Data Storytelling: Problematic Internet Use in Children

GROUP 1

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BIG IDEA

"In this project, the main character is not the ML model, but the data preparation."

We will see how step-by-step data preparation – from raw, imbalanced, noisy data – changes the quality of models and insights for decision makers.

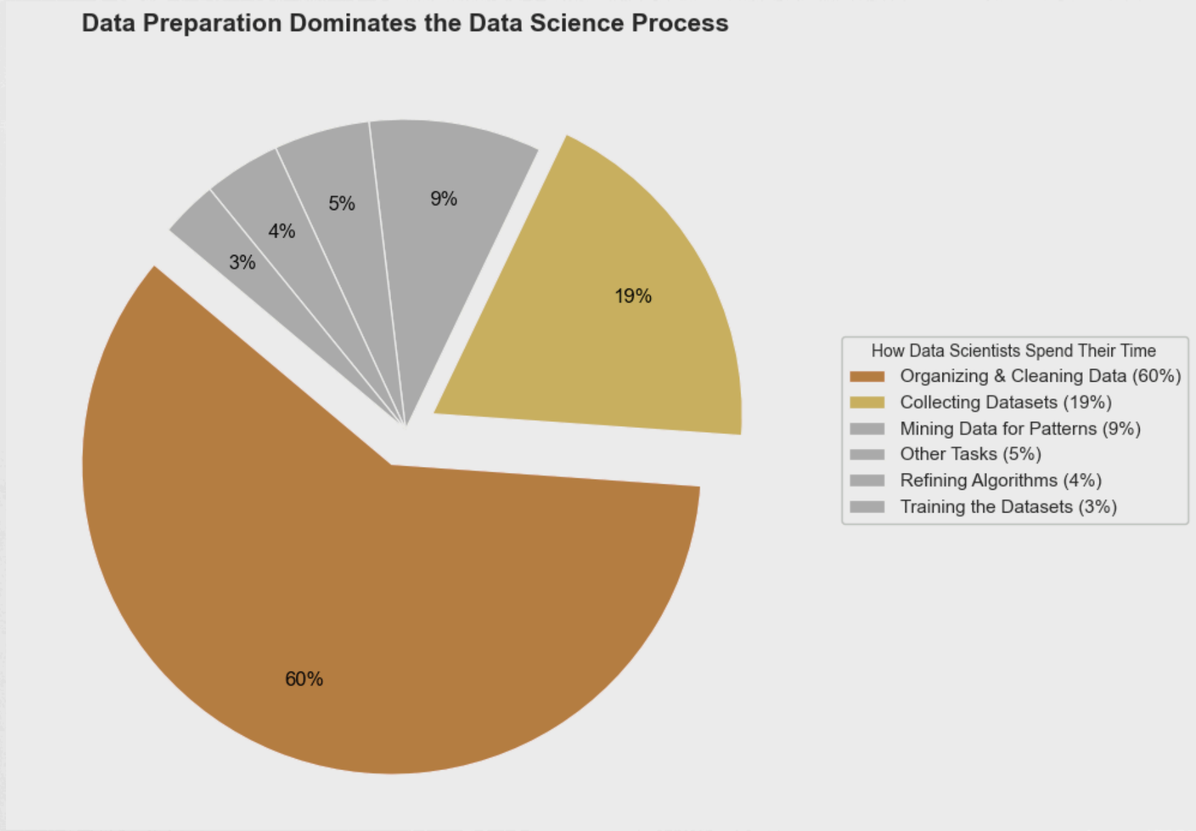
Before talking about models, let's talk about data

60–80% of a data scientist's time is spent on data collection & standardization

Source: multiple industry surveys on data scientist workflows

Garbage in, Garbage out

Good data preparation not only increases accuracy, but also clarifies the 'voice of the data'.

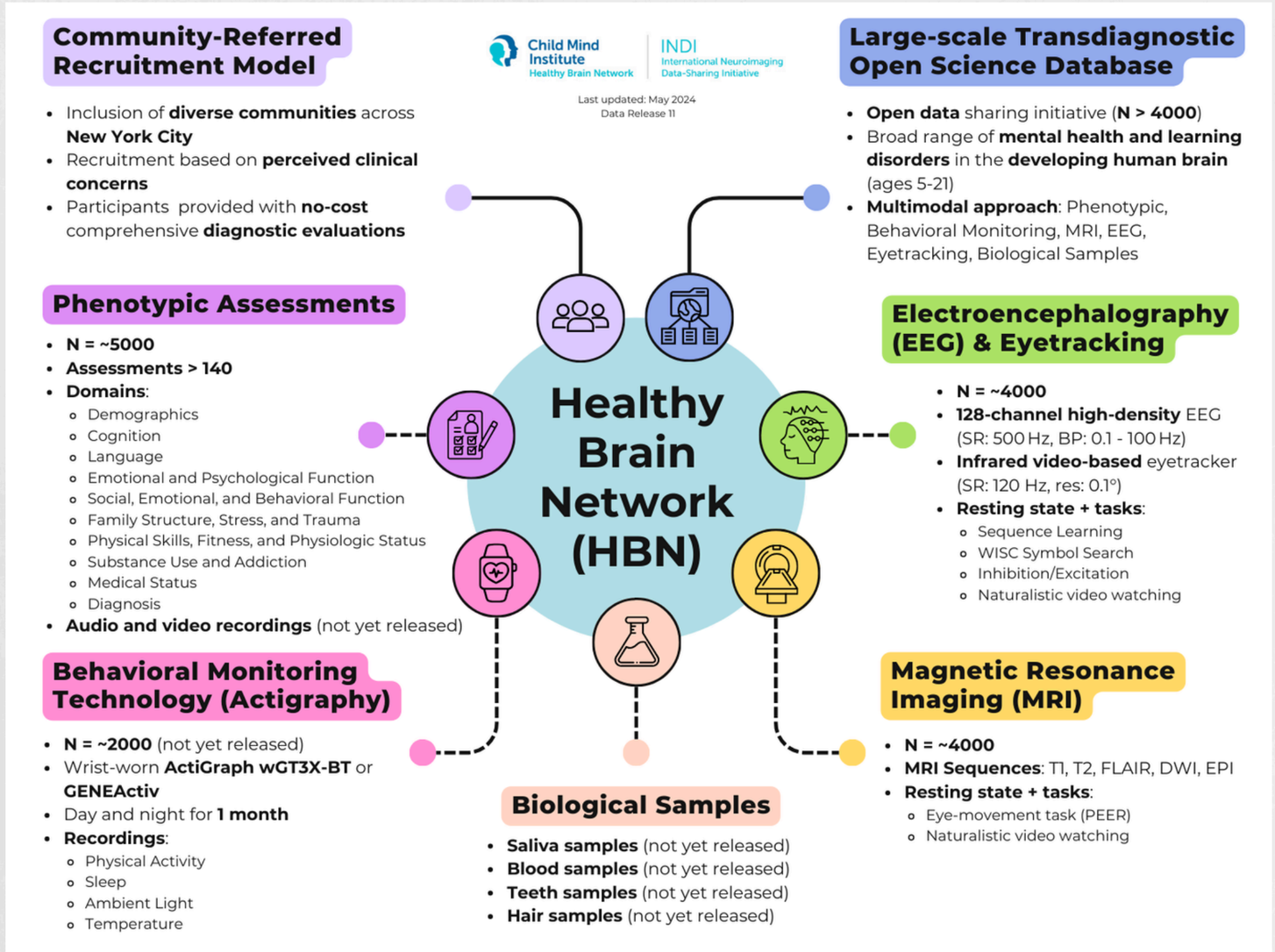


We choose dataset captures the daily lives of children and adolescents — across behaviour, routines, and mental health

Child Mind Institute

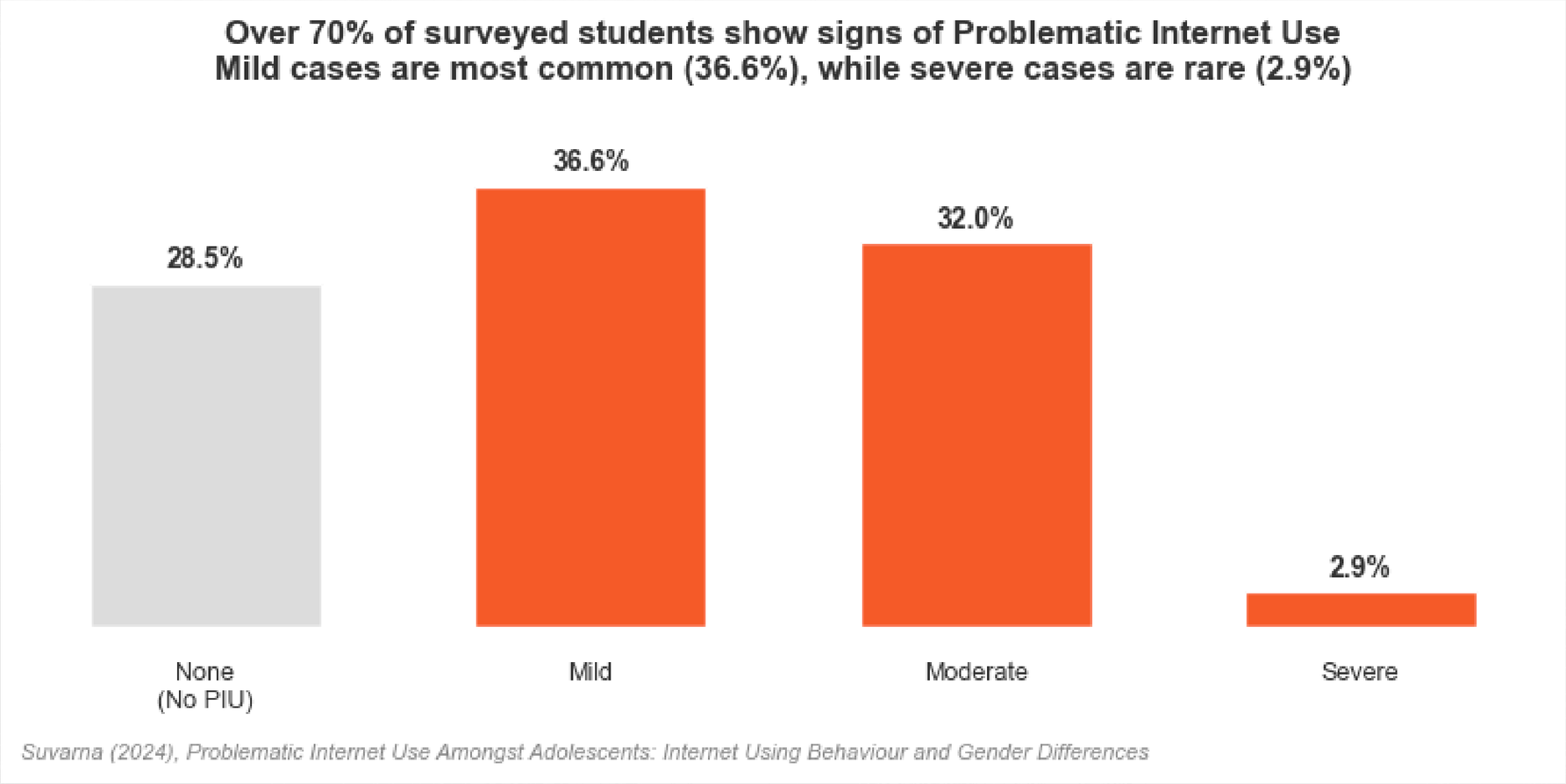
Data Provider

The competition



How serious is Problematic Internet Use today?

A 2024 study published in the **International Journal of Indian Psychology** examined a sample of 610 adolescents aged 12 to 19 and revealed an unexpected prevalence of problematic internet use (PIU).



What components combining to our dataset?

Dataset Overview: Two Data Sources

TABULAR DATA

82

columns

3,960

training observations

20

test observations

ACTIGRAPHY DATA

13

time-series columns

213,423

timesteps per participant
(5-second intervals)

3,960

individual time-series files

Our story is about how messy human data becomes meaningful through preparation.

WHO

Data Scientist

Parents

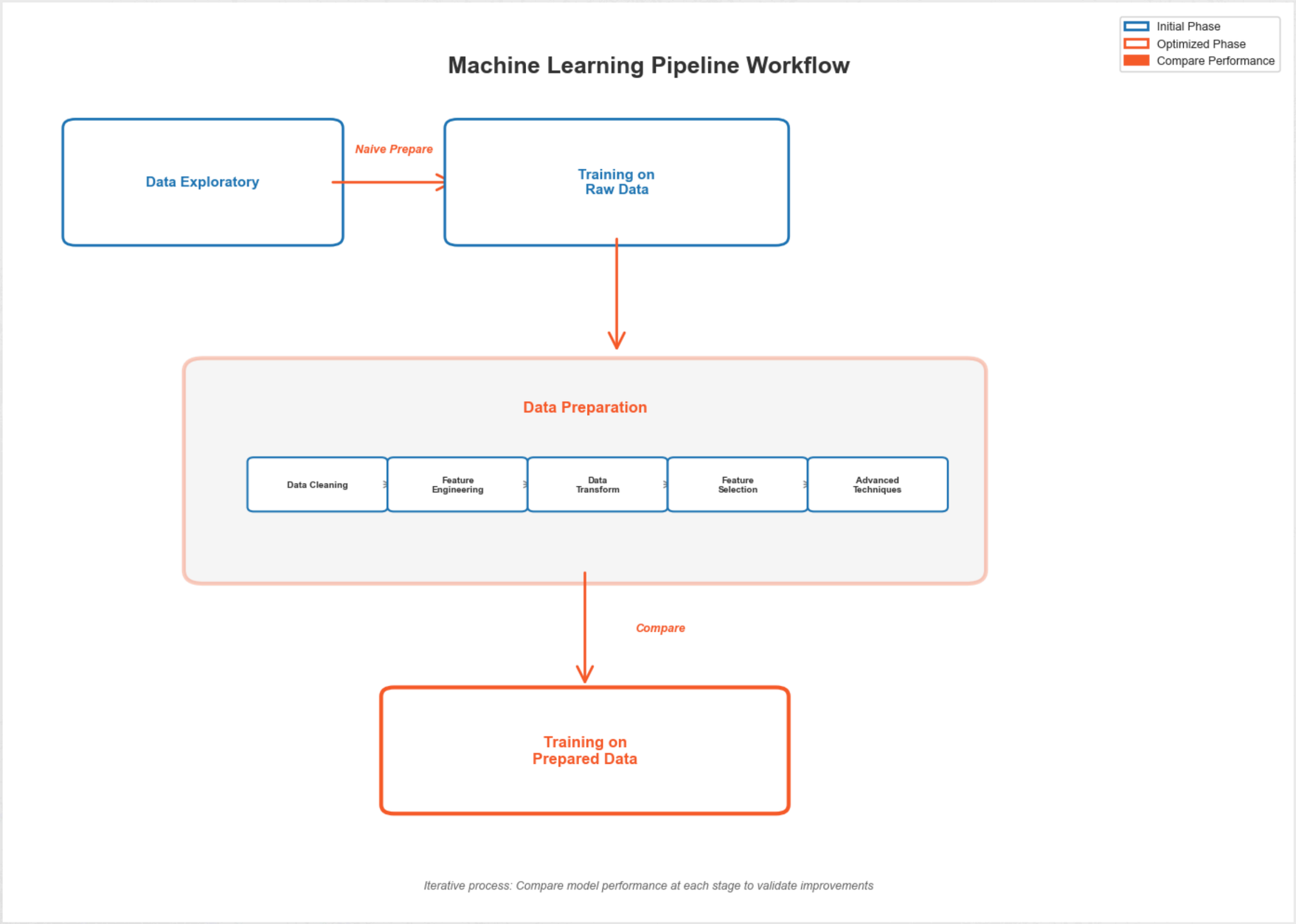
WHAT

Emphasize the difference before and after data preparation:

- *The same prediction task: identifying problematic internet use*
- *A model trained on raw data vs. a model trained on prepared - data*
- *How class distribution, error rates, and recall at higher severity level change dramatically*

Our story is step-by-step

HOW

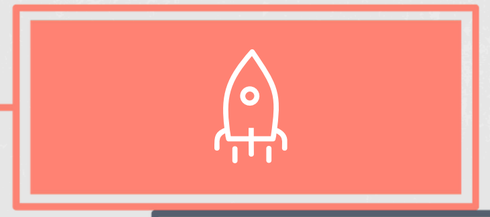


Storytelling strategy: Our story combines two interwoven storylines

Main Story: The technical storyline

Additional Story: The insight storyline

Intro & Context



Tension

"Introduce conflict to keep people engaged."

