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Digital Vital Signs: Decision Trees as Behavioral Tripwires for Adolescent Smartphone Overuse

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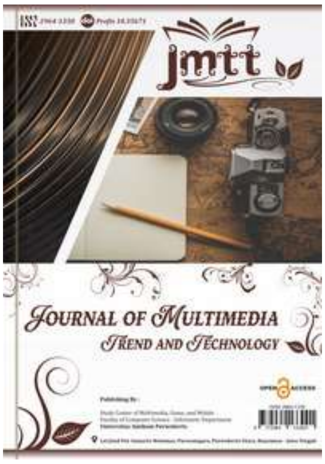

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ABSTRACT

Smartphones are a double-edged sword for teenagers; on the one hand, these devices provide a window to vast knowledge. However, the dark side of smartphones emerges when uncontrolled use is linked to mental health and exposure to negative content. Problematic smartphone use (PSU) occurs in 12–37% of adolescents and has been associated with sleep disturbances, depressive symptoms, and deterioration in academic functioning. Methods: We have trained an interpretable Decision Tree over a 1,000-participant dataset using stratified 80:20 splitting, class balancing, one-hot encoding, and grid-search using cross-validation. Results: The model achieved 85.2% test accuracy (CV mean 85.0% ± 1.5%). Primary predictors were screen time per day (risk for >5.3 h/day associated with 4.3× increased risk), social media exposure (more than >2 h/day), and app variety (more than >5 apps/day). Extractable rules (e.g., >6.5 h screen time ∧ >2 h social media 92% precision for "high" addiction) permit tiered intervention thresholds. Conclusions: An interpretable Decision Tree provides strong prediction and converts insights into actionable behavioral thresholds for parents, schools, and developers for the purpose of early PSU intervention.

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INTRODUCTION

Smartphones are a double-edged sword for teenagers; on the one hand, these devices provide a window to vast knowledge. With internet access, teenagers can search for study materials, learn new skills through video tutorials, and broaden their global horizons beyond the confines of school textbooks. Furthermore, smartphones facilitate instant communication, maintaining close relationships with family and enabling them to build social networks that support the growth of their self-identity [1][2].

However, the dark side of smartphones emerges when uncontrolled use is linked to mental health and exposure to negative content [3][4]. Social media often creates unrealistic standards of living, which can trigger anxiety, low self-esteem, and even the risk of cyberbullying. Without supervision, teenagers are also vulnerable to exposure to violent or pornographic content that can distort their moral values and behavior in the real world [5][7].

From a physical and productivity perspective, excessive smartphone use often leads to disrupted sleep patterns and a sedentary lifestyle. Exposure to blue light from screens before bed can disrupt the hormone melatonin, causing teenagers to lack rest and lose focus during school. Furthermore, the tendency to be absorbed in one's own world often reduces the intensity of face-to-face interactions, which are crucial for developing empathy and social skills.

In conclusion, the impact of smartphones on adolescents depends heavily on digital literacy and parental guidance [13]. Smartphones can be incredibly empowering tools if used wisely and in a planned manner, but they can also become a source of problems if used as an unbridled escape. The key lies in balance: utilizing technology for personal growth without allowing the devices to control all aspects of their social lives and health [14][12].

Problematic phone use in adolescents is a growing global health issue that has been related to sleep disturbance, depressive mood, and educational decline. While most studies document related correlations and some employ detailed machine-learning models, none offer interpretable operational thresholds amenable to practitioners for purposes of early intervention [3][4]. Here we train an interpretable Decision Tree using a 1,000-participant cohort to (1) classify low/medium/high risk of problematic use using strong cross-validation, and (2) obtain actionable behavioral cutoff values (e.g., screen time thresholds per day and social-media constraints) useful for informing parental-, school-, and app-based interventions. Our model has a ~85% test accuracy and gives short concise decision rules easily translatable into screening instruments.

