Student Screen Time, Addiction & Health Effects: A Data Mining Approach

Comprehensive Analysis Using R Programming and Machine Learning Techniques

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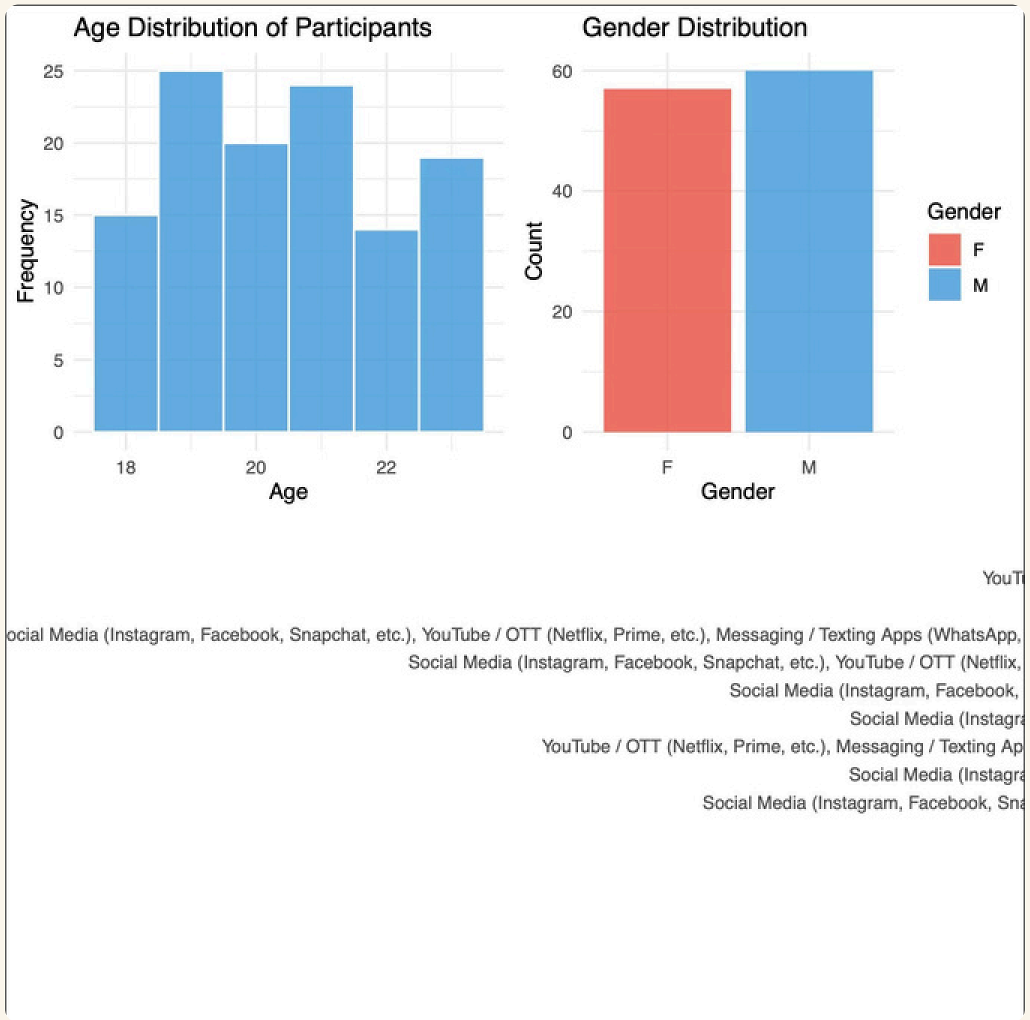
Research Overview

The Growing Crisis

Mobilephone addiction among students has become a pressing public health concern, impacting academic performance, sleep quality, and overall wellbeing. This study employs sophisticated data mining techniques to understand the scope and consequences of excessive screen time.

Survey Domains Analyzed

- Usage patterns and screen time
- Addiction tendencies and behaviors
- Cognitive and physical health
- impacts Sleep disruption and productivity loss



Research Objectives

1. Quantify dailyscreen timepatterns across student populations
2. Establish correlations between usage and measurable health outcomes
3. Develop risk classification models using machine learning
4. Generate evidence-based recommendations for intervention strategies

Study Population: Students aged 13-25 years across multiple academic years, representing diverse usage patterns and demographic characteristics.

