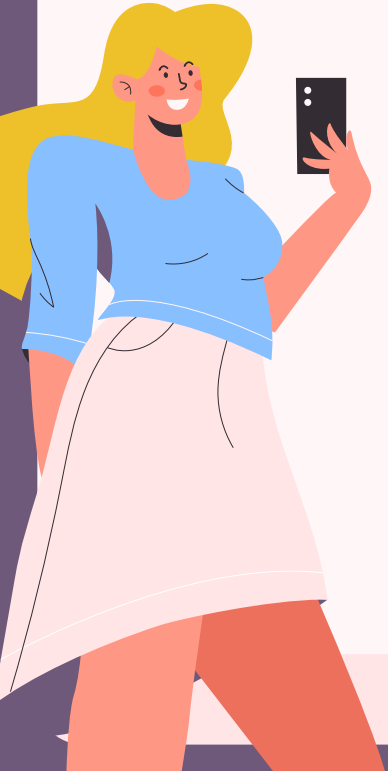




# **Predicting Anxiety and Depression due to Phone Addiction in Teens**



# TABLE OF CONTENTS



**01**

**Our team**

**02**

**Pain points**

**03**

**Business impact**

**04**

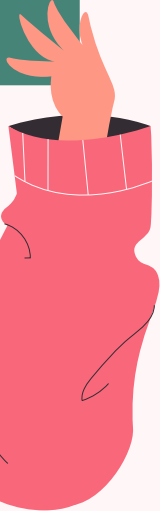
**Feasibility  
check**

**05**

**Proposed  
analytic  
approach**

**06**

**Defining  
success**



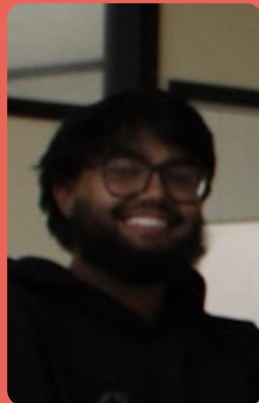
# OUR TEAM



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# The Business Hook

## The Pain Point



### Who is this for?

- Insurance companies, specifically those who cover reactive mental health treatment, also known as crisis therapy

### What problem do we want to fix?

- Crisis therapy is expensive to cover compared to preventative care.
- We hope to save insurance companies money by not having to cover medication for high-risk teens.



# The "So What?" Business Impacts

## Why this matters?

A teen mental-health "crisis episode" often shows up as an ED visit and sometimes an inpatient admission, both are claim events the insurer pays for.

## Benchmark costs:

Youth outpatient mental-health episode: \$2,673 per episode (includes psychotherapy, assessment, medication)

The real episodes can be higher depending on follow-up care.

## What specific decision the model supports

When to trigger parent interventions once a teen crosses the tipping point (e.g., social hours/day +phone checks/day)

**5,320 MILLION**

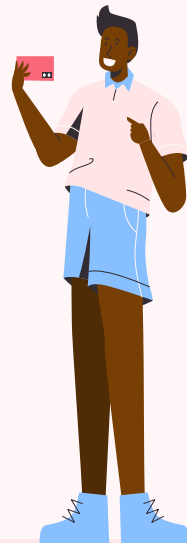
People worldwide who use a cell phone

**6 out of 10**

People are addicted to cell phones

**7,700 MILLION**

Worldwide purchase of cell phones



# Data Reality Feasibility Check



## Dataset Structure

Individual-level data with demographic characteristics, phone usage behaviors (screen time, social media), sleep patterns, and academic performance indicators for each teenager.

## Target Variable

Anxiety\_Level and Depression\_Level serve as the outcome measure, enabling both regression and classification approaches to identify high-risk adolescents.

## Predictive Features

Behavioral predictors include screen exposure patterns, usage frequency metrics, and sleep disruption indicators that correlate with addiction risk.

## Business Value for Insurance Providers

### From Reactive to Preventive Care

This dataset enables insurers to transition from costly reactive interventions such as crisis therapy and medication to earlier, lower-cost preventive care models.