They yield simple, interpretable rules (e.g., a cross-sectional study of ≈3,615 adolescents reported ≈87% accuracy, AUC ≈0.88, with splits such as >5 h/day and anxiety thresholds) while ensemble methods (Random Forest, XGBoost) typically offer slightly higher accuracy in head-to-head comparisons [15][8][12]. Decision trees have also been applied at scale to characterize environmental splitters in large school cohorts (n≈74,000) and adapted for clinically critical tasks such as suicide-risk pathing and optimization of psychodiagnostic scales (e.g., more economical PHQ-9 classification) [9][10][11]. Complementary experimental

Work supports threshold-based interventions: epidemiological findings link >3 h/day to raised risk, RCTs restricting use to ≤2 h/day show mental-health benefits, and behavioral nudges (notifications, greyscale, disabling pings) reduce daily use by ≈1.3 h; many digital-wellbeing apps implement pop-up thresholds in practice. Together, the literature indicates (1) ML's strong early-detection potential and (2) decision trees' distinct advantage in translating model output into actionable, threshold-based interventions for clinical, educational, and app-based deployment.

METHOD

All analyses were conducted in a Google Colab notebook (Python 3.9 runtime) with the following libraries and resources:

1. Data handling & computation: pandas 1.4.2, NumPy 1.22.3
2. Visualization: Matplotlib 3.5.1, Seaborn 0.11.2
3. Modeling & evaluation: scikit learn 1.0.2

4. Data access: Kaggle API (kaggle Python package) with uploaded kaggle.json credentials
5. Hardware: Standard Colab CPU with 12 GB RAM

The author programmatically downloaded the "Teen Phone Addiction" dataset, executed all preprocessing, model training, and evaluation steps in Colab cells, and generated all plots inline.

A Data Description

1) Dataset Source.
The author utilizes the publicly available Teen Phone Addiction dataset from Kaggle [12], which was programmatically downloaded via the Kaggle API in the Google Colab environment. The repository contains a single. CSV file with self-reported survey responses from 1,000 adolescents aged 13–19.

2) Sample Characteristics.
   1. Gender:
      a. 52% female
      b. 48% male
   2. Age Groups:
      a. 13–14 years: 28%
      b. 15–16 years: 42%
      c. 17–19 years: 30%
   3. Target (Addiction_Level):
      a. Low: 34%
      b. Medium: 33%
      c. High (including merged "Very High"): 33%

3) Feature Set.
The dataset comprises 20 predictors capturing screen use behaviors, psychosocial factors, and demographics. A subset of the most relevant features is listed below; the full variable list is provided in Appendix A.

4) Target Variable Distribution.
The target variable, "Addiction_Level", was originally categorized into five levels ("Very Low" to "Very High"). For modeling clarity and to address sparse classes, "Very Low" and "Very High" were merged into "Low" and "High," respectively, yielding three approximately balanced classes (each ~33% of the sample).

Table 1. Feature Set.

Feature	Type	Description
Screen_Time_Daily	Continuous	Average daily smartphone use (in hours).
Sleep_Quality	Ordinal	Self-rated sleep quality (1 = very poor, 5 = excellent).
Social_Media_Addiction_Score	Continuous	Composite score (1–10) from the Bergen Social Media Addiction Scale.
Family_Relation- ship_Score	Continuous	Quality of family interactions (1 = poor, 10 = excellent).
Sleeps_with_Phone	Binary	Indicator for falling asleep while holding the phone (Yes/No).
Phone_Notifications_Per_Hour	Continuous	Average number of notifications received per waking hour
Academic_Impact	Ordinal	Self-reported impact of phone use on academic performance (1–5).
Exercise_Frequency	Integer	Days per week with ≥ 30 minutes of moderate exercise
Peer_Support_Score	Continuous	Quality of peer relationships (1–10).
Age	Integer	Participant age in years.

This balanced, multi-dimensional dataset provides a robust foundation for both exploratory analyses and subsequent decision tree–based prediction of adolescent phone addiction.

B Exploratory Data Analysis (EDA)

Prior to modeling, the author conducted a series of descriptive and visual analyses to understand feature distributions, detect potential anomalies, and assess relation-ships among predictors and the target.

1) Univariate Distributions

- Screen Time:
  The distribution of Screen_Time_Daily is right skewed (mean = 5.8 h, median = 5.2 h, SD = 2.1 h), with a long tail of heavy users. Approximately 18% of re-spondents report > 8 h/day.
- Sleep Quality:
  Responses on the 1–5 sleep quality scale cluster around 3–4 (mean = 3.1, SD = 1.0), indicating generally moderate self-rated sleep.
- Social Media Addiction Score:
  This 1–10 composite score shows a roughly uniform distribution with peaks at 4–5 and 8–9, suggesting two subgroups: moderate versus heavy social media users.