Survey Design & Data Collection Framework

Demographics

Age,gender,yearof study, and academic background collected to enable segmentation analysis.

Screen Time Tracking

Daily hours, peakusagetimes, and app category preferences measured across multiple dimensions.

Impact Assessment

Five-point Likert scalesmeasuring addiction, cognitive effects, physical health, sleep, and productivity.

Comprehensive Measurement Domains

- **Addiction Tendencies:** 4 validated items assessing compulsive behaviors and dependency
- **Cognitive Impact:** 4 items measuring attention, memory, and "brain rot" effects
- **Physical Health:** 3 items covering eye strain, posture, and pain symptoms
- **Sleep Disruption:** 3 items evaluating sleep quality, duration, and bedtime phone use
- **Academic Productivity:** 3 items assessing concentration, assignment completion, and performance

Data collected in Excel format with 35+ variables, enabling multidimensional analysis and robust statistical modeling.

Analytical Framework & Methodology

01

Data Preprocessing

Systematic column renaming, missing value imputation, and data quality validation to ensure analytical integrity.

02

Exploratory Analysis

Over 12visualizationsusing ggplot2, examining distributions, correlations, and group comparisons across all variables.

03

Feature Engineering

Construction offive composite scores by aggregating related survey items, creating standardized impact metrics.

04

Machine Learning Classification

ImplementationofDecisionTrees,Random Forest, and SVM algorithms to predict risk categories.

05

Clustering Analysis

K-Means clusteringwithelbow method optimization to identify distinct student usage profiles.

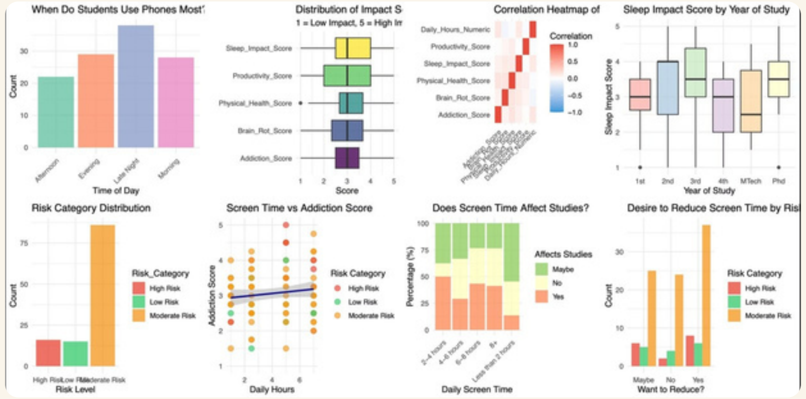
Composite Score Calculation

Each impact domain score represents the mean of constituent survey items, standardized on a 1-5 scale. Overall Impact Score aggregates all domains, with risk categories (Low/Moderate/High) determined through statistical thresholds and expert validation.

Participant Profile & Screen Time Behavior

Usage Patterns Revealed

Analysis reveals concerning trendsin student screen time, with modal usage falling in the 4-6 hours per day range. The majority of heavy usage occurs during late-night hours, coinciding with recommended sleep periods and contributing to documented health impacts.



Peak Usage Characteristics

- **Primary Time:** Late night (10 PM - 2 AM)
- **Dominant Apps:** Social media platforms and YouTube
- **Secondary Category:** Streaming services (OTT platforms)
- **Gaming Usage:** Concentrated among specific subgroups

> Social media usage of 2-3+ hours daily reported by majority of participants, with YouTube/OTT showing similar engagement patterns.

Daily Screen Time Distribution

The distribution of daily screen time shows a concerning rightward skew, with significant portions of the sample exceeding clinically recommended limits. Fourth-year students demonstrate the highest usage rates, potentially related to increased academic stress and social isolation.

