

Balance Analysis Web App

Skeleton site, dual CSV upload, and comparative data analysis pipeline

What was built

- **Single-file skeleton**
Clean HTML/CSS/JS with Chart.js
- **Dual upload zones**
Eyes-open (baseline) and eyes-closed (test) CSVs
- **Auto-trim pipeline**
First & last 5s removed to discard handling artifacts
- **CSV parser + preview**
In-browser parsing, tabbed preview, fullscreen modal

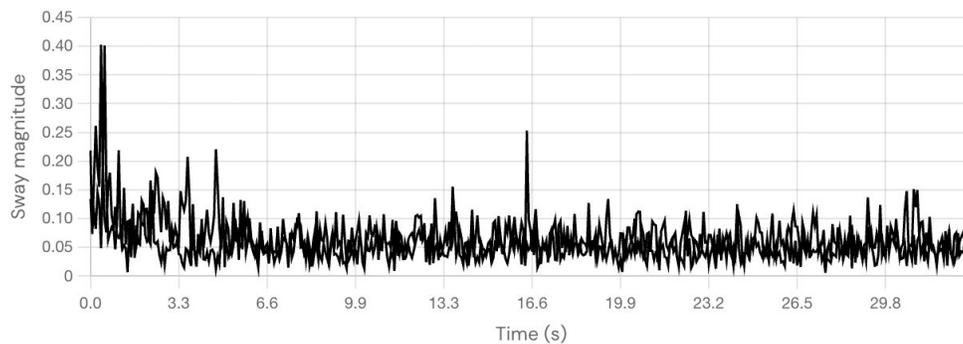
Analysis features

- **Comparison stats**
RMS sway, peak, std dev, jerk, path length
- **7 chart types**
Sway overlay, scatter, 3-axis, rolling RMS, histogram, delta
- **Romberg quotient**
Closed/open RMS ratio with interpretation
- **Auto-insights**
6 contextual findings + stability verdict

Sway magnitude – overlay

Total sway $\sqrt{(x^2+y^2+z^2)}$ for both conditions on a common time axis (trimmed)

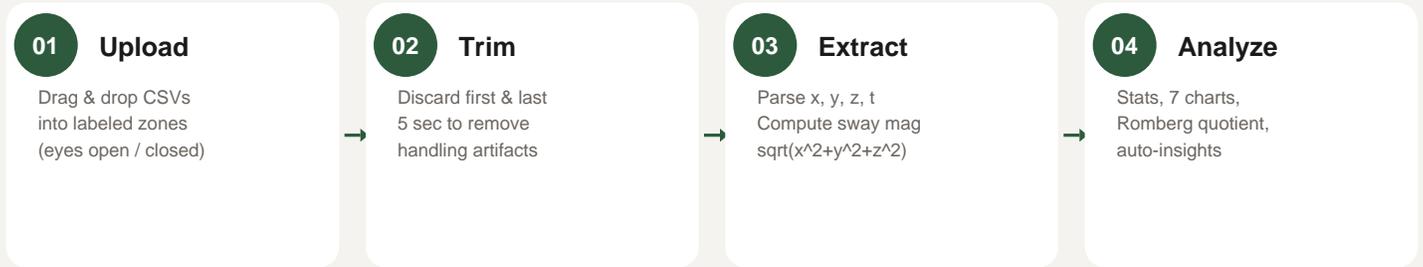
● Eyes open ● Eyes closed



Sway magnitude overlay: eyes open (blue) vs. eyes closed (red) with trimmed accelerometer data

CSV Parsing & Comparative Analysis

From raw Sensor Logger export to automated balance comparison



Computed metrics (per condition)

RMS Sway

Root mean square of sway magnitude

Peak Sway

Max instantaneous sway value

Mean Jerk

Rate of acceleration change (smoothness)