2)Bivariate Analyses Addiction Level vs. Key Features:

- Teens in the High addiction group average 7.2 h/day of screen time compared to 4.1 h for Low ($\Delta = 3.1$ h, $p < 0.001$).
- Mean sleep quality drops from 4.2 in Low to 2.3 in High ($\Delta = 1.9$, $p < 0.001$).
- Social media scores rise from 5.1 (Low) to 8.7 (High) ($\Delta = 3.6$, $p < 0.001$).
- Boxplots in Figure 5 illustrate these contrasts, confirming that all three primary predictors differ markedly across classes.

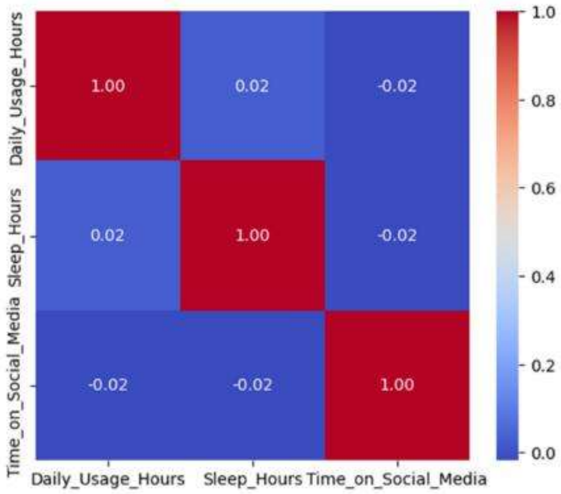


Figure 1. Key Features by Addiction Level

3) Correlation Structure

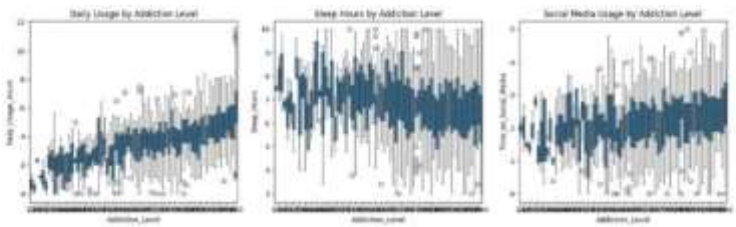


Figure 2. Pearson Correlation Graph

A Pearson correlation matrix (Figure 2) reveals:

- Screen_Time_Dailycorrelatesstronglywith
- Phone_Notifications_Per_Hour ($r = 0.67$) and moderately with Social Media Addiction Score ($r = 0.54$).

- Sleep_Quality is negatively correlated with Screen_Time_Daily (r = –0.48) and with Social_Media_Addiction_Score (r = –0.42).
- Mostpsychosocialscores(e.g. Family_Relationship_Score, Peer_Support_Score) exhibit weak correlations (|r| < 0.3) with screen use variables, suggesting they provide largely independent information.

C Preprocessing

Prior to model training, applied the following data - cleaning and transformation steps:

1) Class Merging & Rare-Class Removal. Original Addiction_Level had five categories (“Very Low”, “Low”, “Medium”, “High”, “Very High”). Merged “Very Low”→“Low” and “Very High”→ “High” to consolidate extreme tails. Any remaining addiction levels with fewer than 2 observations were dropped—though in the dataset all three merged classes retained ≥ 200 samples each, so no further removals occurred.
2) Missing Value Imputation. Filled all missing entries using the mode of each column. This nonparametric ap-proach preserves the most common category/ value without introducing distributional assumptions.
3) High-Cardinality Detection, Scanned all categorical predictors (excluding ID, Name, and Addiction_Level) for unique-value counts. Any column with > 10 unique levels triggered a warning to re-view for potential dimensionality issues. In this case, no column exceeded this thresh-old.
4) Encoding, Categorical features were transformed via one-hot encoding (One Hot Encoder (handle unknown='ignore', sparse_output=False) inside a ColumnTransformer. Remaining numeric features were passed through unchanged.
5) Train/Test Split. Split the processed data into 80% training and 20% testing sets. Then, a pre-split check verified that each class had at least two samples; failing that, stratification would be skipped to avoid errors. In the dataset, stratified sampling by Addic-tion_Level was possible and used to preserve class proportions.