Source: Cole, Storytelling with data

Resolution

"Resolve the tension by showing how your solution changes the world."

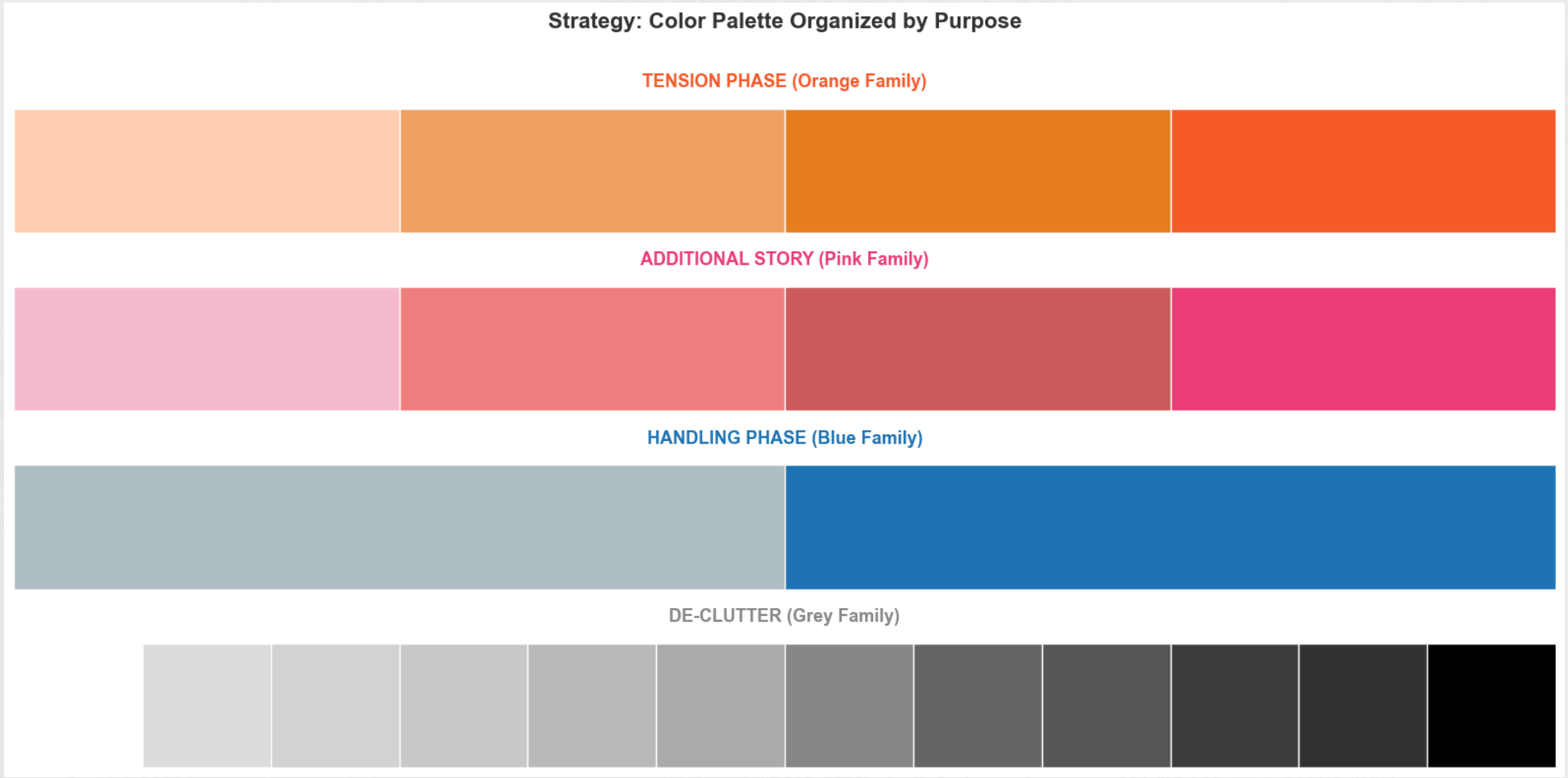
Source: Cole, Storytelling with data

Compare & End

"Humans understand contrast better than absolute numbers."

Source: Cole, Storytelling with data

Storytelling strategy: Color using



Storytelling strategy: *"Charts are not the story - they are the evidence."*

Visual titles must contain an actionable message, answer: "So what does this show?"

Visuals should be clean and minimal, using only one highlight color to direct attention.

Storytelling strategy: Progressive Reveal

Avoid overwhelming your audience with too much information at once.

Reveal the story gradually, following a clear and logical sequence.

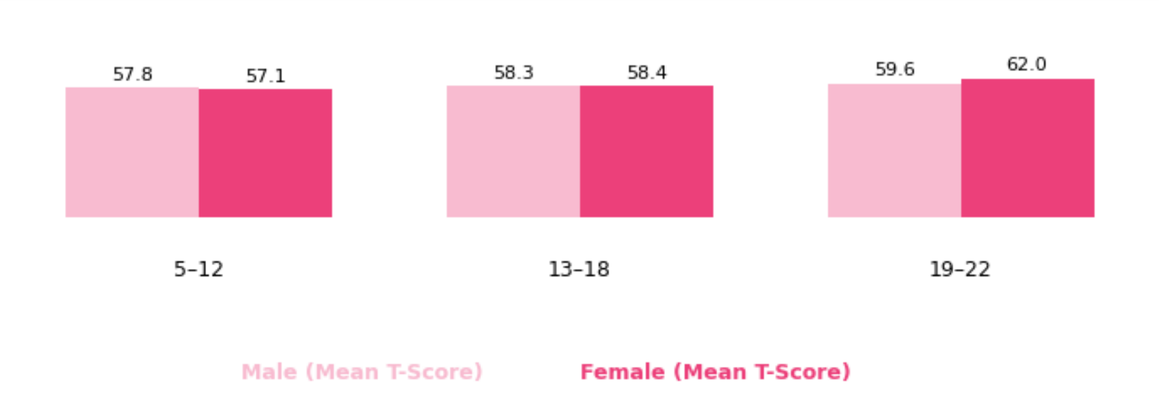
In our narrative, we move from data → problem → insight → model, and only then to solution → transformation → outcome. This progression reflects the natural arc of an effective data story.

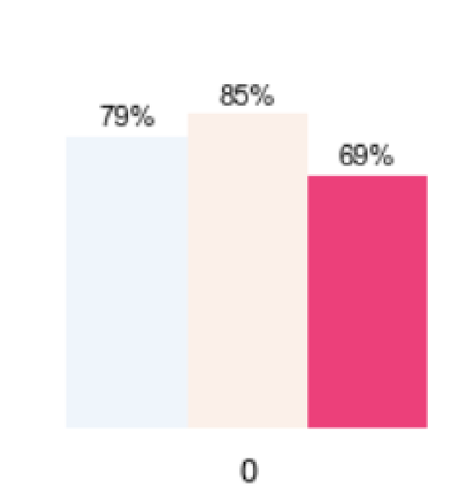
Storytelling strategy: Eliminating clutter

We intentionally remove anything that does not directly support the message

We eliminate unnecessary gridlines, borders, shadows, and decorative elements.

We also avoid heavy color usage, relying instead on a clean white background for both slides and charts, which reduces visual noise and keeps attention on the data itself.

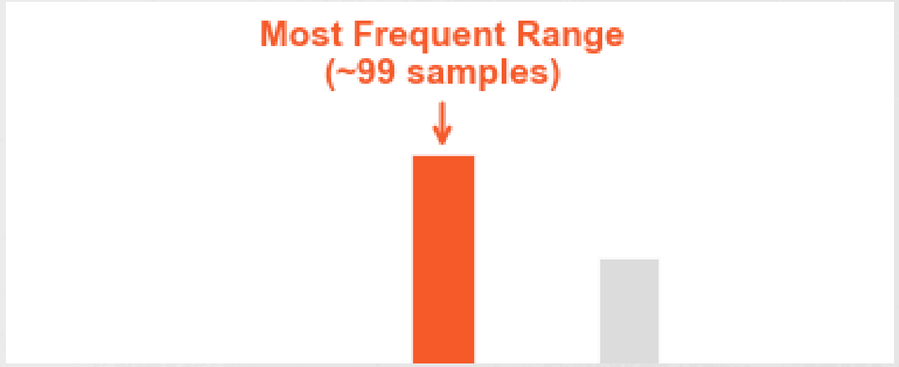




- Only one highlight color is used to direct focus, while all other elements remain neutral.
- Labels are placed directly on the visual whenever possible to avoid forcing the audience to decode legends.
- We simplify axes, reduce ink, tighten spacing, and ensure that each chart communicates a single, unambiguous point.

Storytelling strategy: Annotation

Write the insight directly on the chart.



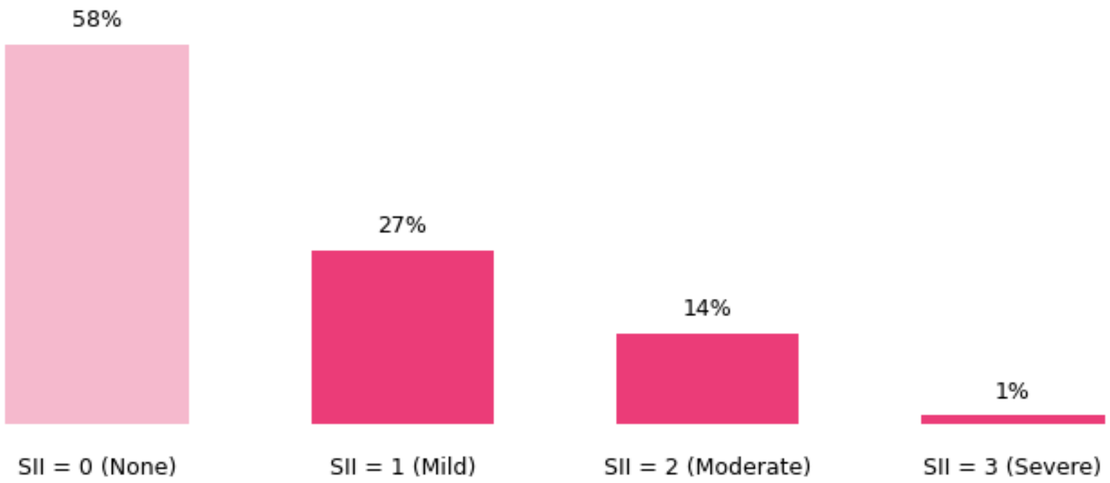
Annotations highlight the exact insight we want the audience to see.
By labeling data directly on the chart and placing explanations where the eye lands, we remove ambiguity and reduce cognitive load.

Additional storyline

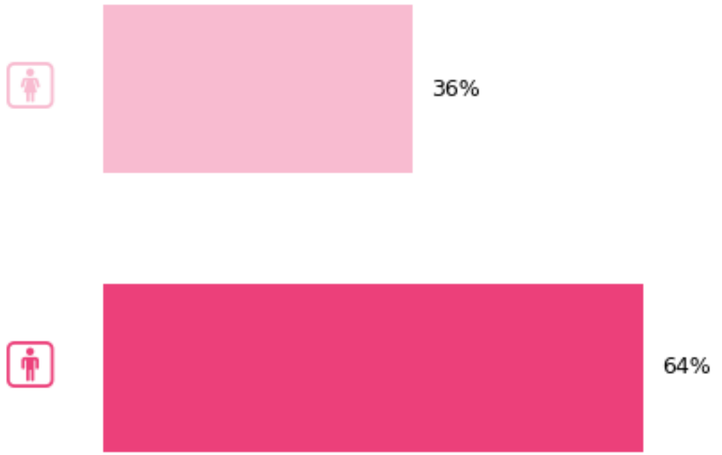
The storyline explain what the data reveals, therefore, creating the complete narrative of our work.

Problematic Internet Use patterns differ sharply by severity level, age group, and gender

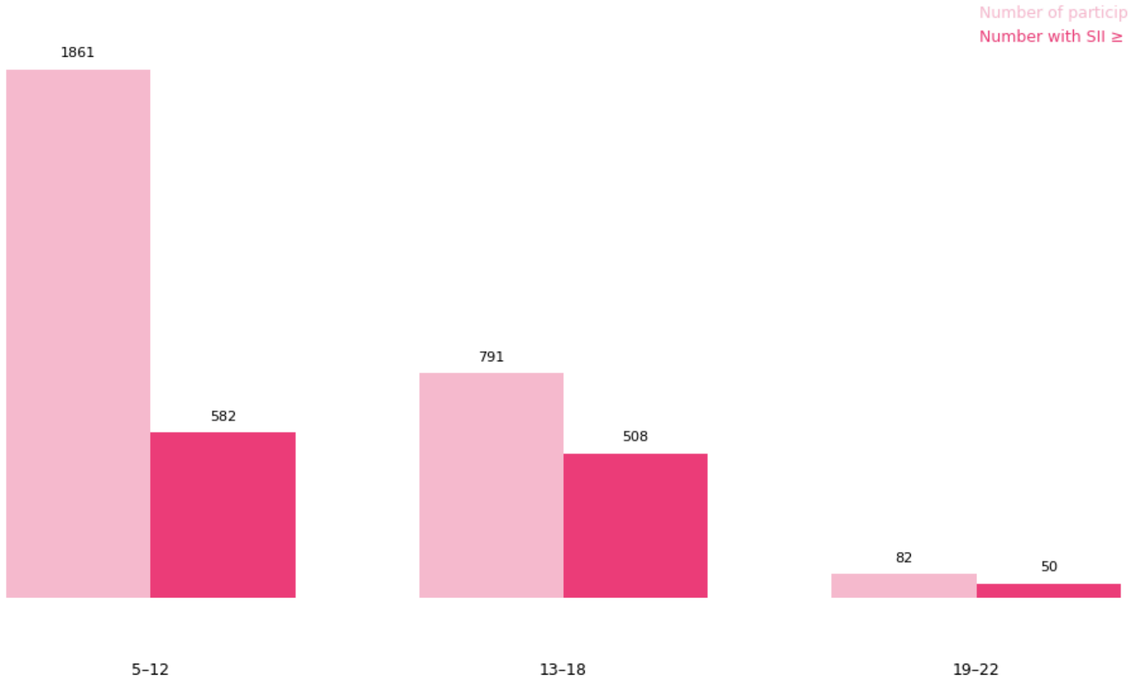
Severity distribution: higher SII levels are progressively rarer