Path Length

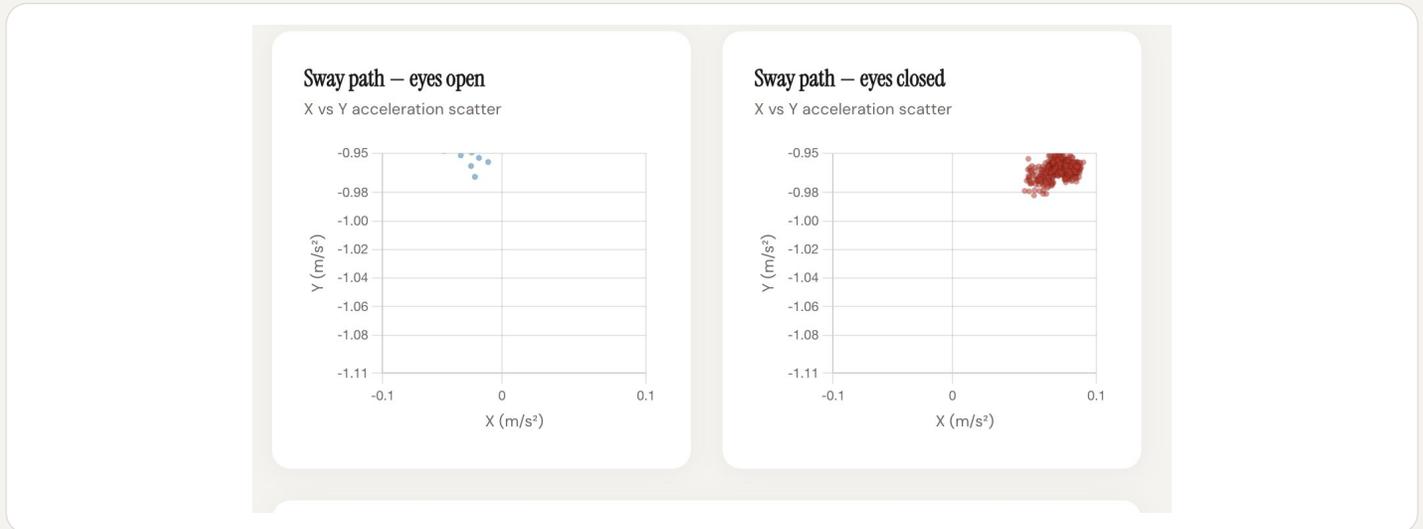
Cumulative XY displacement

Sway Area

Std_x * Std_y ellipse proxy (spread)

Romberg Q

Closed/open RMS ratio (key metric)



Sway path scatter: eyes open (left, tight cluster) vs. eyes closed (right, wider spread)

Smartphone vs. Clinical Posturography

Can consumer accelerometers approximate lab-grade balance assessment?

Research thesis

Consumer smartphone accelerometers have reached sufficient precision to approximate clinical posturography for screening purposes, but significant validation gaps remain before they can replace lab-grade force plates.

Essay structure

■ Clinical gold standard

How posturography works in a clinic. Force plates (e.g. NeuroCom SMART Balance Master) measure center-of-pressure at 100Hz+. The Sensory Organization Test (SOT) protocol with six conditions.

■ What smartphones measure

Accelerometers capture trunk sway, not COP. Chest-mounted phone = different biomechanical signal. Tradeoff: zero cost + accessibility vs. lower precision.

■ Literature comparison

Survey studies (2015–2024) comparing smartphone IMUs to force plates. Typical correlations $r = 0.6–0.85$. Which features transfer across modalities.

■ Romberger as case study

Our pipeline demonstrates full feasibility: Sensor Logger → CSV → trim → extract → Romberg quotient → visual comparison. Map computed metrics to clinical equivalents.

■ Validation gaps

Sensor placement variability, self-administered vs. clinician-observed, phone model differences, and the fundamental issue: trunk acceleration \neq COP.

Technical next steps

→ 500+ labeled recordings

Multi-participant data collection for classifier training

→ SVM classifier

RBF kernel on 6 extracted features, in-browser or backend

→ Grouped cross-validation

Leave-one-subject-out to prevent data leakage

→ Persistent database

Store uploads with sample ID, session, label, prediction

→ Confidence scoring

Probability output instead of binary classification

Key research questions

- Q1.** How well does trunk-mounted accelerometer sway correlate with force-plate COP displacement?
- Q2.** Which extracted features (RMS, jerk, spectral) are most discriminative across both modalities?
- Q3.** Can a smartphone Romberg quotient achieve clinically meaningful sensitivity/specificity (>80%)?
- Q4.** What minimum sample size produces a generalizable classifier across age, height, and phone models?