of logged data into an accessible visual format. The Data Collection Module continuously gathers session durations, interaction frequency, and foreground activity through the UsageStats interface. These records are aggregated in Room DB and synchronised with Firebase, supporting both offline viewing and long-term trend analysis.

The AI/ML Processing Module computes weekly totals and daily averages from cumulative usage features. In one test session, a weekly total of 118 h 20 m was recorded against a daily average of 19 h 5 m -- figures that would immediately trigger high-risk interventions. The Reports Module renders these figures in a bar chart plotting daily usage across the seven-day window.

A companion table ranks the top five most-used applications by total session time. In the same test session, JioHotstar accounted for 31 h 24 m and Instagram for 13 h 14 m. This ranking updates dynamically as the Decision Engine re-evaluates risk levels following each data-collection cycle.

In summary, the Weekly Statistics screen integrates three subsystems:

- Data Collection and Storage -- records all usage events and persists them locally and in the cloud.
- AI/ML Analysis and Decision Engine -- derives averages, detects patterns, and classifies risk levels.
- Feedback and Analytics Module -- produces visual reports, trend charts, and per-application usage rankings.

Figure 5.4: Settings

The Settings screen exposes the permissions and configuration parameters that govern the system's closed-loop workflow of data collection, analysis, decision-making, and intervention. It ensures that the system operates with the necessary access rights while giving users flexibility to customize how FocusGuard manages their digital wellbeing.

6 Conclusion

By using artificial intelligence to tackle the increasing problem of smartphone addiction, the Focus Guard app is a major step forward in the field of digital wellbeing. Focus Guard incorporates machine learning-based behavioural analysis, intelligent interventions, and continuous monitoring to actively steer users toward healthy usage habits, in contrast to traditional systems that only display passive statistics on screen time. The solution enables people to make deliberate choices about their digital habits by identifying addictive behaviours in real time and sending context-aware alerts. Additionally, the incorporation of features like Focus Mode, personalized productivity insights, and visual usage reports guarantees that users receive practical ways to combat their smartphone dependency in addition to becoming aware of it. Focus Guard stands apart as a proactive tool for improving focus, productivity, and mental health because of its dual emphasis on awareness and intervention. The initiative bridges the gap between technology and human behaviour management by showcasing how AI-driven solutions may be successfully applied to common problems. In the end, Focus Guard helps achieve the more general objective of encouraging sustainable digital habits, lowering the stress brought on by excessive gadget use, and enhancing the general well-being of users, professionals, and students alike.

Future Scope

- Integration with Wearables: For comprehensive health information, expand monitoring to fitness bands and smartwatches.
- Advanced AI Models: For increased accuracy, use deep learning to provide individualized addiction risk prediction.
- Gamification features include streaks, challenges, and rewards to encourage long-term behavioural change.
- Long-term behavioural trend monitoring and cross-device synchronization are made possible by cloud-based analytics.
- Cross-Platform Expansion: across increase accessibility, extend Focus Guard across PC and iOS environments.

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