Male make up the larger share of the sample



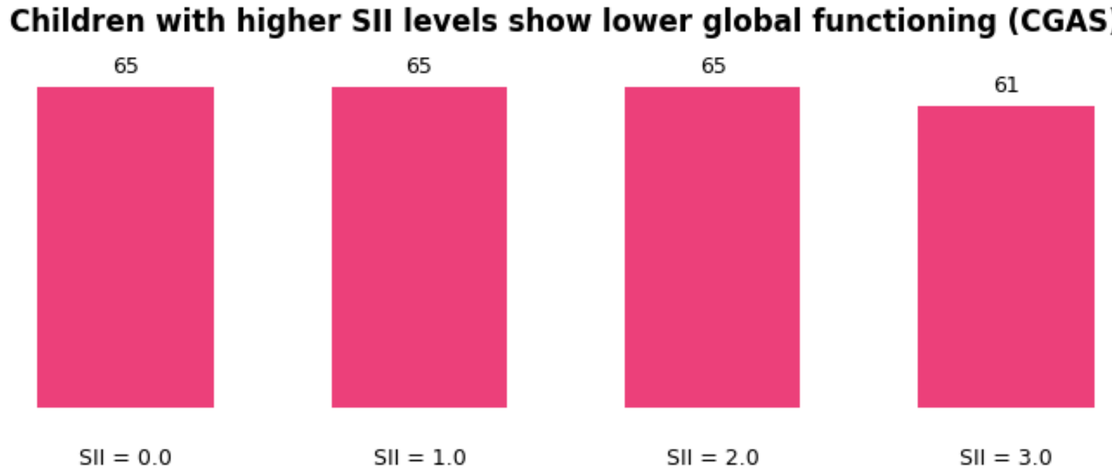
Problematic Use Becomes More Common in Older Age Groups

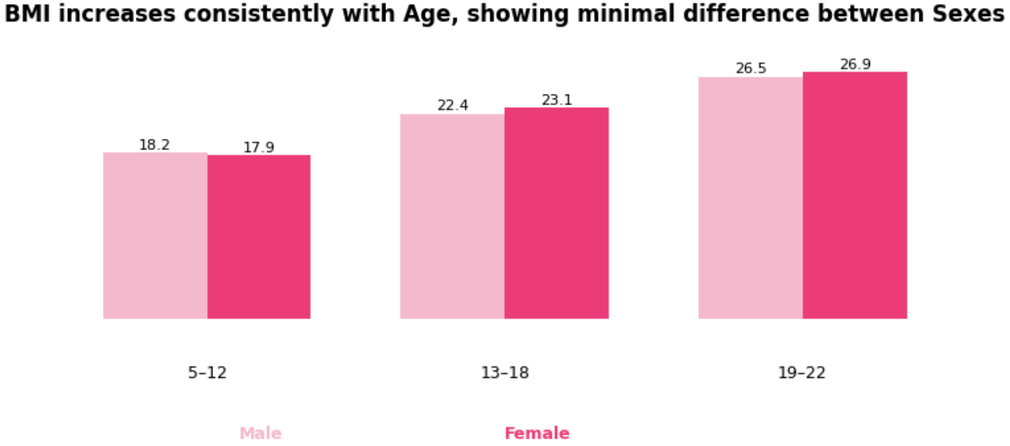


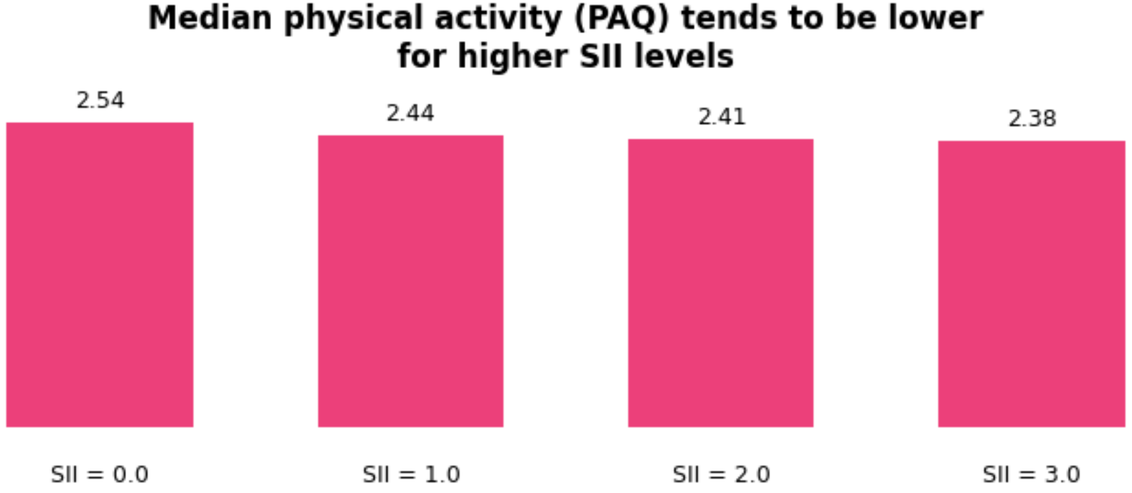
Share of children with problematic internet use (SII ≥ 1)
Visualised separately for boys and girls

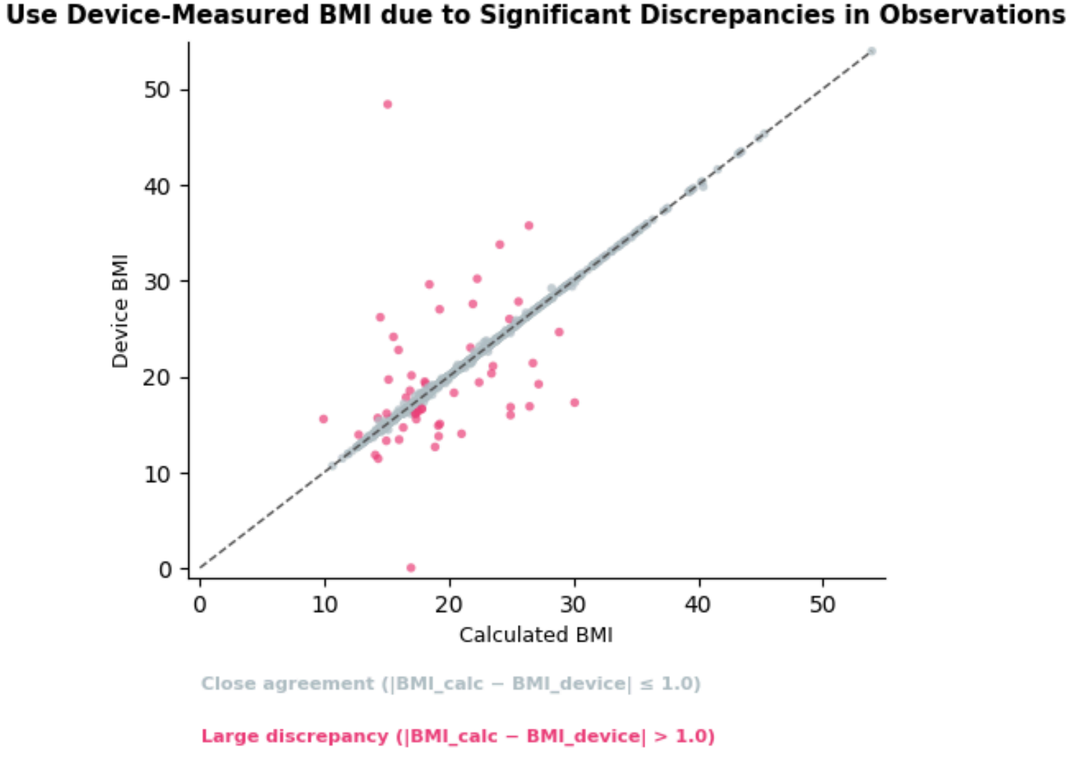
PIU

Physical and Behavioral Indicators Shift Systematically with PIU Severity — Reinforcing the Need for Reliable Measurements

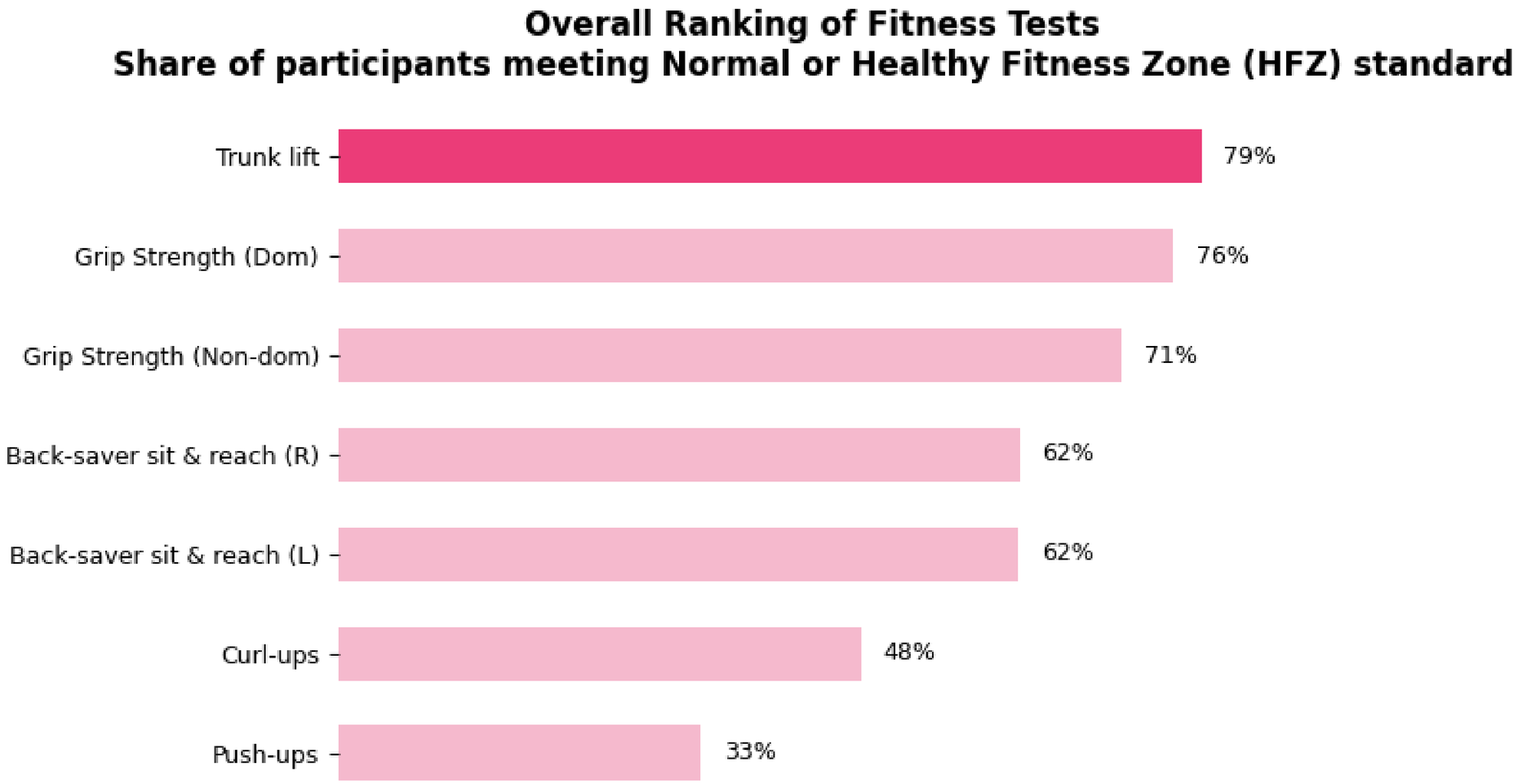




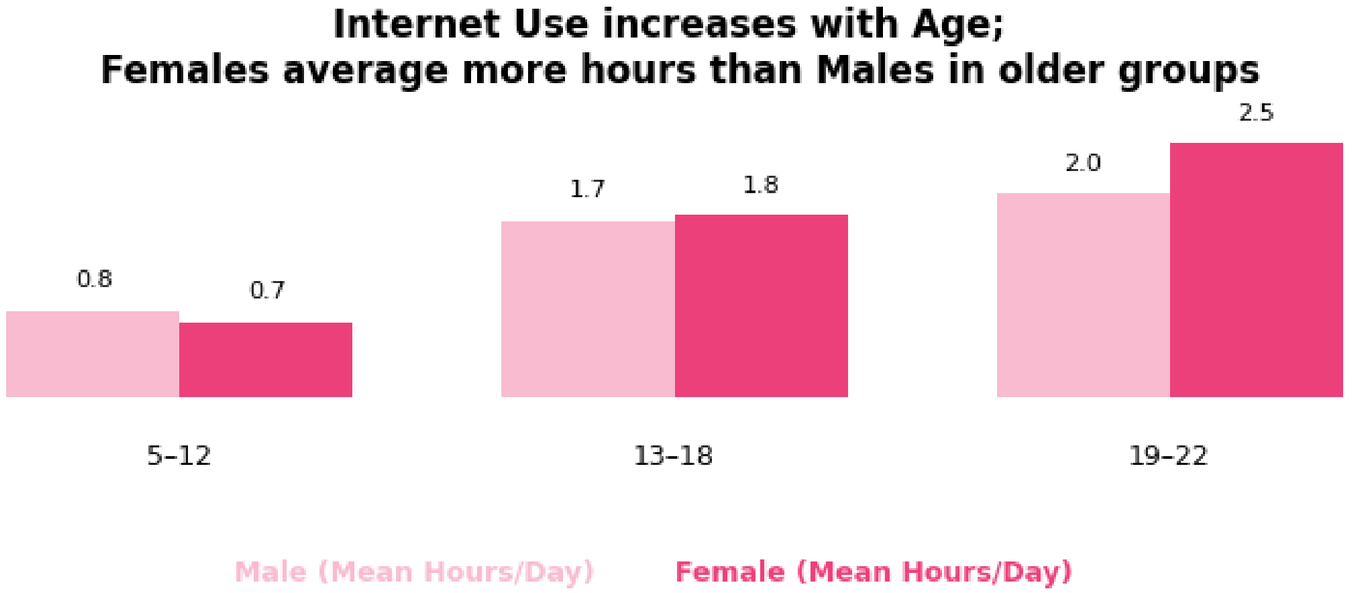


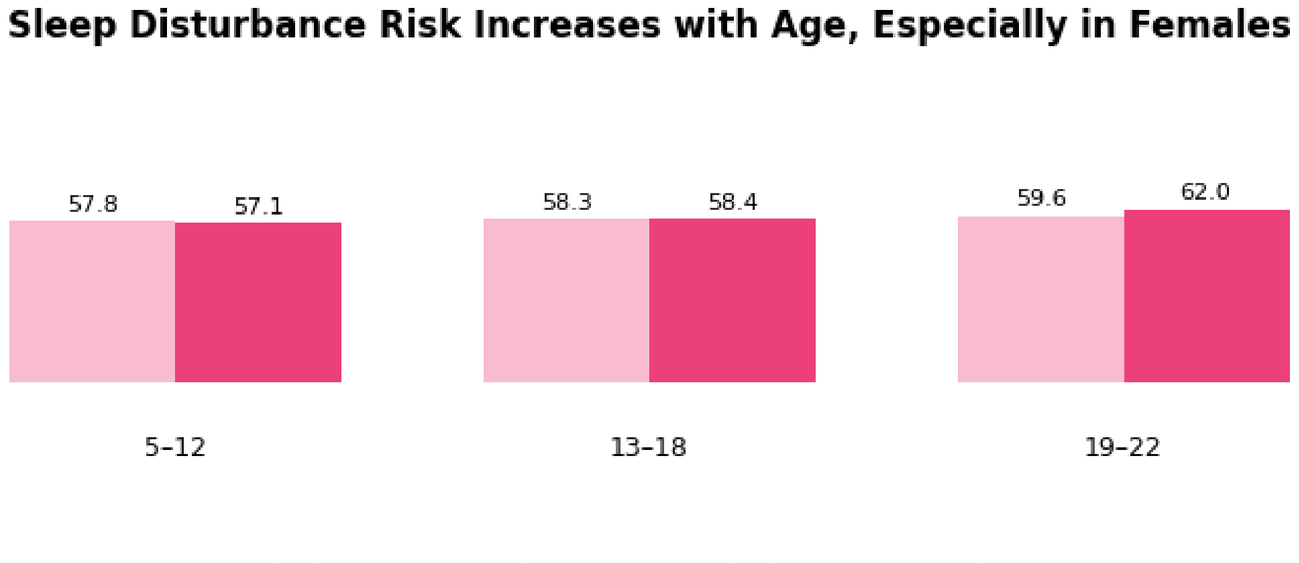


Most Participants Meet Basic Flexibility Standards, But Strength Tests Remain Challenging