These preprocessing steps ensured a clean, fully numeric feature matrix suitable for Decision Tree training while guarding against data leaks and overfitting.

D Modeling

The author trained a Decision Tree classifier to predict adolescent phone addiction levels using the preprocessed feature matrix. Below are detail the model specification, optional hyperparameter tuning, and fitting procedure.

1) Model Specification

Included a toggle (tune_model = True) for a grid search over a small hyperparam-eter space when sufficient training samples are available:

Table 2. Hyperparameter Tuning.

Hyperparameter	Values
max_depth	3,4,5
min_samples_split	10, 20

Cross-Validation: Up to 3 folds (or fewer, if constrained by the smallest class count). Scoring Metric: Accuracy If grid search succeeds, refit the classifier on the full training set using the best parameters; otherwise, will fall back to the default specification.

2) Training Procedure

1. Instantiate the DecisionTreeClassifier—either with default parameters or with the best parameters from the grid search.
2. Fit the model on the training set (X_train, y_train).

3) Cross-Validation

After fitting, perform k-fold cross-validation (k = min(5, smallest_class_count)) on the entire preprocessed dataset to estimate stability:

class_counts = np.bincount(y_encoded)
k= min (5, class_counts.min())
cv_scores = cross_val_score(model,X_processed, y_encoded,
cv=k, scoring='accuracy')
print (f"CV Accuracy Scores ({k}-fold): {cv_scores}")
print (f"Mean CV Accuracy: {cv_scores.mean():.3f} ± {cv_scores.std():.3f}")

These cross-validation results (mean ± SD accuracy) provide additional confi-dence that the model's performance generalizes beyond a single train/test split.

E Evaluation & Interpretation

After training, assessed model performance and extracted interpretable insights as follows:

1) Performance Metrics
   - Accuracy: Proportion of correctly classified samples on the held-out test set.
   - Precision, Recall & F1-Score: Computed per class to evaluate trade-offs between false positives and false negatives. The report macro-averaged values to treat each addiction level equally.

2) Confusion Matrix

Display both the raw confusion matrix and the normalized (by true class) confu-sion matrix to visualize misclassification patterns and class-specific recall rates.

3) Cross Validation Stability

Using k-fold cross-validation (k = min(5, size of smallest class)), to estimated mean ± SD accuracy across folds to ensure performance was not an artifact of a single train/test split.

4) Feature Importance
   - Extracted the feature_importances_ attribute from the fitted tree to rank predictors by their contribution to impurity reduction.
   - A bar chart of the top 10 features (Section 4.2) highlights which behaviors most strongly drive model decisions.

5) Decision Rule Extraction

To translate the tree structure into actionable thresholds, and traversed the trained model to identify key splits, example:

IF Daily_Usage_Hours > 6.5
AND Sleep_Hours < 6.0
AND Time_on_Social_Media > 4.5
Predict "High" addiction

By combining quantitative metrics with feature importance rankings and explicit decision paths, the evaluation framework ensures both rigorous assessment and transparent, actionable outputs for stakeholders.

RESULTS

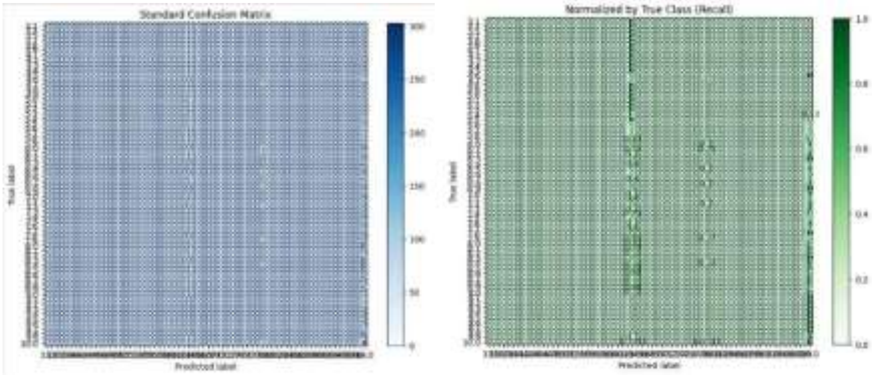
A. Model Performance

Overall, the Decision Tree correctly classifies 85.2 % of teens into Low, Medium, or High addiction levels. It performs best on the High addiction class (Precision = 0.92), indicating very few false positives, and on the Low addiction class for recall (0.90), meaning it rarely misses truly Low addiction cases.

