

## **1 What “disrupted sleep / behaviour pattern” ACTUALLY means (non-clinical)**

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You are **NOT** detecting depression/anxiety.

You are detecting **deviations from a user’s own baseline**.

### **Examples of non-clinical signals**

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<b>Category</b>	<b>Behaviour Signal (Safe &amp; Non-Medical)</b>
Sleep	Sleep duration variability, bedtime drift, wake-up inconsistency
Activity	Reduced daily movement, irregular active hours
Digital habits	Late-night screen usage, app usage spikes/drops
Routine	Missed routines, inconsistent daily structure
Engagement	Reduced interaction with platform features

#### **👉 Important principle:**

- | You never compare users to “healthy people”.
- | You compare **user vs their past self**.

## **2 How do we get this data automatically (without spying)?**

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This is the most important part.

### **✗ What you should NOT do**

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- No microphone
- No camera
- No reading private messages
- No GPS tracking
- No medical records

### **✓ What you CAN do (privacy-first)**

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#### **A. Passive, permission-based signals (web / mobile)**

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## 1. Time-based usage signals (web-safe)

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Collected **only when user uses your app**:

- Login times
- Session duration
- Time of last activity
- Usage gaps

Example:

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User usually logs in between 9–11 PM

Now logging in at 2–4 AM consistently → sleep disruption signal

## 2. Optional device integrations (explicit opt-in)

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- Google Fit / Apple Health (only aggregates)
- Screen time APIs (daily totals, not content)
- Wearables (steps, sleep duration)

| You store **numbers**, not raw logs.

## B. Lightweight self-check inputs (guided, optional)

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Instead of medical questionnaires:

- “How regular did your sleep feel this week?” (slider)
- “Did your routine feel predictable?” (Yes/Somewhat/No)
- “Energy level today?” (Low–Medium–High)

👉 These **calibrate the model**, not diagnose.

## 3 Turning raw data into “behaviour patterns”

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This is where AI comes in.

## Step 1: Build a personal baseline

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First 2–3 weeks = learning phase

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Average sleep time  
Sleep variance  
Typical activity window  
Normal usage frequency

No predictions yet.

## Step 2: Extract pattern features (ML-ready)

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Feature	Example
Sleep variance	Std dev of sleep hours
Circadian drift	Bedtime shift over days
Routine entropy	Daily schedule irregularity
Engagement change	% drop vs baseline
Consistency score	Stability across days

These become numbers like:

python

```
sleep_variance = 1.8
routine_entropy = 0.62
usage_shift = +35%
```

## 4 What AI/ML model do we actually use?

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⚠ This is NOT a disease classifier

### Best model choices (non-clinical & ethical)

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#### ◆ 1. Anomaly Detection (BEST choice)

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- Isolation Forest
- One-Class SVM
- Autoencoders

👉 Detects “this week looks unusual for YOU”

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Output: Risk deviation score (0-1)

#### ◆ 2. Trend-based ML (secondary)

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- Rolling averages
- Change-point detection
- Simple regression trends

Example:

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Sleep consistency declining steadily over 14 days

## Avoid

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- Diagnostic labels
- Binary “healthy / unhealthy”
- Medical datasets

## **5 How the system explains results (VERY IMPORTANT)**

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You must be **transparent and uncertainty-aware**.

### Example output (GOOD)

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“We noticed a **moderate deviation** from your usual sleep and activity routine over the last 10 days.  
This **may indicate increased strain**, but many factors can cause this.”

### Bad output

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“You are at risk of depression” 

## **6 Web interface: how the UI should guide the user**

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### Key UI sections

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#### 1. Consent & control panel

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- Toggle data sources
- Pause tracking
- Delete data anytime

#### 2. Insight dashboard

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- Trend graphs (no scary numbers)
- “What changed” explanation
- Confidence level indicator

#### 3. Action suggestions (non-medical)

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- “Try stabilizing bedtime”

- “Consider short breaks from late-night screen use”
- “Would you like to reflect on your routine?”

## 7 Ethics, privacy & safety (you MUST mention this)

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### Mandatory safeguards

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- Local preprocessing where possible
- Anonymized user IDs
- No raw logs stored
- Explicit consent per data source
- No diagnosis language
- Clear disclaimers

### Data handling model

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User device → Feature extraction → Encrypted summary → AI model

## 8 Final system architecture (simple view)

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User Data (opt-in)
  ↓
Feature Extraction (privacy-safe)
  ↓
Baseline Modeling
  ↓
Anomaly / Trend Detection
  ↓
Risk Indicator (non-clinical)
  ↓
Transparent UI + Suggestions
```

## 9 Can this be built with your current skills?

YES — and this is a **strong hackathon / research / startup-level project**.

### Suggested tech stack

- Frontend: React / Next.js
- Backend: Python (FastAPI)
- ML: scikit-learn / PyTorch (simple)
- DB: SQLite / PostgreSQL
- Privacy: Hashing + aggregation

### 🔥 If you want next steps

I can:

1. Design **exact ML features**
2. Help you write **problem → solution → innovation** section
3. Create a **step-by-step build roadmap**
4. Help you avoid **medical & legal red flags**

Just tell me what you want next 🌟