Older Adolescents Show Higher Internet Use and Greater Sleep Disturbance, Most Noticeably in Females





Tension phase

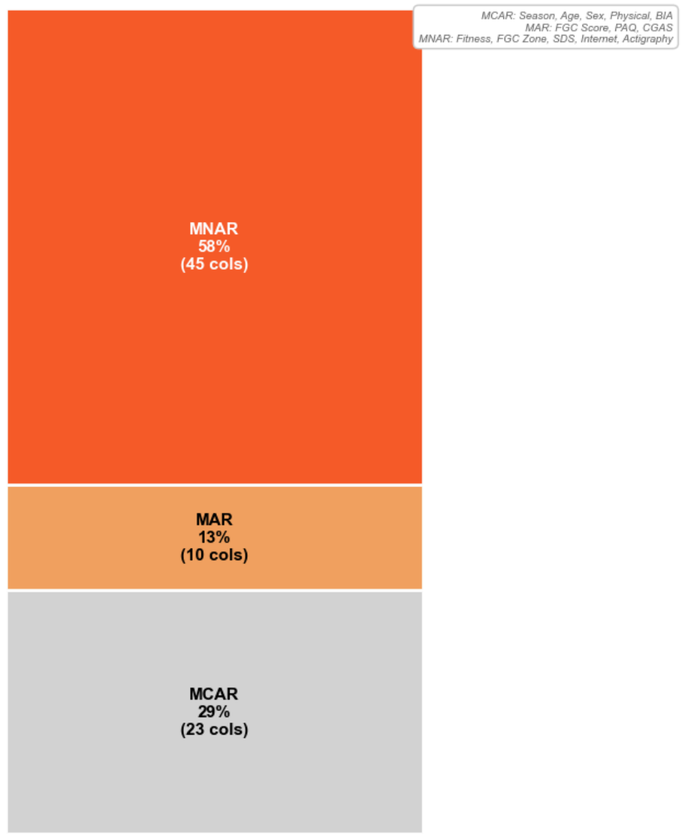
Tension drives the need for transformation.

Missingness is severe, widespread, and mostly Non-Random, creating a major modeling risk

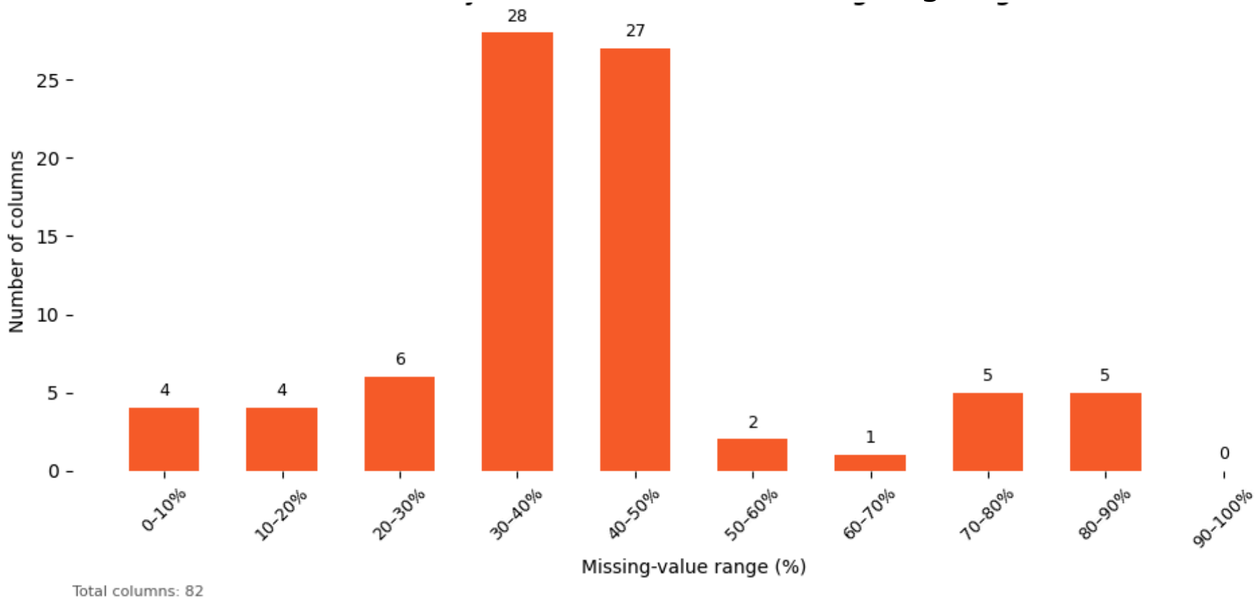
78/82

columns have missing values

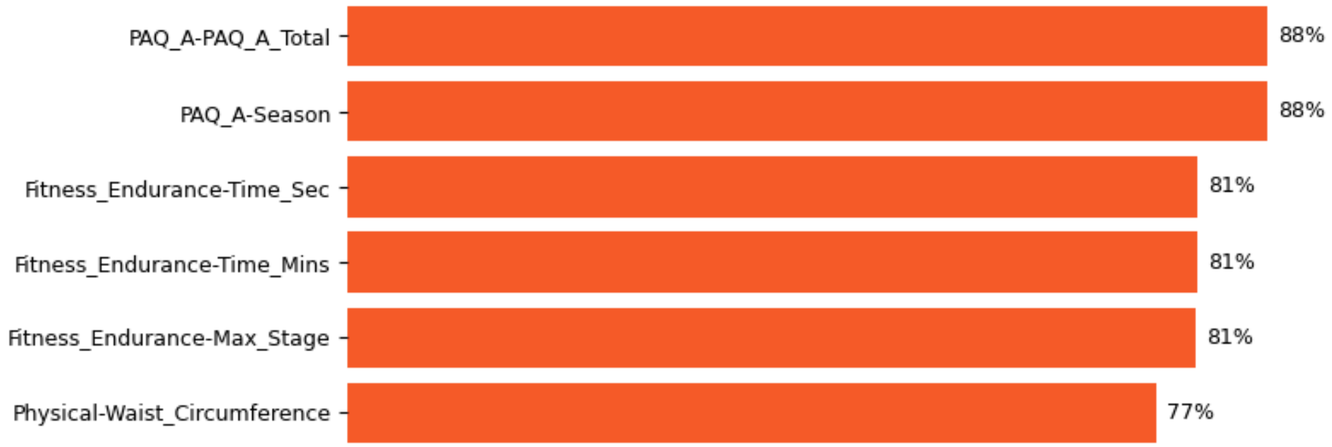
Most missing data is MNAR (58%), requiring careful handling
MAR accounts for 13%, while MCAR is 29%



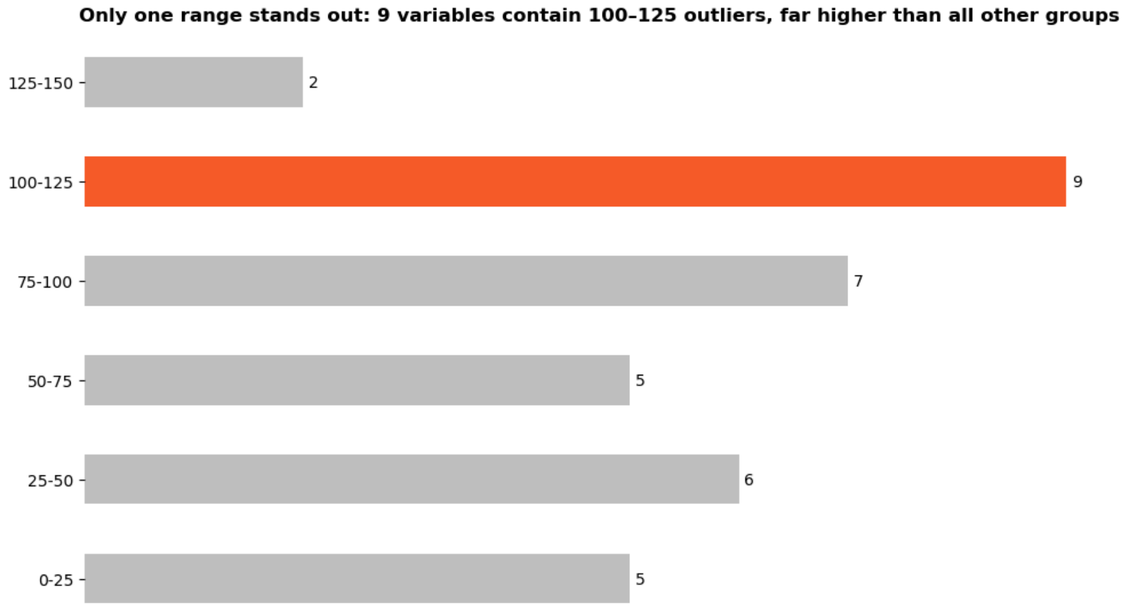
Over 30% of columns have >50% missing

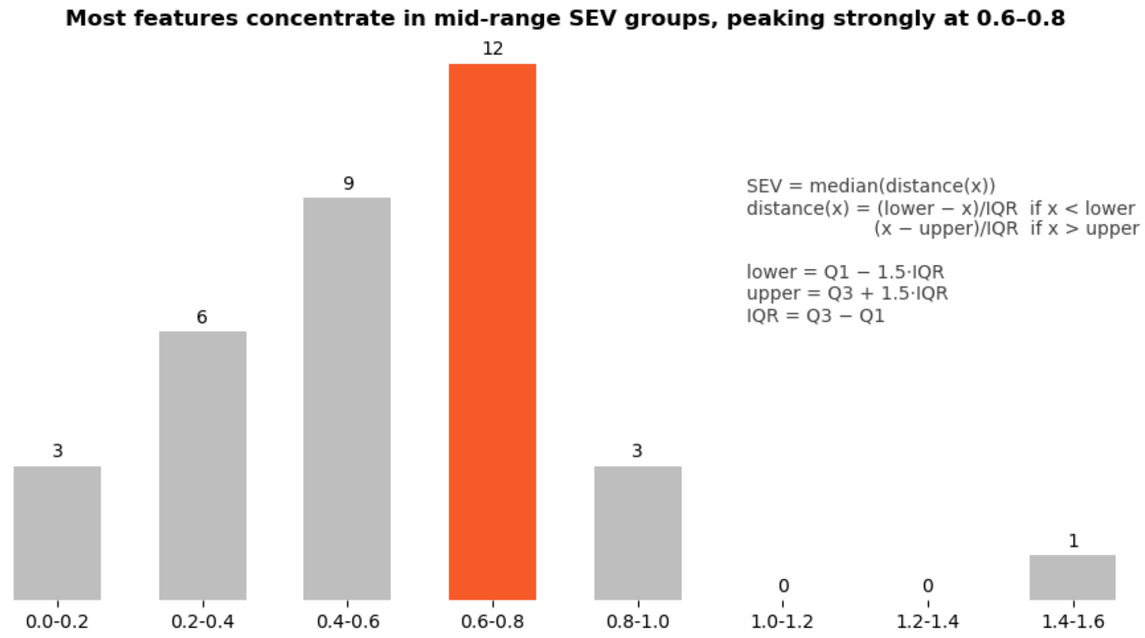


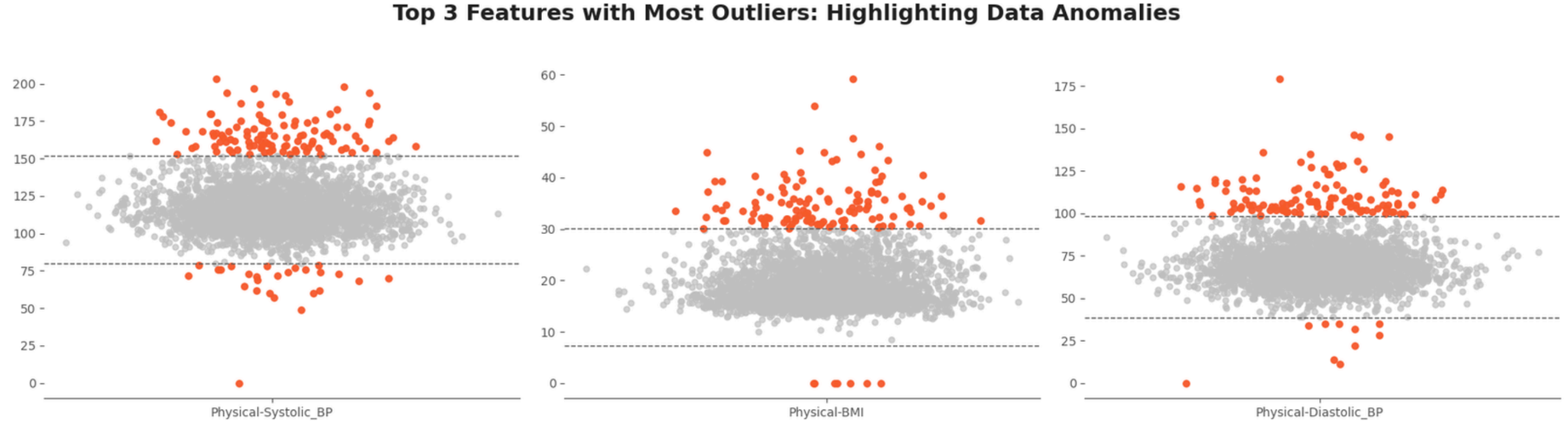
6 columns with more than 75% missing values



