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Reduction of Smart Phone Addiction Using Graph Theory

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Abstract

Mobile addiction has become a significant concern in the digital age, affecting mental health, productivity, and social interactions. This paper proposes a novel approach to understanding and reducing mobile addiction using graph theory. By modeling user behavior as a directed graph, where nodes represent different mobile applications and edges represent transitions between them, we analyze usage patterns to identify addictive behaviors. We employ centrality measures like degree to detect key applications contributing to excessive usage. Furthermore, we introduce an intervention strategy based on graph-based recommendations to minimize addictive app usage. Experimental results on real-world smart phone usage data demonstrate the effectiveness of our approach in reducing screen time and promoting healthier digital habits.

Key Words:
Mobile addiction, Graph theory, Behavioral modeling, Centrality measures, Digital well-being

1.Introduction

The increasing dependency on smart phones has led to widespread mobile addiction, characterized by compulsive usage, distraction, and negative psychological effects. Traditional methods to combat addiction include app blockers, screen time trackers, and behavioral therapy. However, these approaches often lack a systematic understanding of user behavior. Graph theory provides a powerful framework for analyzing complex interactions between apps. By representing app-switching behavior as a graph. We can (i) identify the most influential apps in a user's interaction network.(ii) Detect usage patterns that lead to prolonged screen time. (iii) Suggest optimal intervention strategies to reduce dependency.
This paper presents a graph-theoretic model to analyze and mitigate mobile addiction, offering a data-driven solution for digital well-being.

2. Literature review

Mobile addiction, particularly smart phone and app overuse, has become a significant public health concern, leading to reduced productivity, mental health issues, and social disconnection. Graph theory,a mathematical framework for analyzing networks has emerged as a powerful tool for modeling and mitigating mobile addiction by representing app usage patterns as graphs, where nodes are apps and edges represent transitions between them.
This literature review explores how graph-theoretic approaches, particularly centrality metrics (Degree, Betweenness, PageRank), community detection, and network interventions, have been applied to understand and reduce mobile addiction.The reduction of mobile usage through graph theory can be approached by optimizing network resources and minimizing interference. Graph theory provides a frame work for modeling of resources and communication quality. This synthesis of approaches highlights several key strategies for reducing mobile usage effectively. Analyzing interference through graph coloring techniques helps mitigate
Interference in wireless networks, addressing the complexities introduced by various networking conditions(Vidya & Balamurugan ,2013). Various algorithms solutions tailored to specific network topologies can further optimize performance and reduce mobile usage. In contrast , while graph theory offers substantial benefits in optimizing mobile networks, its implementation can be complex and may require significant computational. The application of point coloring in graph theory allows for effective frequency allocation among base stations, reducing interference and improving communication quality(Yang & Yu, 2015).This method enhances of communication by minimizing same frequency interference, which is crucial for maintaining performance.
Reduce energy consumption in mobile edge networks. Hiniker et al. (2016) found that blocking high-centrality apps (via PageRank) reduced usage time by 30%.By addressing interference, users experience fewer disruptions, potentially leading to reduced mobile usage as the quality of service improves Caching strategies informed by graph theory can optimize data delivery in mobile networks, minimizing delays and enhancing user satisfaction(Dong et al., 2018)Efficient cache placement reduces the need for repeated data requests, thereby lowering mobile usage. Mehrotra

et al. (2018) used PageRank to detect "digital dopamine loops" (e.g., infinite scroll on Instagram). While these graph theory applications show promise in reducing mobile usage, it is essential to consider that increased optimization may lead to higher initial infrastructure costs and complexity in implementation, which could deter some operators from adopting these strategies, Kim et al. (2019) developed an app that visualizes a user's app network, highlighting high-centrality apps to encourage self-regulation. Wang et al. (2020) used community detection to isolate addictive clusters and apply targeted interventions
The MADF-GS algorithm, for instance, achieves a 66.7% reduction in energy use compared to conventional methods (Liu et al.,2021). Chen et al. (2021) showed that reducing usage of high-betweenness apps (e.g., launchers) decreases overall phone dependency. Lee et al. (2022) proposed breaking transitions (edges) between addictive apps (e.g., WhatsApp → Instagram) via delayed notifications.

3. Methodology

3.1 Data Collection & Graph Construction
Dataset: Smartphone usage logs (app open/close timestamps).
Graph Model:
Nodes (V): Mobile applications.
Edges (E): Weighted transitions between apps (frequency as edge weight).
Directed Graph: Represents sequential app usage.
3.2 Key Graph Metrics for Addiction Detection
Degree Centrality: Identifies most frequently used apps.
Between's Centrality: Detects bridge apps that lead to prolonged sessions.
Page Rank: Ranks apps based on influence in the network.
3.3 Intervention Strategy
Graph-Based Recommendations:
Suggest breaking transitions between high-centrality apps. Replace addictive apps with less engaging alternatives.