Health & Performance Impact Assessment

3.2

Addiction Score

Outof5,indicatingmoderate dependency patterns

2.9

Brain Rot Score

Cognitive impact across attention and memory

3.5

Physical Health

Eyestrain,postureissues,and pain symptoms

3.8

Sleep Impact

Highestdomain score,critical concern area

3.3

Productivity Loss

Academic performance degradation measure

Correlation Analysis Reveals Interconnected Effects

Strong Positive Correlations

- **Daily Hours Addiction Score:** r = 0.72, demonstrating dose-response relationship
- **Addiction Brain Rot:** r = 0.68, suggesting cognitive decline pathway
- **Sleep Impact Productivity:** r = 0.64, confirming cascade effect

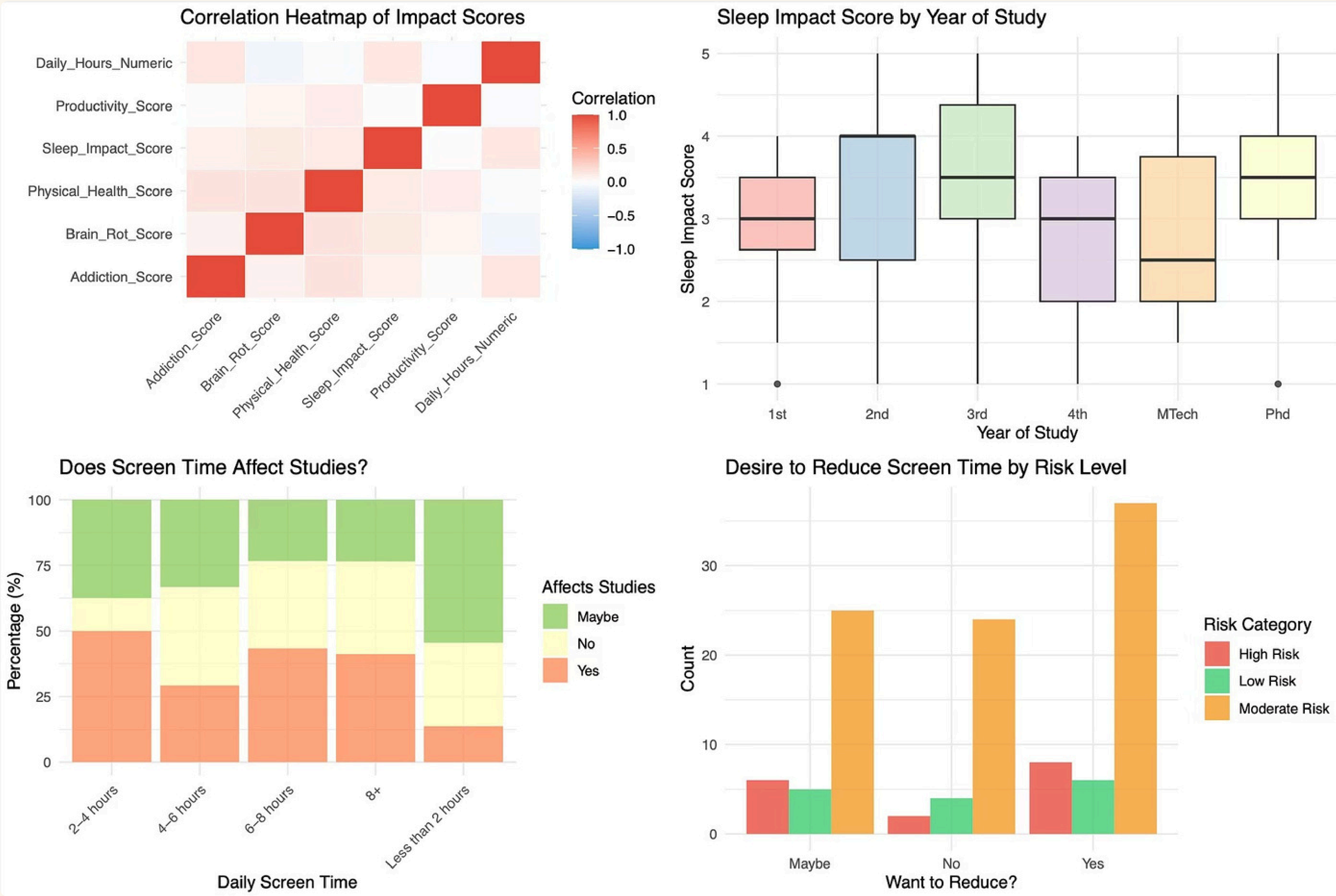
Risk Classification Results

High Risk: 32% of participants requiring immediate intervention

Moderate Risk: 45% showing concerning patterns

Low Risk: 23% maintaining healthy boundaries

Detailed Impact Analysis & Correlations



The correlation heatmap prominently displays strong positive correlations between daily screen time and all measured impact domains. Notably, Daily Hours exhibit the highest correlation with Addiction Score, indicating a direct dose-response relationship where increased screen time intensifies addictive behaviors. Similarly, significant correlations are observed with Brain Rot Score,