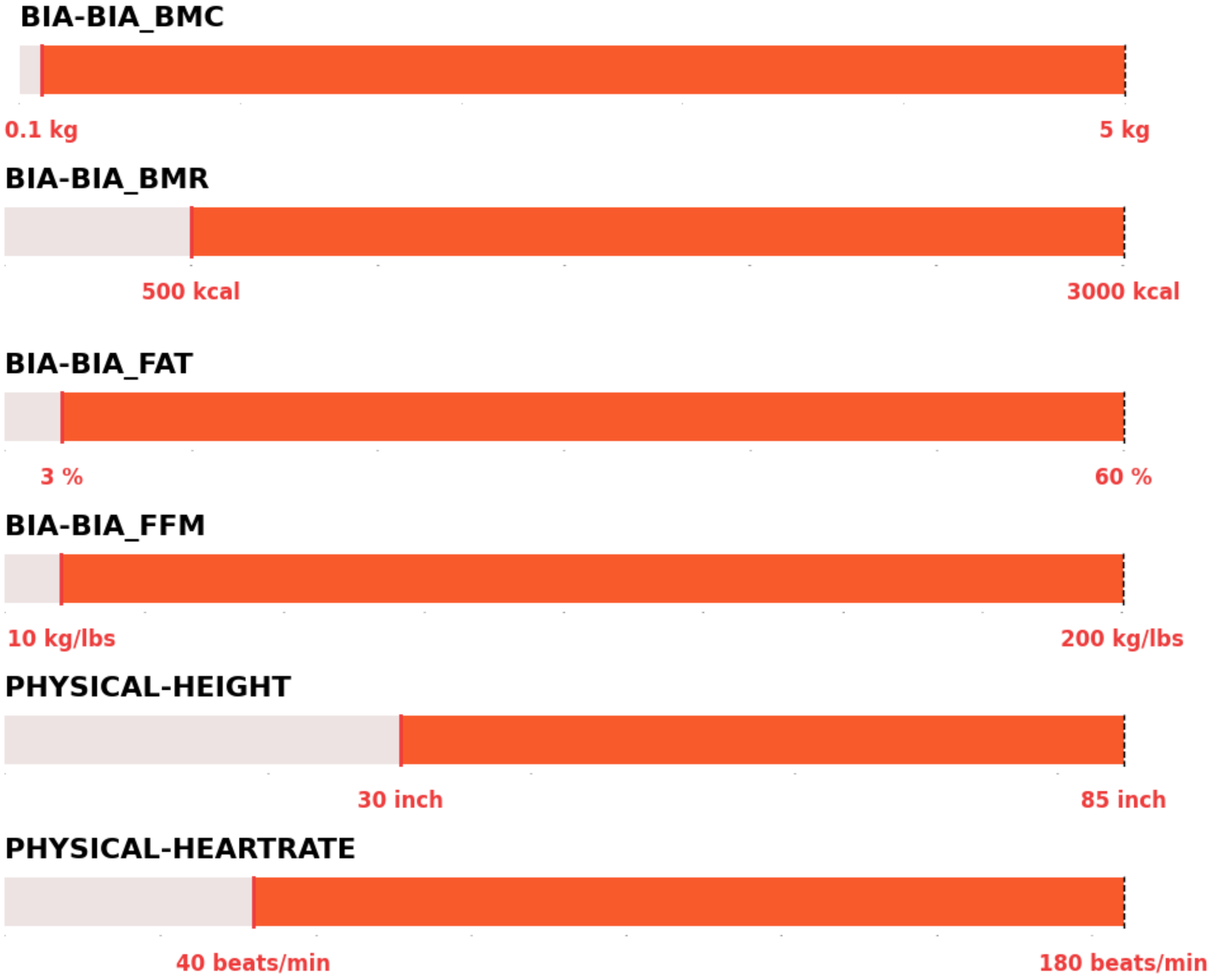
Outliers are concentrated and severe — Distorting key physical measures



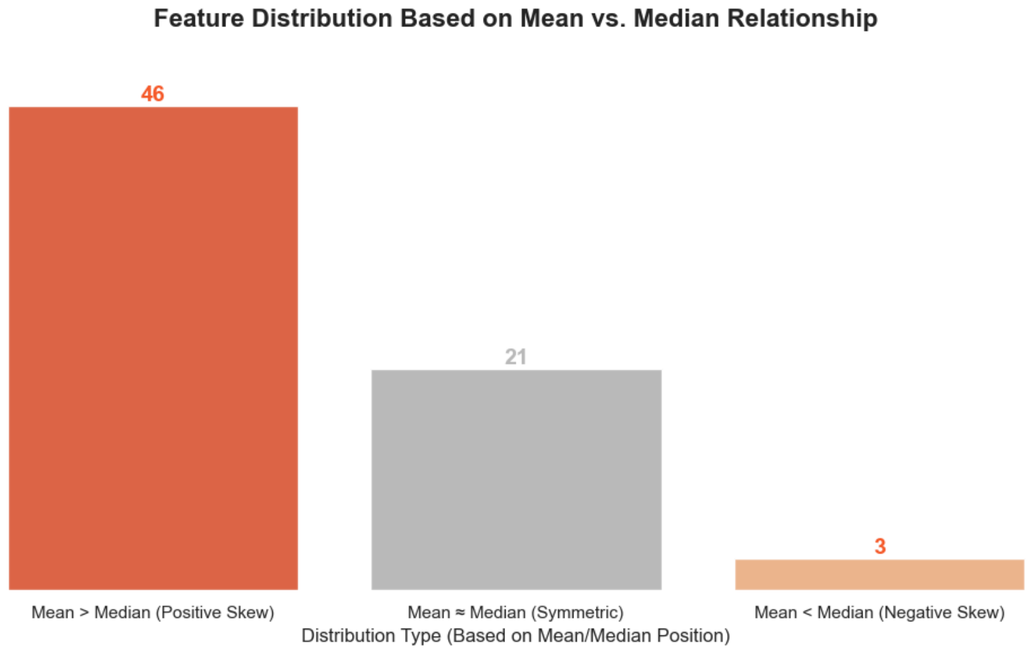


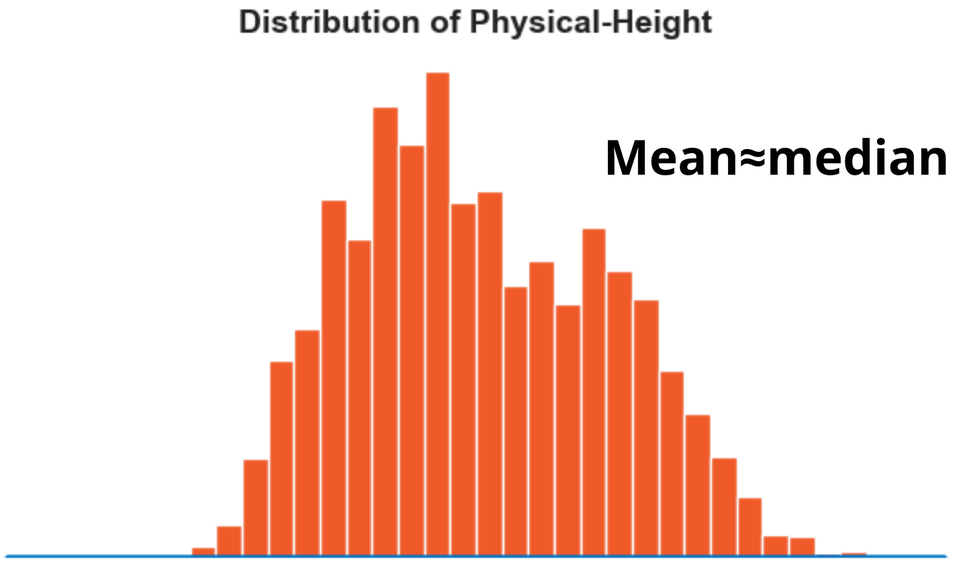


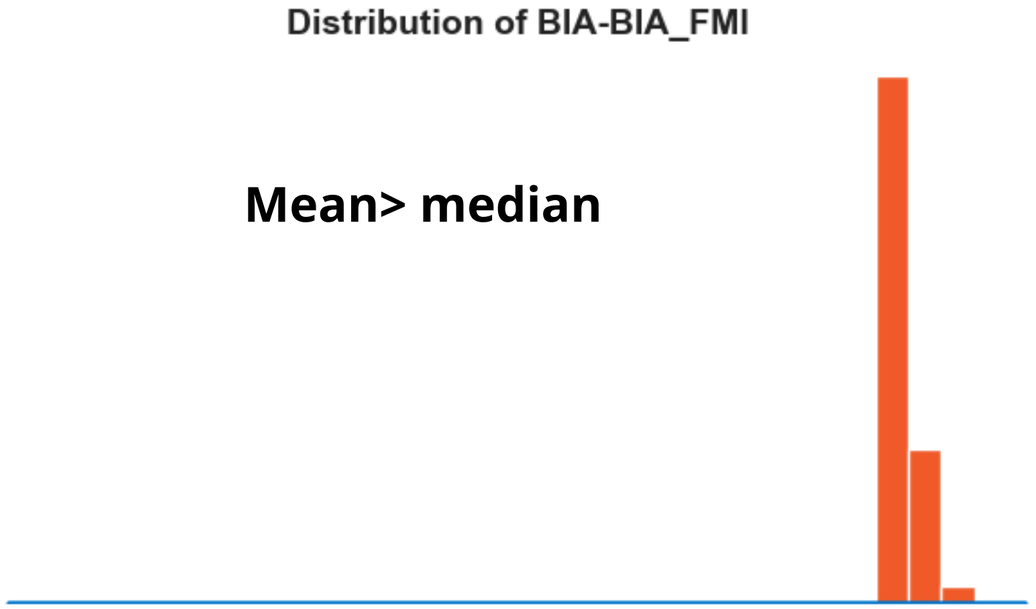
ILLOGICAL DATA



Most features are strongly positively skewed - requiring transformation before modeling







Most participants have no actigraphy data — Leaving a critical signal missing

This missingness is non-recoverable: no sequences exist for 1,740 participants.