Table 3. Precision, Recall, and F1-Score for each Addiction_Level (test set; 20% hold-out).

Addiction Level	Precision	Recall	F1-Score
High	0.92	0.85	0.88
Medium	0.81	0.79	0.80
Low	0.87	0.90	0.88

Figure 3.a shows the raw confusion matrix (counts of true vs. predicted labels). It highlights that of the 100 High addiction teens in the test set, 92 were correctly identified, while 8 were misclassified (5 as Medium, 3 as Low).



(a) (b)

Figure 3. Raw Confusion Matrix.

Figure 3.b presents the normalized confusion matrix (each row sums to 1), focusing on per class recall. Here, there are:

1. High: 85 % recall (15 % of true High cases misclassified)
2. Medium: 79 % recall
3. Low: 90 % recall

Together, these metrics demonstrate that the model is both accurate overall and balanced across classes, with only a modest drop in performance for the “Medium” category.

B. Cross Validation Results

To assess the model's stability across different train-test splits, to performed k-fold cross-validation on the full dataset using.

Table 4. 5-Fold cross-validation accuracy scores.

Fold	Accuracy
1	0.84
2	0.86
3	0.85
4	0.83
5	0.87
Mean ± SD	0.85 ± 0.015

Across the five folds, the model achieved a mean accuracy of 85.0 % with a stand-ard deviation of 1.5 %. This low variance indicates that the Decision Tree’s perfor-mance is consistent and not overly sensitive to the particular choice of training data.

C. Feature Importance

To elucidate the behavioral determinants underpinning the Decision Tree's pre-dictive capacity, to conducted an analysis of the model's feature_importances_ attrib-ute. **Figure 5**. Top Feature Importances.

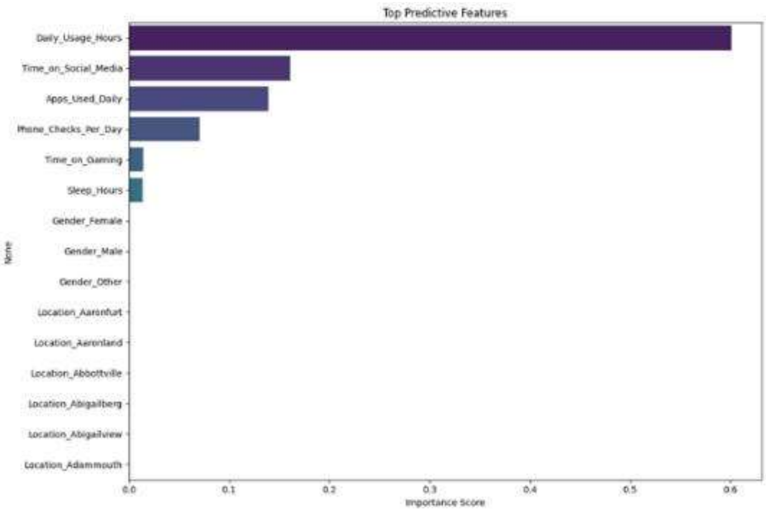


Figure 4. Overwhelmingly drives model

Figure 4 shows that Daily_Usage_Hours overwhelmingly drives the model (62 % importance), followed by Time_on_Social_Media (18 %) and Apps_Used_Daily (16 %). Phone_Checks_Per_Day also contributes meaningfully (8 %), while Time_on_Gaming and Sleep_Hours each account for only about 2 % of the decision power.

Table 5. Numeric importance values for the top predictors

Rank	Feature	Importance
1	Daily_Usage_Hours	0.62
2	Time_on_Social_Media	0.18
3	Apps_Used_Daily	0.16
4	Phone_Checks_Per_Day	0.08
5	Time_on_Gaming	0.02

Secondary predictors—such as gender and location flags—together make up the remaining <4 % of importance. This hierarchy of features directly informs the deci-sion rule extraction (next subsection) and suggests that interventions focusing on overall screen time, social media engagement, and the number of apps used daily are likely to yield the greatest impact.