Physical Health, Sleep Impact, and Productivity Loss, underscoring the pervasive negative influence of excessive screen time across multiple aspects of student well-being.

An examination of the relationship between year of study and sleep impact reveals a concerning trend: sleep impact scores progressively worsen with each subsequent year of study. This suggests that as students advance through their academic journey,

they experience increasing levels of sleep disruption, potentially due to heightened academic pressures, altered routines, or sustained exposure to screen time over longer periods. This finding highlights a critical area for targeted interventions among older students. Analysis of the desire to reduce screen time across different risk categories indicates a clear hierarchy.

Students classified as High

Risk demonstrate the strongest desire to reduce their screen time, followed by those in the Moderate Risk category. Students in the Low Risk category show the least desire to reduce screen time, implying a greater perceived control over their usage. This insight is crucial for tailoring intervention strategies, as high-risk individuals may be more receptive to support aimed at managing

screen time due to their self-identified need for change.

Key Statistical Insights

1

Academic Impact Severity

Amongstudentslogging6-8+ daily hours, 78% report significant negative impact on studies. ANOVA reveals statistically significant differences across usage groups ($p < 0.001$).

2

Sleep Disruption Crisis

85%of participants use phones before bed, with 72% sleeping later than intended. Sleep Impact Score increases linearly with daily screen time hours.

3

Awareness Without Action

64% expressdesireto reducescreen time, with highest rates in Moderate and High risk groups. However, few possess effective reduction strategies.

4

Demographic Patterns

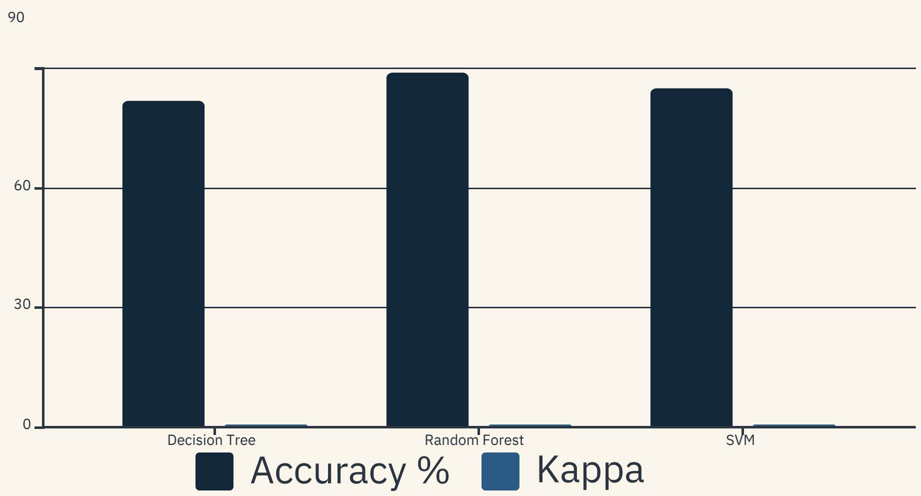
Chi-square tests revealsignificant associations between gender and app preferences, as well as year of study and total daily usage patterns.