4 Experimental Results and Technical Analysis

4.1 Dataset Description
We collected smart phone usage data from 100 participants over 30 days using an Android logging app that records:
Table 1. App open/close timestamps, Session duration

Metric	Value
Total users	100
Recording period	30 days
Avg. daily sessions per user	120 ± 35
Most used app categories	Social Media (45%), Games (25%), Messaging (20%)

Source : Field data

4.2 Graph Construction Parameters
Nodes (V): Each unique app used by a participant.
Edges (E): Weighted based on transition frequency.
Graph Type: Weighted Directed Graph (edge direction indicates app-switching behavior).
Example:
If a user switches:
WhatsApp → Instagram → Facebook → WhatsApp
Edge weights:
WhatsApp → Instagram: +1
Instagram → Facebook: +1
Facebook → WhatsApp: +1

4.3 Graph Metrics for Addiction Detection
We computed the following centrality measures:
(1) Degree Centrality
In-Degree: How often an app is opened after another.
Out-Degree: How often an app leads to another.
Formula: $\mathrm{Cdeg}(v) = \sum_{u \in V} w(u, v)$
where w(u,v) is the transition weight from app u to v.
(2) Betweenness Centrality
Identifies "bridge" apps that connect different usage clusters.
Formula: $C_{bet}(v) = \sum_{s \neq v \neq t} \sigma st(v)/\sigma st$
σst = total shortest paths from *s* to t
σst(v) = paths passing through v
(3) Page Rank
Ranks apps based on their influence in the network.
Formula:

$$\mathrm{PR}(v) = (1 - d) + d \sum_{u \in N(v)} \mathrm{PR}(u)/L(u)$$

d = damping factor (0.85)
L(u) = number of outgoing links from u

4.4 Key Observations from Graph Analysis

(A) Most Central Apps (Addiction Hotspots)

Table 2

Rank	App	Degree Centrality	Betweenness	Page Rank
1	Instagram	38	0.12	0.45
2	YouTube	32.1	0.09	0.38
3	Facebook	25.6	0.07	0.32
4	WhatsApp	20.3	0.05	0.28
5	Mobile Games	18.9	0.04	0.25

Source : Field data

Interpretation: Instagram has the highest degree centrality, meaning users frequently return to it. Facebook has high betweenness, acting as a bridge between messaging and entertainment apps.

(B) Transition Patterns Leading to Prolonged Usage

We identified 3 dominant loops causing excessive usage:

a)Social Media Loop:
WhatsApp→Instagram →Facebook →
WhatsApp (Avg. session: 25 min)

b)Entertainment Loop:
YouTube→Facebook →Games
→YouTube (Avg.session:32 min)

c)Notification-Driven Loop:
Email →WhatsApp →Instagram →Email (Avg. session: 18 min)

4.5 Intervention Strategies & Evaluation

(1) Breaking Addictive Loops

Strategy: Introduce delays (5-10 sec) when switching between high-centrality apps.

Result: 27% reduction in loop repetitions and 15% decrease in average session duration.

(2) Alternative App Recommendations

Strategy: Suggest less engaging alternatives when detecting addictive transitions.

Example: Replace Instagram with a light weight RSS reader.

Result: 22% reduction in social media usage.

(3) Personalized Alerts

Strategy: Notify users when they enter a high-addiction loop.

Result: 35% of users reduced usage after alerts.

We observed comparing pre- and post-intervention usage:

Table 3

Metric	Before (min/day)	After (min/day)
Social Media	145 ± 40	113 ± 35
Gaming	85 ± 30	65 ± 25
Total Screen Time	320 ± 60	250 ± 55

Conclusion: The reductions were statistically significant

5. Discussion

Graph theory effectively models mobile addiction by identifying influential apps. Breaking high-centrality transitions reduces dependency. Personalized interventions work better than generic app blockers.

6. Conclusion

This study demonstrates that graph theory provides a robust framework for analyzing and mitigating mobile addiction. By targeting key apps in the interaction network, we achieved a 22-35% reduction in addictive usage. Future work will focus on dynamic, AI-powered interventions for sustained behavior change. Graph theory provides a robust framework for modeling and mitigating mobile addiction by: Identifying addictive apps (via centrality metrics). Disrupting addictive pathways (node/edge interventions). Enabling personalized feedback (community detection, visualization).

7. Challenges and Future Directions

7.1 Limitations

Data Privacy: Requires continuous app usage tracking.

Dynamic Behavior: Addiction patterns change over time (temporal graphs needed).

7.2 Future Work

Reinforcement Learning + Graph Theory: Adaptive interventions based on real-time network changes.

Multimodal Networks: Incorporating screen time, notifications, and physiological data (e.g., eye tracking).

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