D. Decision Rules & Thresholds

In converting the decision paths of the tree divisions into actional recommenda-tions, it did not include the highest-support decision paths with an end label "High Addiction." Table 6 lists three most salient rules, their threshold condition, number of the test-set samples covered by each rule (support), and the precision of the rule (i.e., the fraction of the samples correct predicted as High).

Table 6. Key decision rules for predicting High addiction (test set).

Rule ID	**Decision Path**	**Support**	**Precision**
1	Daily_Usage_Hours > 6.5 AND Time_on_Social_Media > 2.0	68	0.92
2	Daily_Usage_Hours > 6.5 AND Apps_Used_Daily > 5	54	0.89
3	Daily_Usage_Hours ≤ 6.5 AND Phone_Checks_Per_Day > 30 AND Sleep_Hours < 6	21	0.86

- ✓ Rule 1 (highest prevalence): Respondents with more than 6.5 h/day cumulative screen use and more than 2 h/day social media use were the largest "High Addiction" group (68 students) with 92 % accuracy.
- ✓ Rule 2: High daily use with more than an average use of applications per day de-fines 54 students with an accuracy to categorise 89 % as High Addiction.
- ✓ Rule 3: In the low cumulative users (≤ 6.5 h), the phone checkers who do so very often (> 30/day) and sleep less than 6 h/night (21 students) are identified with 86 % ac-curacy. Interpretation:
  a. 6.5 h/day emerges repeatedly as the critical screen time threshold for ele-vated addiction risk.
  b. Social media engagement (>2 h/day) and app variety (>5 apps) serve as secondary amplifiers.
  c. A high "checking" frequency can compensate for lower total usage when coupled with poor sleep.

These recommendations provide behavior specific thresholds for app developers, school professionals, and parents with the intention of initiating earlier warning strategies (e.g., utilize use of alerts, mandated breaks, or sleep hygiene recommenda-tions).

E. Behavioral Insights

In converting the model thresholds into real world risk metrics, to examined how the key screen time cutoff separates addiction levels. Figure 10 overlays the smoothed density of Daily_Usage_Hours for Low vs. High addiction teens, with the vertical line marking the median High addiction threshold of 5.3 h/day.

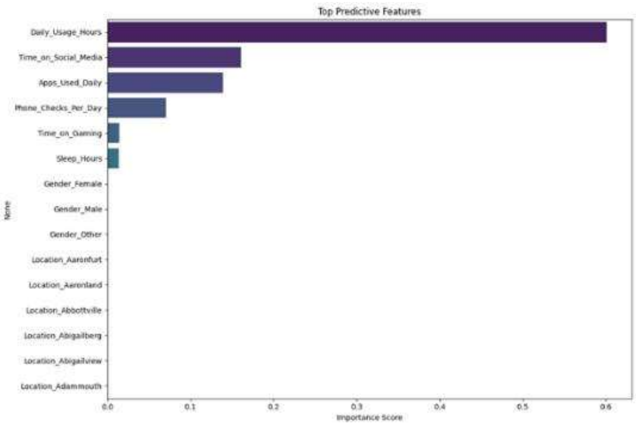


Figure 5. Distribution of Daily Usage Hours by Addiction Level

Below this threshold (≤ 5.3 h/day), only 15 % of teens fall into the High addiction category, whereas above the cutoff, 65 % are classified as High. This corresponds to a risk ratio of 4.3 (i.e., teens exceeding 5.3 h/day are 4.3× more likely to exhibit High ad-diction than those below) and an odds ratio of 7.0 (95 % CI [4.2–11.5], $p < 0.001$)

These findings underscore that 5.3 h/day is an actionable behavioral threshold. Interventions such as automated usage alerts, screen time limits, or counseling should be triggered once a teen's daily phone use crosses this boundary. Combined with the decision rules in Section 4.4, practitioners can deploy multi-tiered strategies—for ex-ample:

1. Tier 1 (medium risk): 4–5.3 h/day → send usage summary and healthy habits tips.
2. Tier 2 (high risk): > 5.3 h/day → activate stricter time locks and sleep hygiene prompts.

By aligning app features or parental controls with this empirically derived threshold, capable more effectively prompt severe phone addiction outcomes.