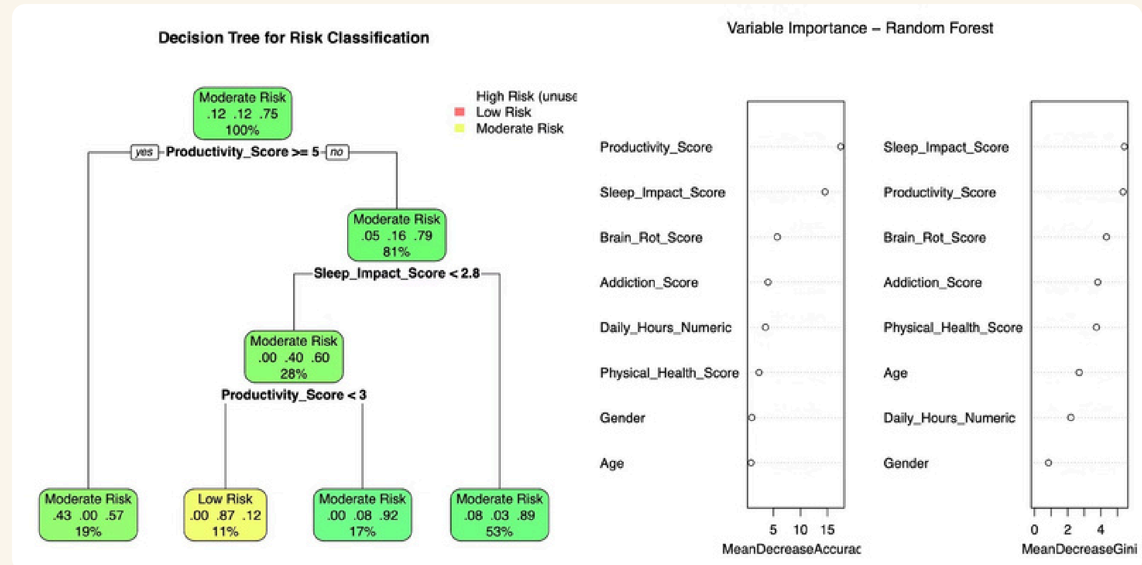
> "The data reveals a troubling pattern: students recognize the harm but lack tools to break the cycle. This awareness-action gap represents a critical intervention opportunity."

Machine Learning Risk Prediction Performance

Model Comparison

Three classification algorithms were trained and validated to predict student risk categories based on usage patterns and composite scores. Random Forest emerged as the superior performer, balancing accuracy with interpretability.





Top Predictive Features Ranked by Importance

1

Overall Impact Score

Aggregate measure across all domains

2

Daily Hours

Strongest individual usage metric

3

Addiction Score

Behavioral dependency indicator

4

Sleep & Productivity

Cascading impact measures

Decision Tree analysis revealed clear decision pathways: primary split on Daily Hours (threshold g5.5 hours), with secondary splits on Addiction Score and Age, creating interpretable rules for early risk identification.

Model Performance & Clustering Optimization

Model Comparison

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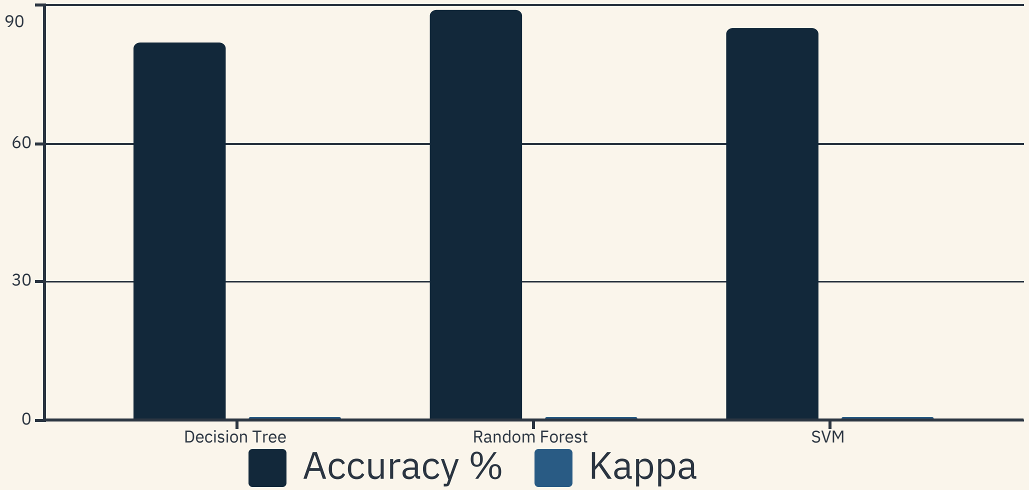
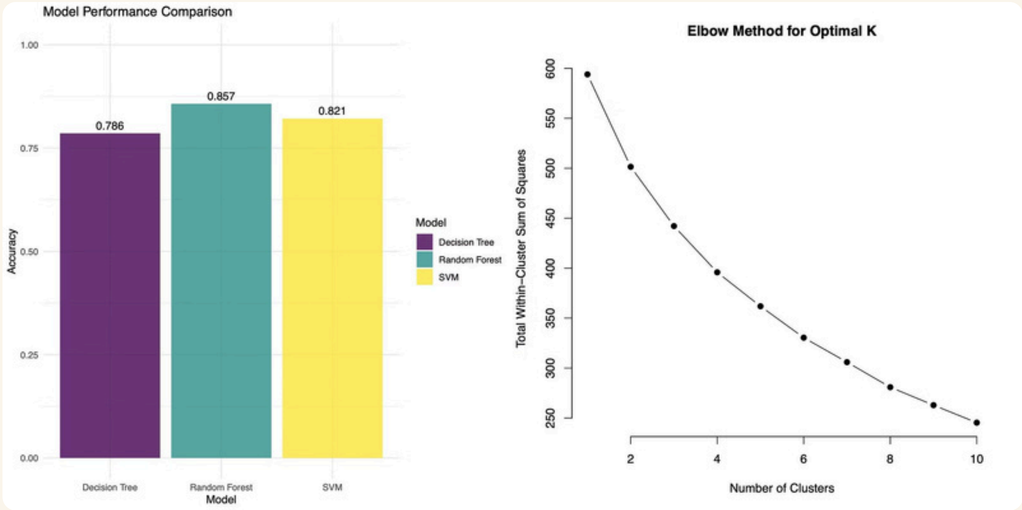