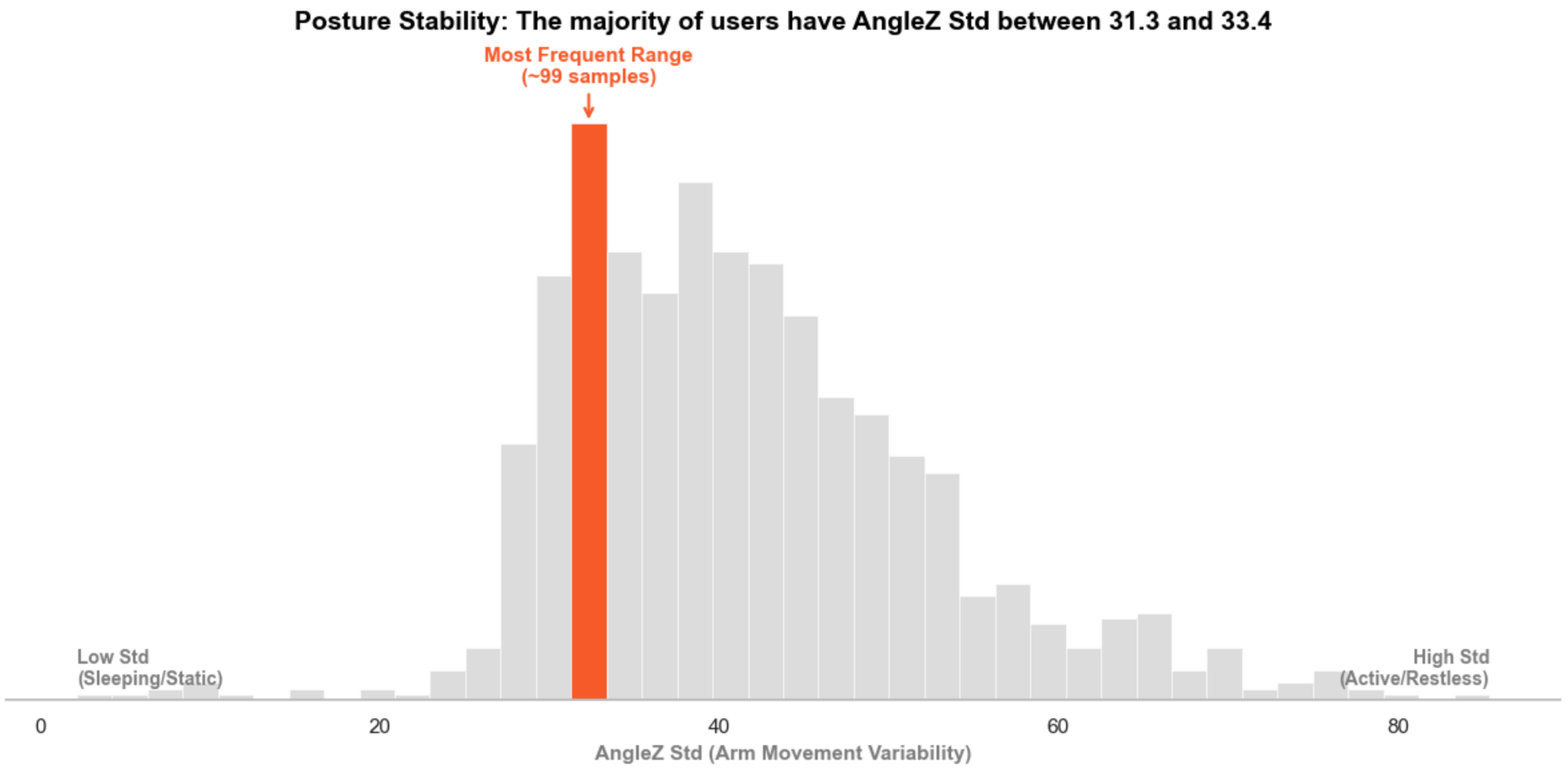
63.6%

1,740 out of 2,736 IDs

of participants have no actigraphy data

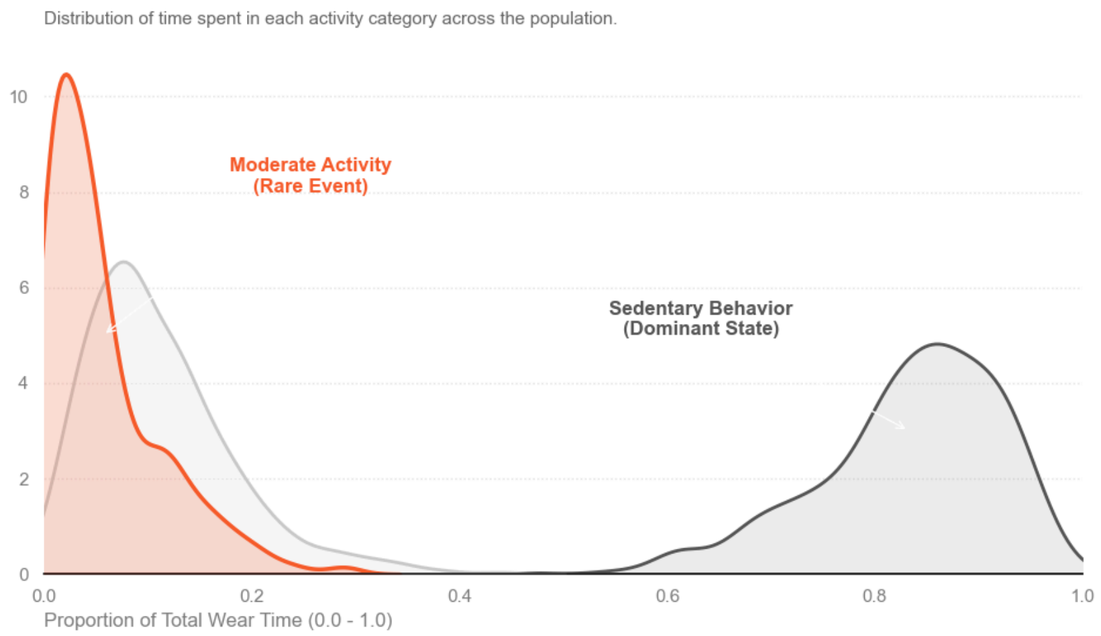
are missing all actigraphy measurements

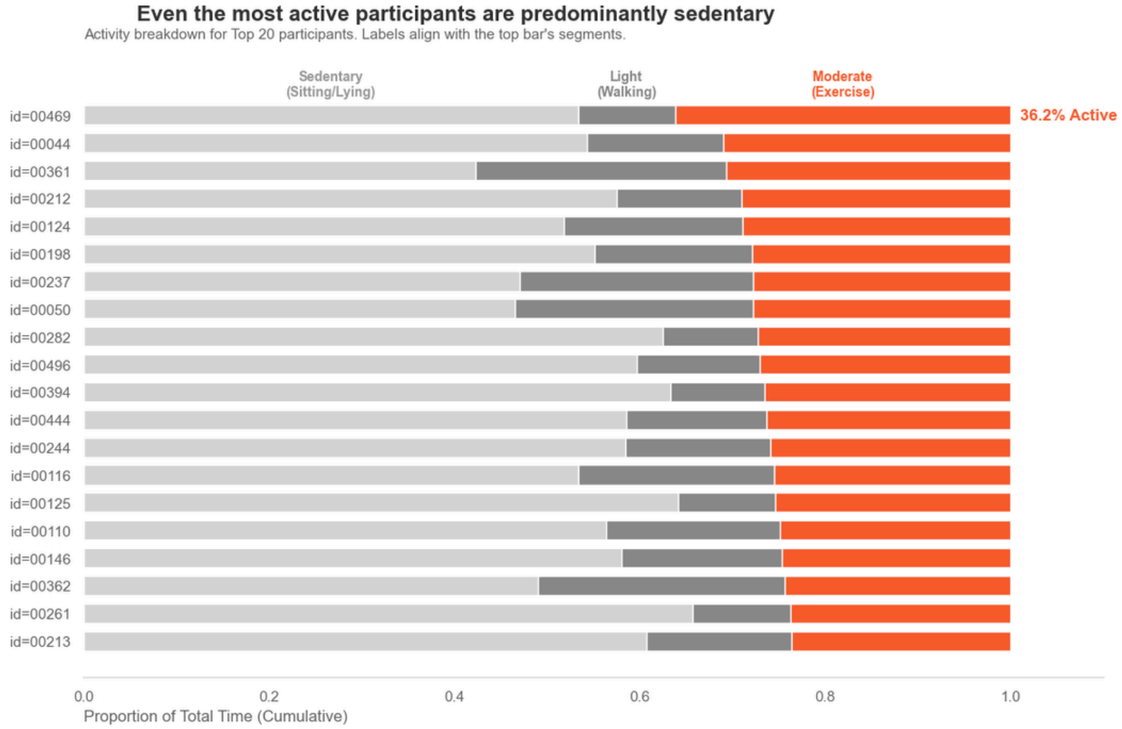
Most participants show moderate movement variability — Reflecting stable daily posture patterns



Sedentary Behavior Dominates: Moderate Activity Is Rare in Raw Actigraphy Data.

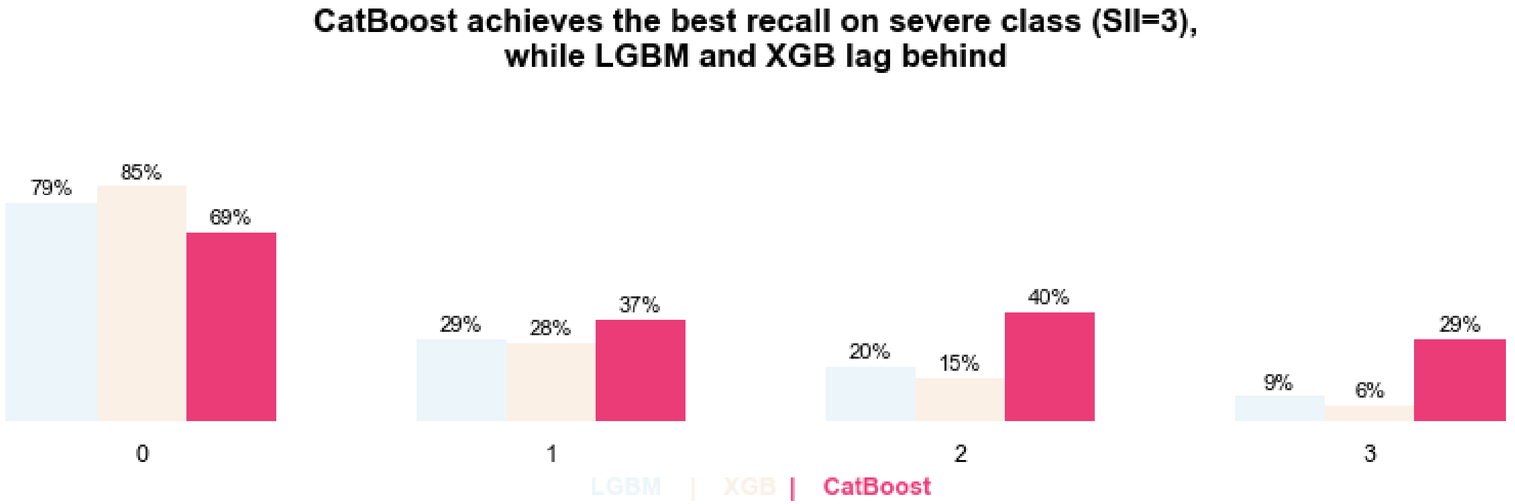
Participants spent about 85% of wear-time in sedentary states

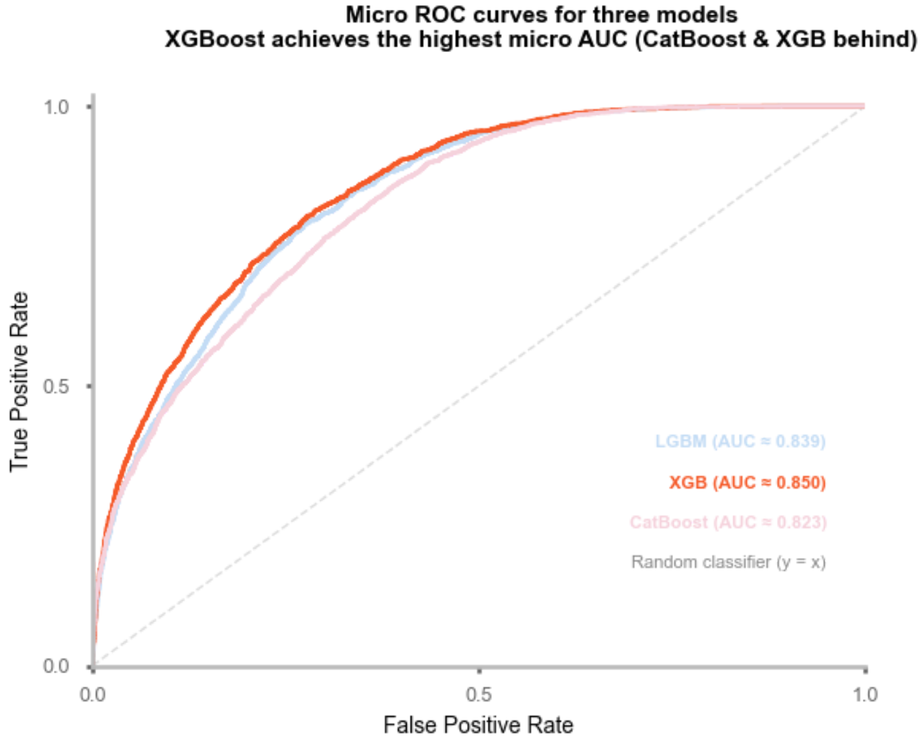




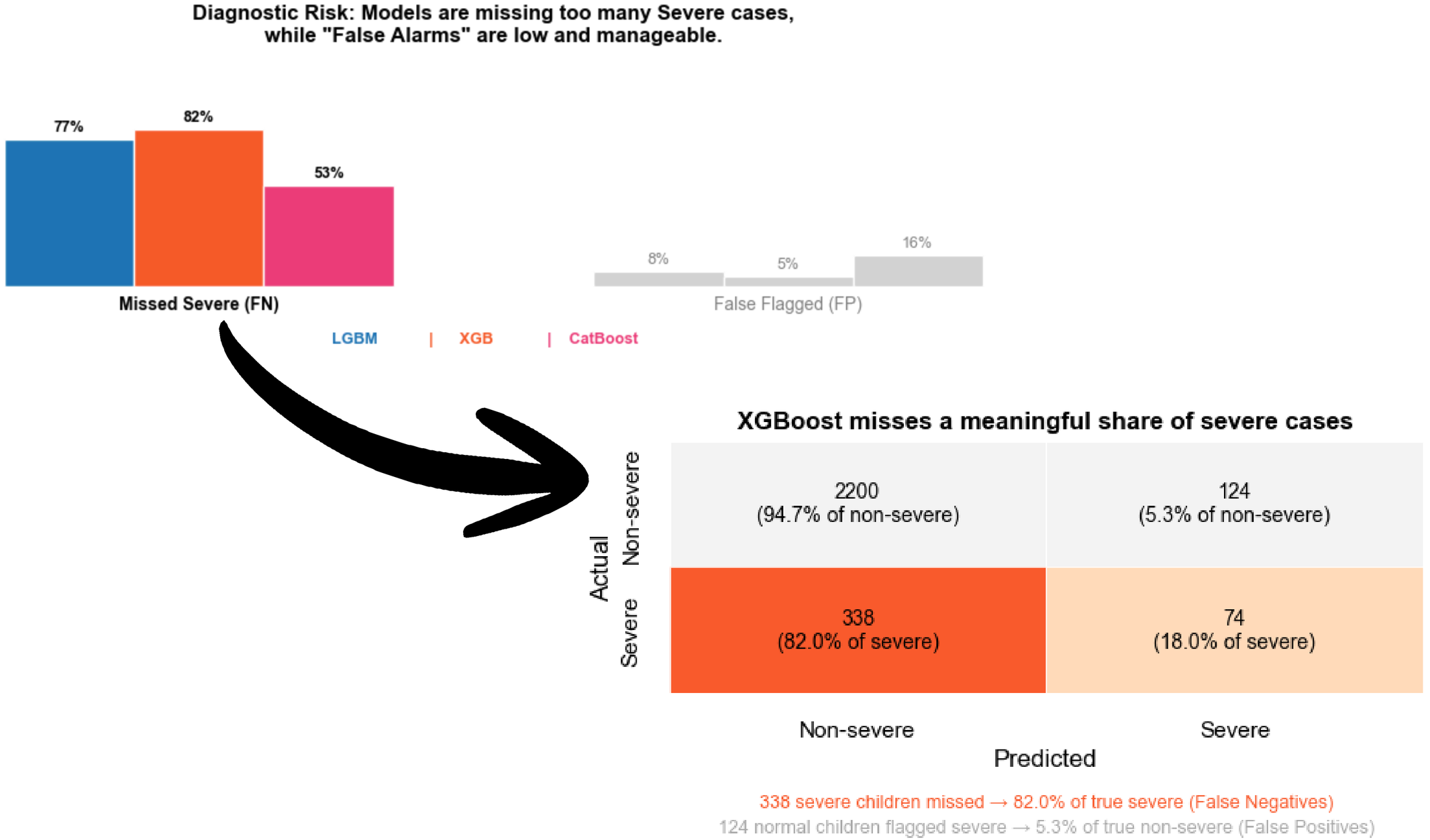
Raw actigraphy reveals imbalanced daily activity patterns — a behavioral signal that requires careful preparation

CatBoost Excels on the Most Critical Class (SII=3), While XGBoost Leads in Overall AUC.



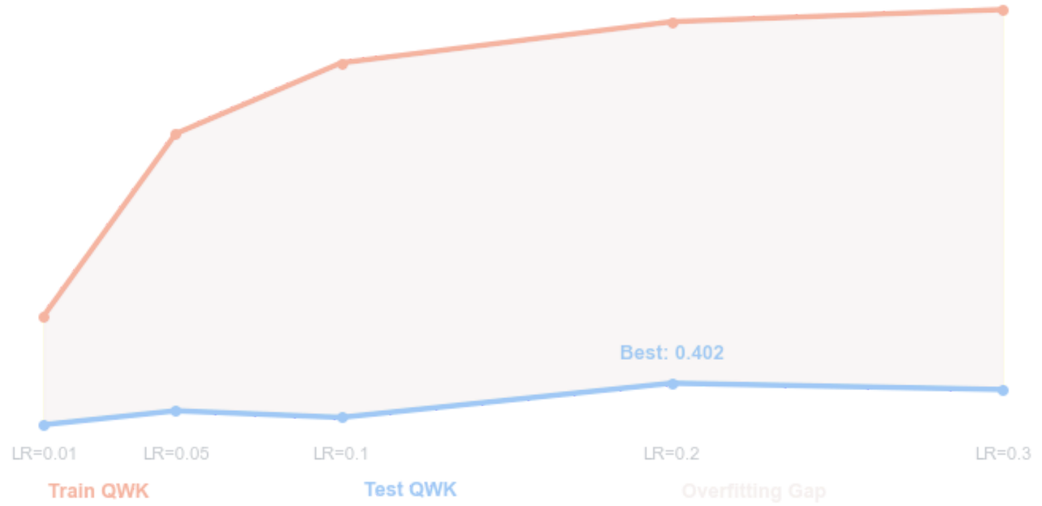


The Most Dangerous Errors Are the Ones We're Making the Most: Missing the Severe Cases

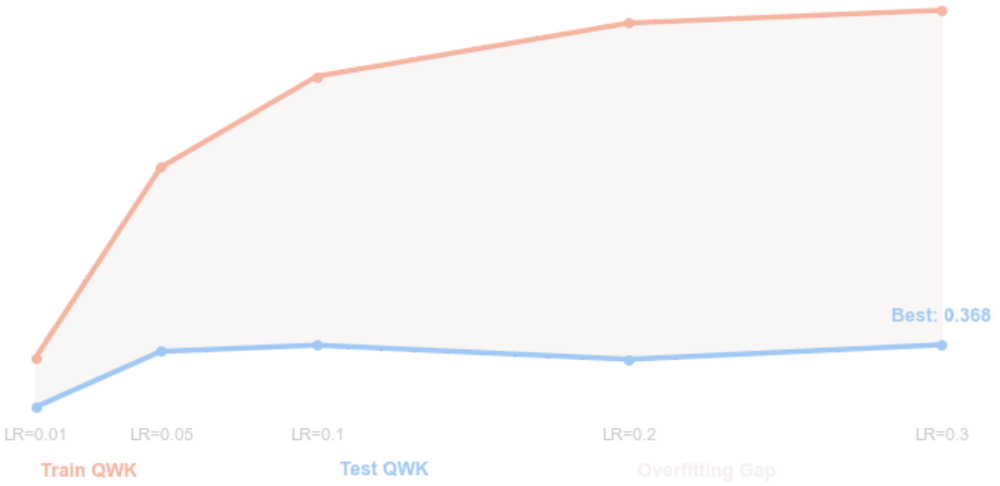


All Models Suffer From Significant Overfitting, Especially as Learning Rate Increases.