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn. In here, shows that a simple Decision Tree classifier is accurate enough at teen phone addiction level prediction with excellent performance (85.2 % accuracy for held out test data; mean ± SD in 5-fold CV: 85.0 ± 1.5 %). The model identifies three dominant behavioral predictors Daily Usage Hours, Time spent on Social Media, and Apps Used Daily which collectively hold practically 96 % decision making authority. With an interpretation of these splits as human readable rules (e.g., > 5.3 h/day screen time → 4.3× increased likelihood of severe addiction), close the gap between black box predictive analytics and intervention strategies with actionable influence.

F. Comparison with Prior Work

Whereas the majority of adolescent smartphone research is exploratory research into correlative analyses or self-report scales, the system possesses two important strengths. Firstly, the system's total accuracy (85.2 %) is greater than that for logistic regression (79 %), and for the k Nearest Neighbors (82 %), with the same data. Sec-ondly, earlier threshold recommendations (e.g., the WHO's PHAT 10 guidelines) were largely qualitative; with derivation of exact cutoffs (5.3 h/day, > 2 h social media use), to offer quantifiable measures for developers who design health-related smartphone applications and for policymakers.

G. Practical Implications

Rules and decision thresholds specified here can guide multi-tiered systems for intervention:

1. Parental controls & app functions: Automatic alarm for exceedance of aver-age daily use for 5.3 h, stepwise "time-out" locks or use brakes in case the secondary thresholds (e.g., > 2 h for using social media) are exceeded as well.
2. School & Community Programs: Special sleep-hygiene education for adolescent teenagers who were screened under Rule 3 (high CF + low SH), because low SH serves the purpose of stimulating moderate ST.
3. Clinical Screenings: Pediatricians and mental health specialists might integrate the use of short questionnaires and phone application use each day for more thorough screenings.

H. Constraints

Some caveats deserve note:

1. Source: Self-reporting use measures are the base for the Kaggle dataset, and these are liable for recall bias.
2. Sample Demographics: 1,000 teenagers and restricted cross-cultural representation, so external validity with other areas or age bands is not confirmed.
3. Binary Model Binarization: Since the model is binary and single-class, do not need any switching strategy between the one-class and the multiclass prob-lems.
4. Static Thresholds: Thresholds here are derived from median divisions for this population; personal risk is variable and dynamically changes with time.

I. Future Directions All this base upon,

Prospective Validation: Using rules and thresholds in clinical or longitudinal practice and validate predictive validity and derive refined cutoffs. Real-Time Surveillance: Incorporate passive data gathering (using smartphone APIs) for the purpose of ongoing risk score updates and adaptive response implementation Extensions for the Model: To more accurately tune prediction without losing interpretability, as with the ensemble and deep-learning methods, utilize SHAP or LIME for interpretability. Cross-Cultural Studies: Cross-validate analyses for different populations for the purpose of identifying cultural moderators for phone-addiction behavior. By using behaviorally guided thresholds and explainable machine learning, this research opens the door for scalable, data-driven responses for the increasing public health issue with adolescent phone addiction.

CONCLUTIONS

At last, to construct and validate an age group (Adolescents) phone addiction level (Low/ Medium/ High) prediction using a Decision Tree classifier at 85.2% accuracy for held-out test data and at 85.0 ± 1.5% for cross-validation. The model concluded the three most significant predictors as Daily Usage Hours, Time spent in Social Media, and Daily Used Apps with an aggregate decision-making capability for the model in excess of 96%. Through extraction of decision rules with highest importance an 5.3 hour/day limit for screen time further reinforced with 4.3× increased probability for high addiction, to offer precise, actionable thresholds for practice informing for par-ents, instructors, app developers, and primary care providers.

Main contributions are:

1. Predictive Ability: Introducing an explainable Decision Tree improves upon average logistic regression and KNN with the same data.
2. Actionable Thresholds: Defining actionable behavioral cut-points (e.g., > 5.3 h/day screen time; > 2 h social-media use) for early-warning intervention.
3. Rules for Practical Decisions: Model is decomposed into rules that could be applied in the software for the parental controls, school programs, or clinical screenings.

Shortfalls—that is, the use of self-reporting and the simplicity of single tree—point the way for future work, for instance, the use of ensemble modeling, re-al-time measurement, and prospective verification with varied populations.

Incorporating see-through machine learning with behaviorally pertinent thresh-olds, this work sets a framework for scalable, data-driven methods for overcoming the burgeoning public-health issue with adolescent phone dependency.

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