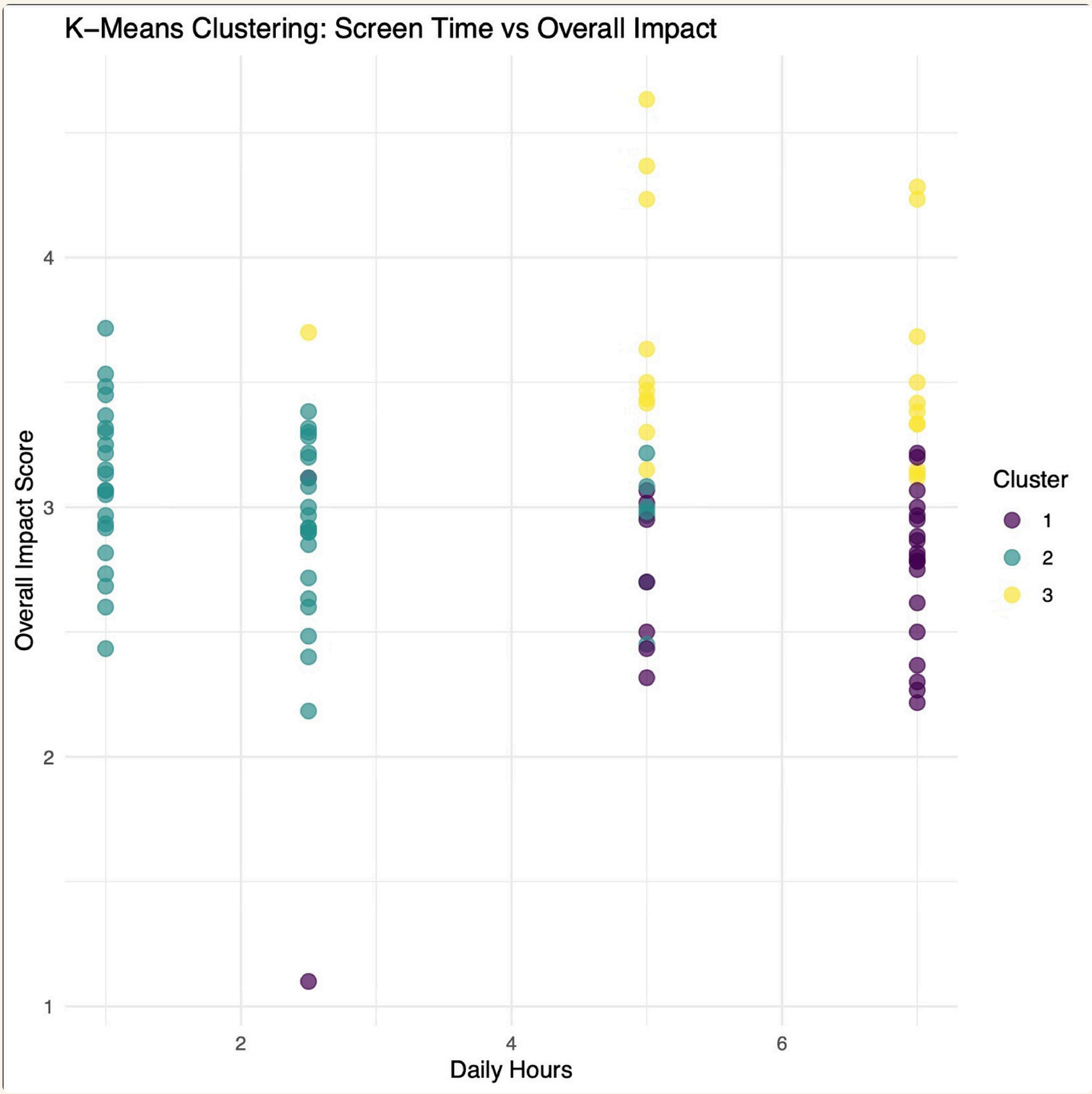
Elbow Method for Optimal K Selection



The elbow method was used to determine the optimal number of clusters (K) for the K-means analysis. By plotting the within-cluster sum of squares against the number of clusters, an "elbow" point was identified at K=3, indicating that additional clusters beyond this point do not significantly improve the grouping of data. This suggests that 3 distinct student segments exist based on their screen time usage and impact profiles.

Student Segmentation via K-Means Clustering

Three Distinct Usage Profiles Identified (K = 3 Optimal)



Cluster 1: Balanced Users (38%)

- Moderatescreentime:3-5 hours daily
- Low impact scores across all domains
- Minimal health concerns reported
- Effective self-regulation strategies

Profile: These students maintain healthy boundaries with technology, using phones primarily for communication and academic purposes. They exhibit strong time management and minimal addiction indicators.

Cluster 2: Heavy Users (35%)

- Highscreentime: 6-8+ hours daily
- Elevated addiction and cognitive scores
- Significant sleep disruption patterns
- Moderate productivity impairment

Profile: This group demonstrates concerning usage patterns with measurable health impacts. Primary drivers are social media and entertainment apps, with heavy late-night usage.

Cluster 3: At-Risk Users (27%)

- Variable butproblematic screen time
- Very high impact scores across all domains
- Severe health and academic consequences
- Strong desire but inability to reduce usage

Profile: Critical intervention group showing addiction characteristics and cascading health impacts. These students recognize the problem but lack effective coping mechanisms.