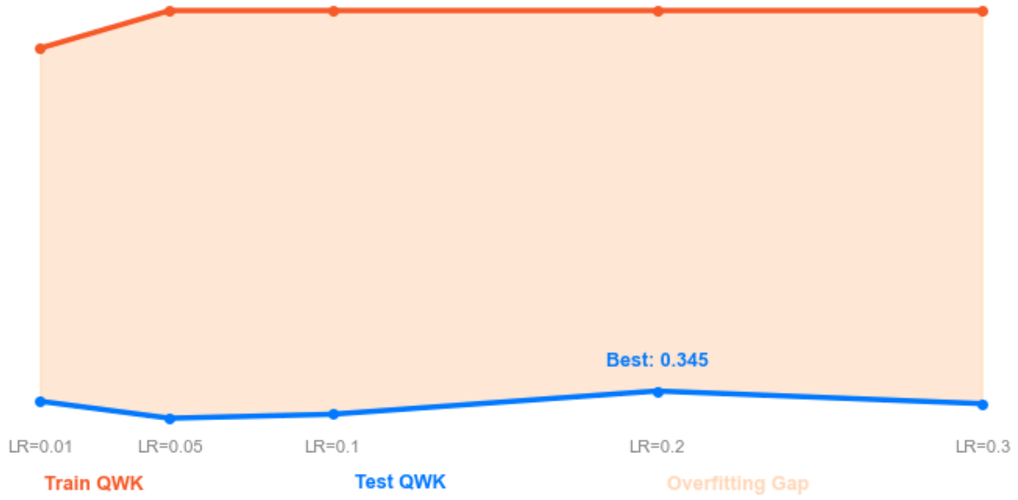
XGBoost is truly overfitting: Overfitting increases significantly when LR is too high



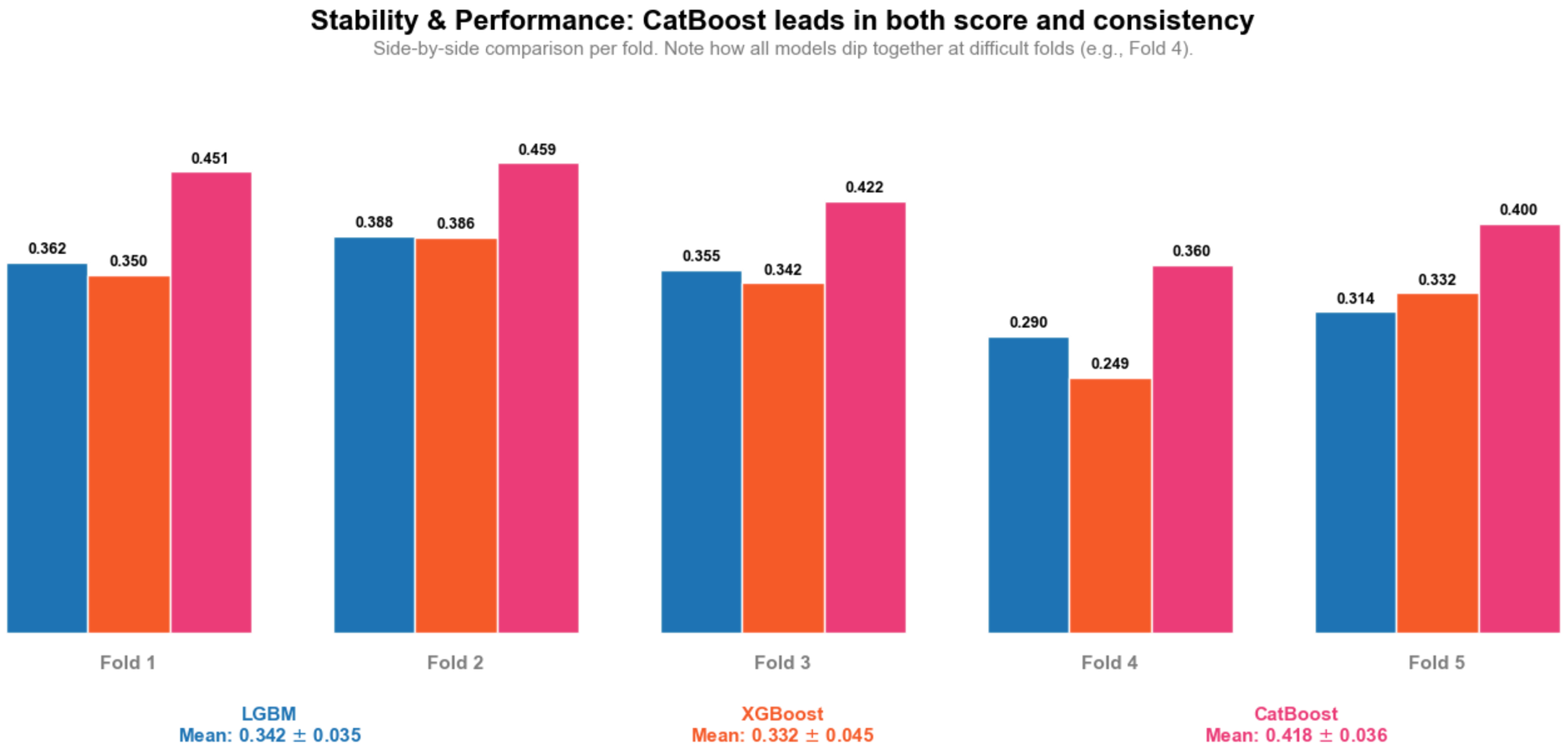
CatBoost: also overfitting



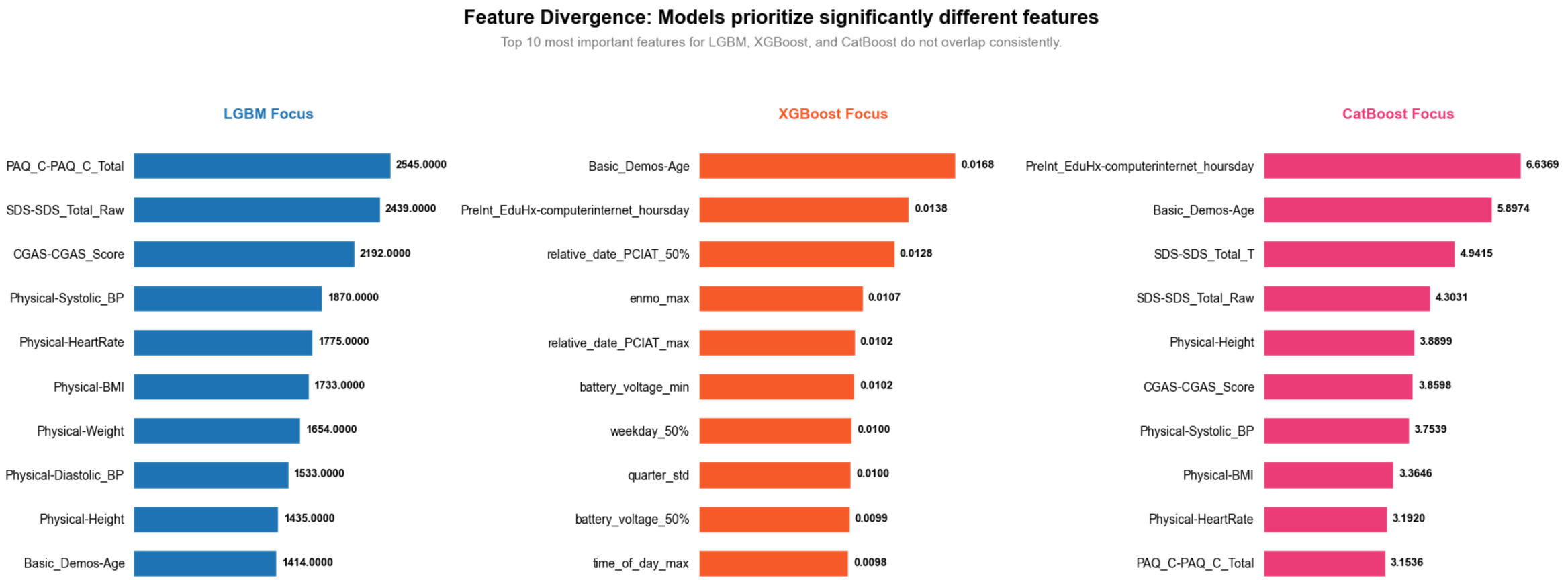
LGBM: Perfectly overfitting!!!



Stability & Performance concerning



Feature Importance concerning



Resolution phase

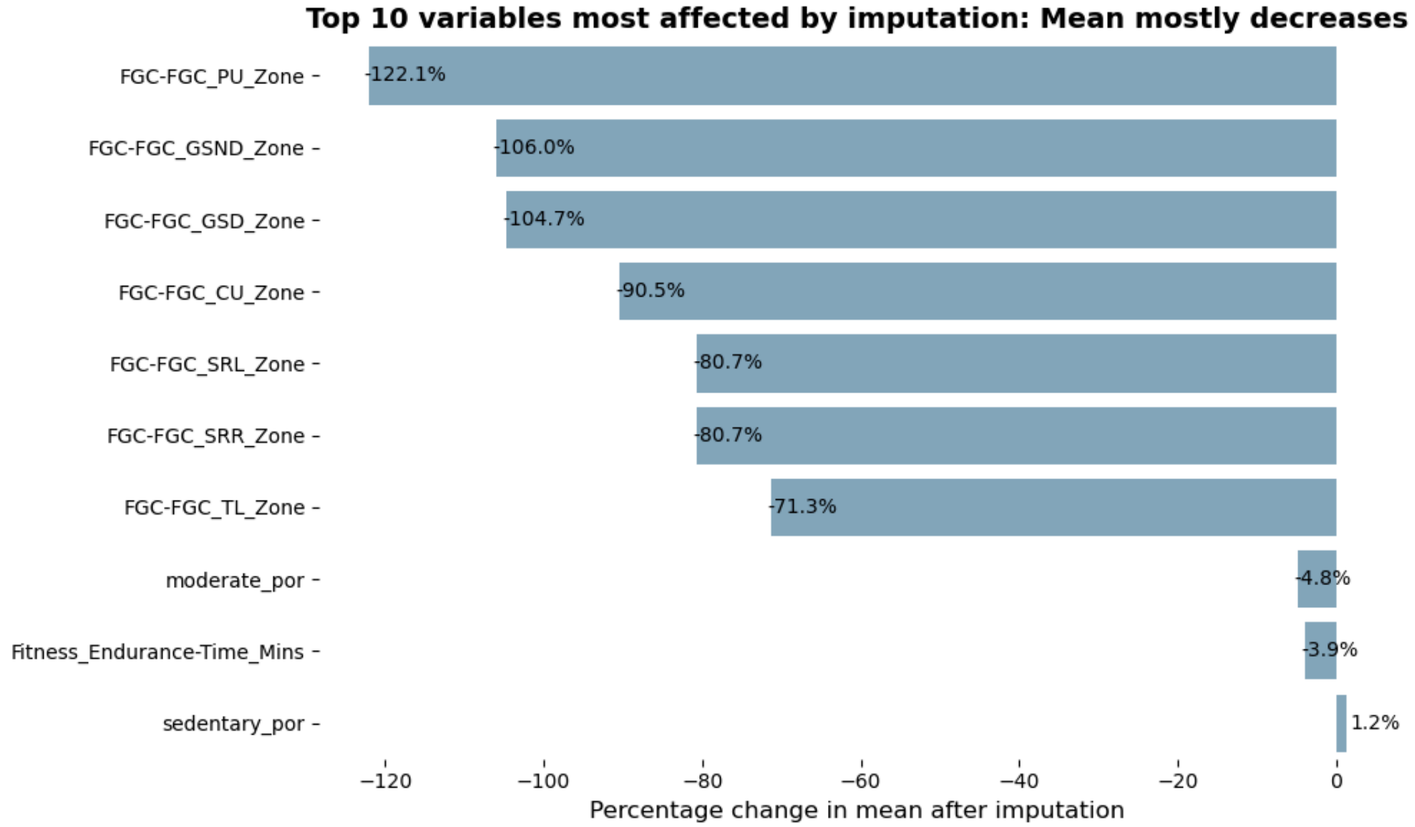
Where the problems in the data begin to resolve, and the story becomes clearer.

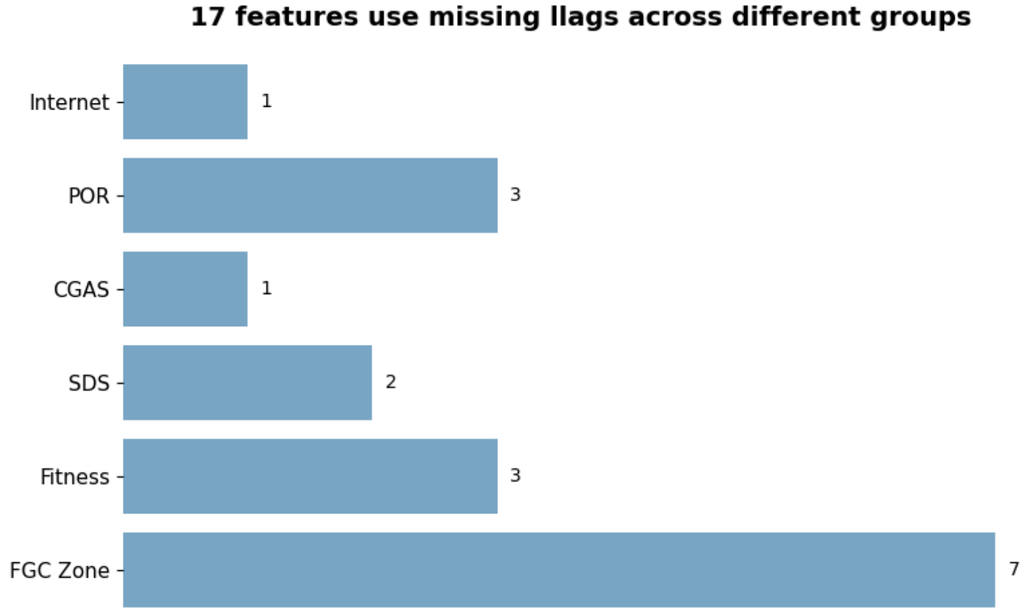
After cleaning

After data cleaning

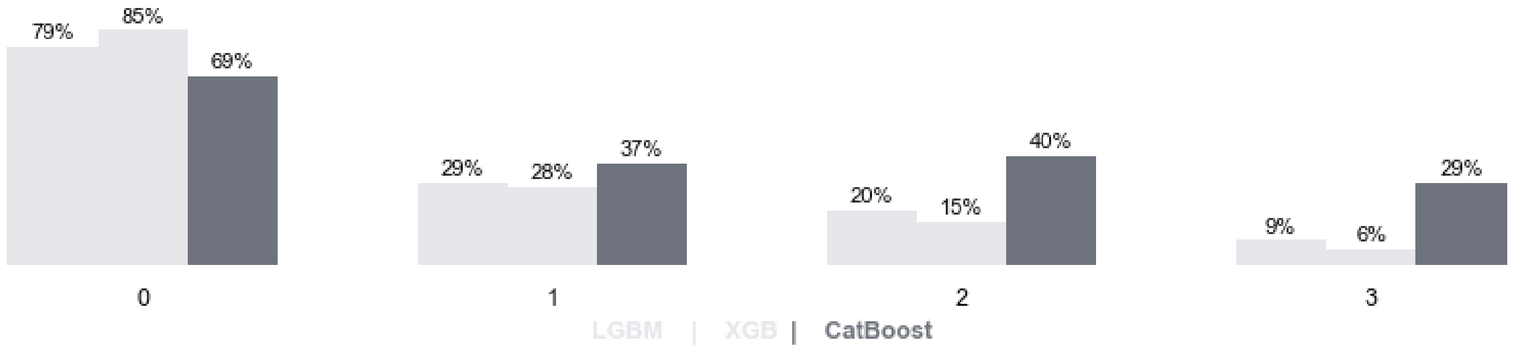
0

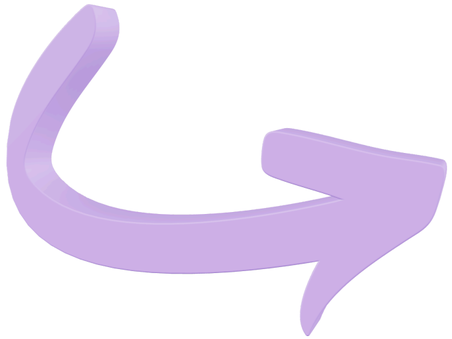
columns have missing values
and outliers