Early identification of teens at high risk of phone addiction and associated mental health issues creates a practical pipeline from risk prediction to targeted early intervention.

The result: significant reduction in mental health treatment costs while improving patient outcomes.

URL : [Dataset](#)

ID	Name	Age	Gender	Location	School_Grade	Daily_Usage_Hours	Sleep_Hours	Academic_Performance	Social_Interactions	Exercise_Hours	Anxiety_Level	Depression_Level	Self_Esteem	Parental_Control	Screen_Time_Before_Bed	Phone_Checks_Per_Day	Apps_Used_Daily	Time_on_Social_Media	Time_on_Gaming	Time_on_Education	Phone_Usage_Purpose
1	Shannon Francis	13	Female	Hansonfort	9th	4	6.1	78	5	0.1	10	3	8	0	1.4	86	19	3.6	1.7	1.2	Browsing
2	Scott Rodriguez	17	Female	Theodorefort	7th	5.5	6.5	70	5	0	3	7	3	0	0.9	96	9	1.1	4	1.8	Browsing
3	Adrian Knox	13	Other	Lindseystad	11th	5.8	5.5	93	8	0.8	2	3	10	0	0.5	137	8	0.3	1.5	0.4	Education
4	Brittany Hamilton	18	Female	West Anthony	12th	3.1	3.9	78	8	1.6	9	10	3	0	1.4	128	7	3.1	1.6	0.8	Social Media
5	Steven Smith	14	Other	Port Lindsaystad	9th	2.5	6.7	56	4	1.1	1	5	1	0	1	96	20	2.6	0.9	1.1	Gaming



# Proposed analytics approach



## Binary Classification

We are going to build a Classification Model with **Decision Trees**. This algorithm has a high degree of explainability which is important to offer recommendations.

We need to flag teens who cross the "Clinical Threshold" to trigger an intervention. To achieve this we will create a binary target called High\_Risk\_Claimant.

- Class 1 (High Risk): Anxiety OR Depression Level > 7
- Class 0 (Low Risk): All other users

## Key Hypotheses

Hypothesis A - "Screen exposure as driver":

- Variables: *Screen\_Time\_Before\_Bed* & *Sleep\_Hours*
- High blue light exposure immediately before bed disrupts sleep cycles, which is a leading physiological precursor to anxiety spikes

Hypothesis B - "Social media as driver":

- Variables: *Phone\_Checks\_Per\_Day* & *Time\_on\_Social\_Media*
- High-frequency checking (fragmented attention) is likely more correlated with depression than long, sustained sessions of Gaming or Education



# Defining Success: Crisis Prevention



For health insurers, success isn't measured by algorithmic accuracy alone, it's defined by meaningful reductions in costly acute interventions and sustained improvements in member health outcomes.



## Primary Goal

**Reduce crisis-related claims** within the first few months resulting in fewer hospitalizations, emergency therapy sessions, healthier teens.



## Preventative Shift

Increase utilization of **low-cost preventative care** as counseling apps, wellness coaching triggered by early alerts.



## Predictive Precision

Achieve **90%+ recall** to catch high-risk cases with **14-30-day lead time** before clinical crisis emerges.

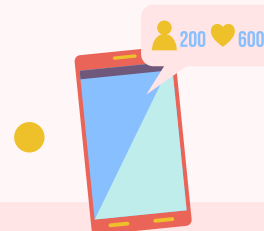


## Economic Impact: The Bottom Line

Metric	Definition of Success	Impact
Cost Avoidance	Prevent acute interventions through early action	Save \$\$\$ per avoided crisis
Lifetime Value	Improved long-term outcomes reducing chronic claims	Sustained savings into adulthood
Engagement Rate	Parents take action after receiving alerts	Less booking consultations



**Critical Context:** In mental health prediction, false negatives carry far greater costs than false positives. Missing a high-risk teen leads to crisis; flagging a healthy teen enables preventative support, a worthwhile investment.





**Thank You!**