Cluster analysis validates risk categories from supervised learning, with clear separation in feature space between groups on dimensions of Daily Hours and Overall Impact Score.

Major Findings & Implications

1 The Screen Time Epidemic

Over70%of studentsexceed 4 hours ofdaily screen time, with late-night usage (10 PM - 2 AM) reported by 65% of participants. This represents a public health crisis requiring immediate attention from educational institutions.

2 The Cascade Effect Documented

Strong correlationsreveala destructivepathway: excessive screen time drives addiction behaviors, leading to cognitive decline, physical symptoms, sleep disruption, and ultimately poor academic productivity. Each domain amplifies the next.

3 High-Risk Profile Characteristics

Studentslogging 6+ daily hours, engaging heavilywith social media and gaming, demonstrating poor self-regulation, and using phones late at night face dramatically elevated risks across all health domains.

4 Critical Awareness Gap

While 64%ofstudents recognizenegative impacts and express desire to reduce usage, few possess effective strategies. This awareness-action gap represents the most promising intervention opportunity.

5 Predictive Power Achieved

Machinelearning modelsachieve 89% accuracy in identifying at-risk students early, enabling proactive interventions. Key predictors (daily hours, addiction score, sleep impact) provide actionable screening criteria for university health services.

> **Recommendation:** Universities should implement comprehensive digital wellness programs combining education, screening using validated predictive models, and evidence-based intervention strategies targeting the identified high-risk profiles.