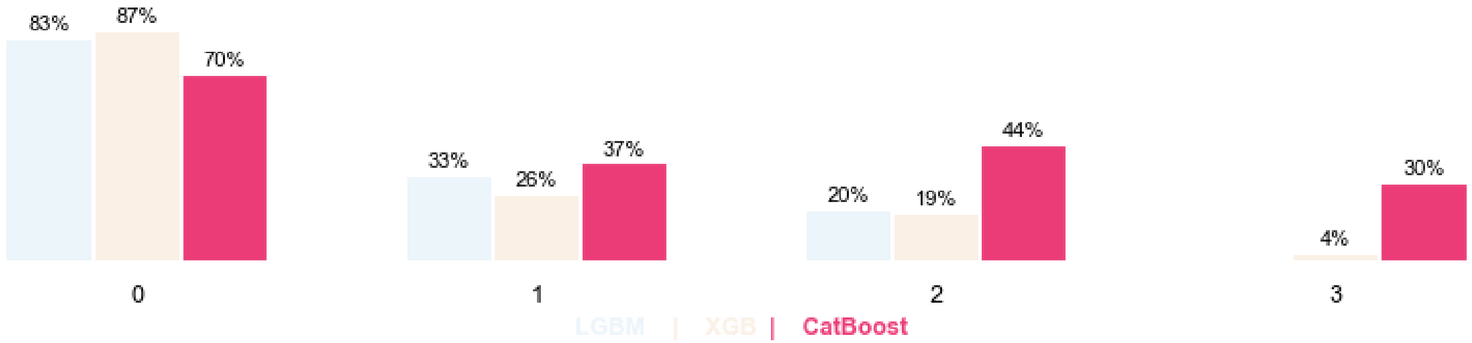


After cleaning

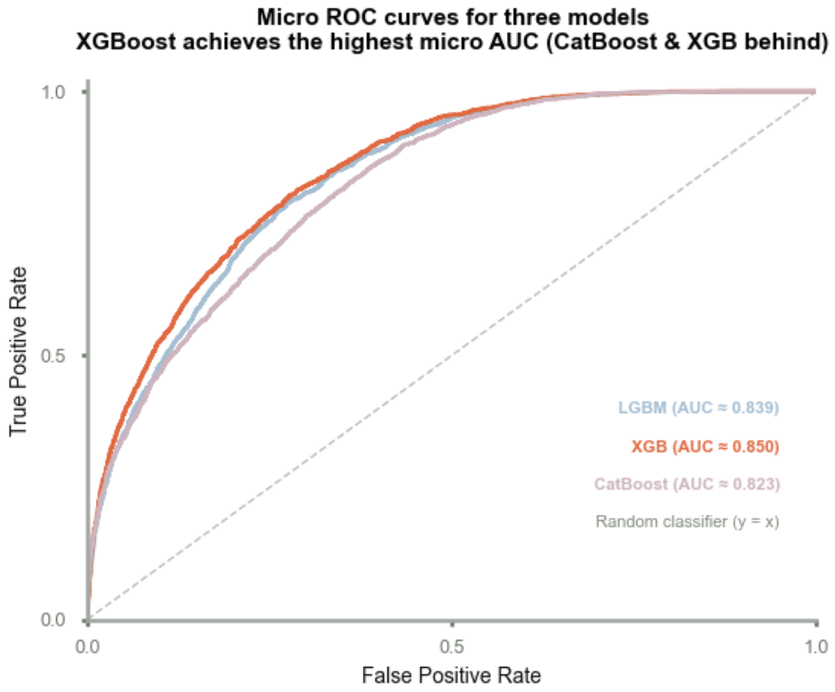


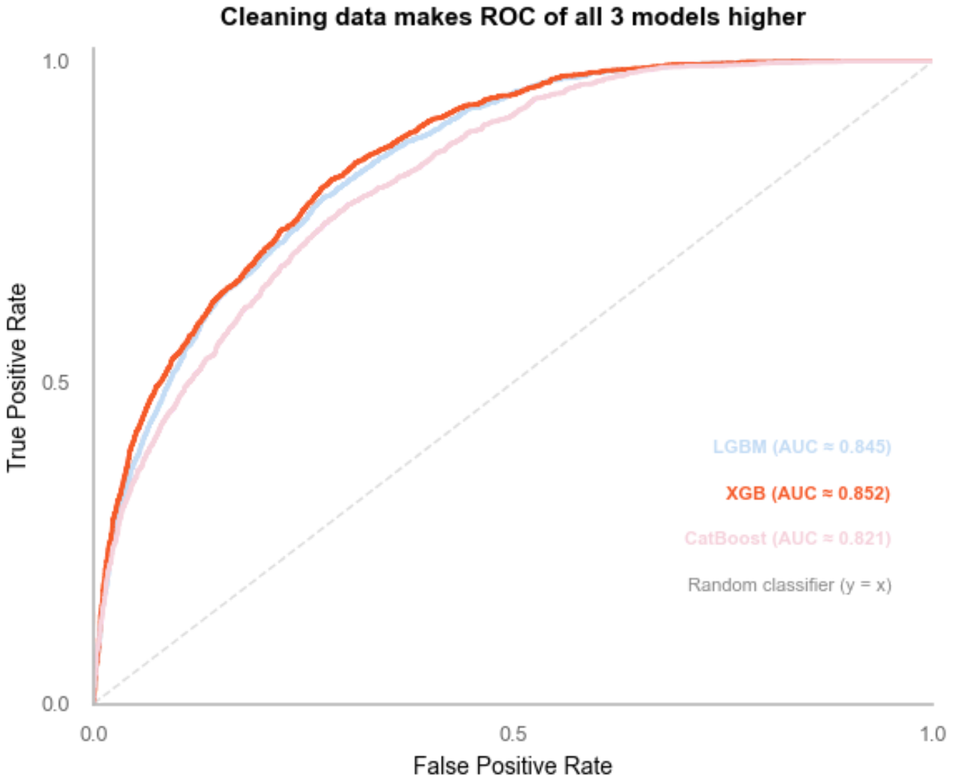


Recall higher after cleaning



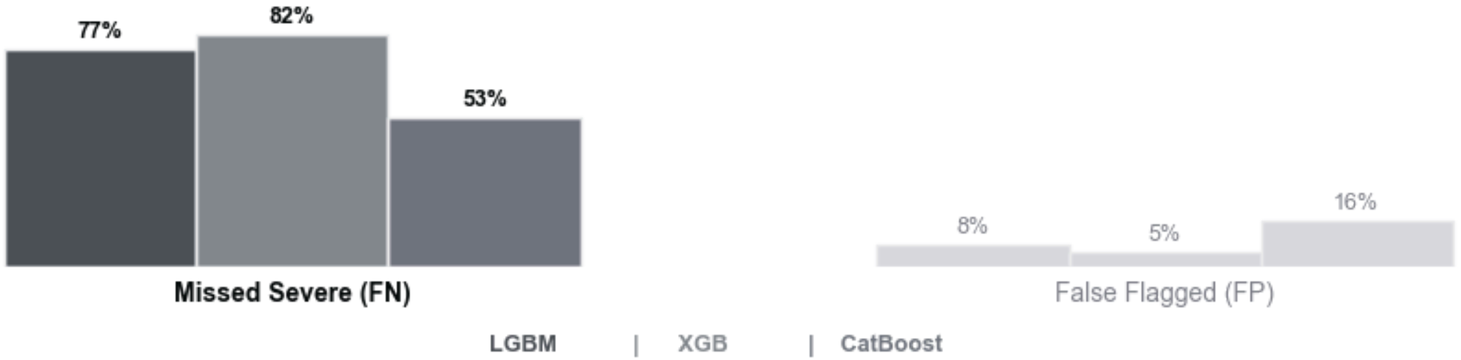
After cleaning



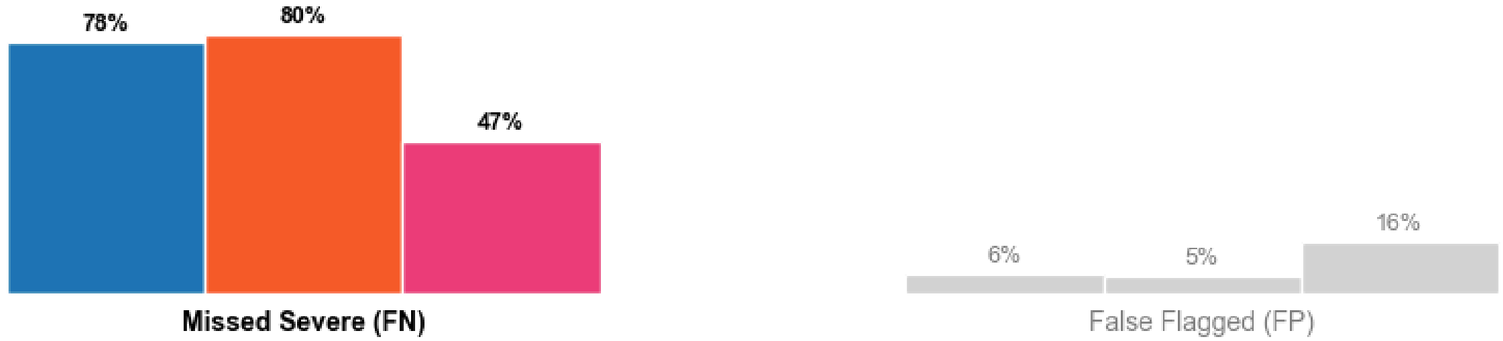


After cleaning

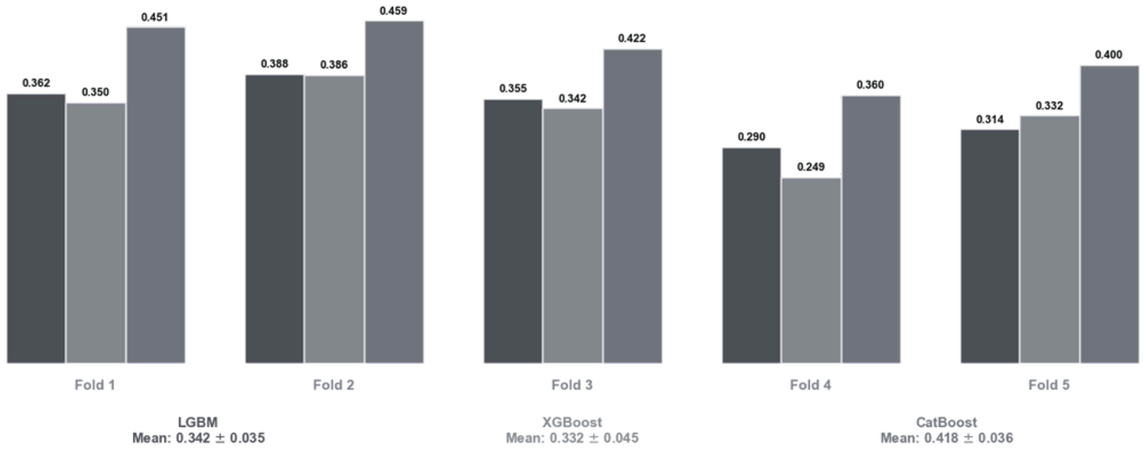
Diagnostic Risk: Models are missing too many Severe cases, while "False Alarms" are low and manageable.



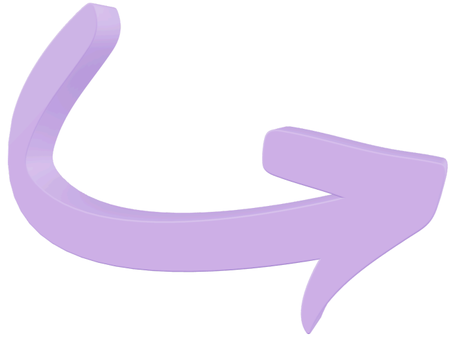
Diagnotic Risk reduces in almost models after data cleaning.

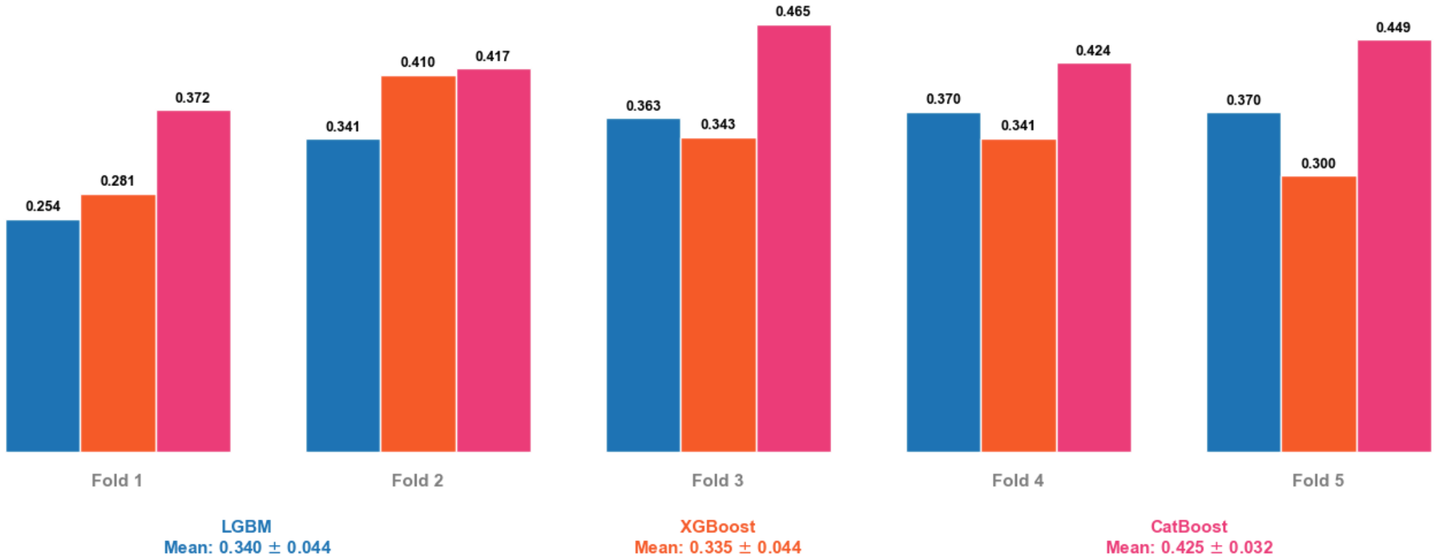


After cleaning

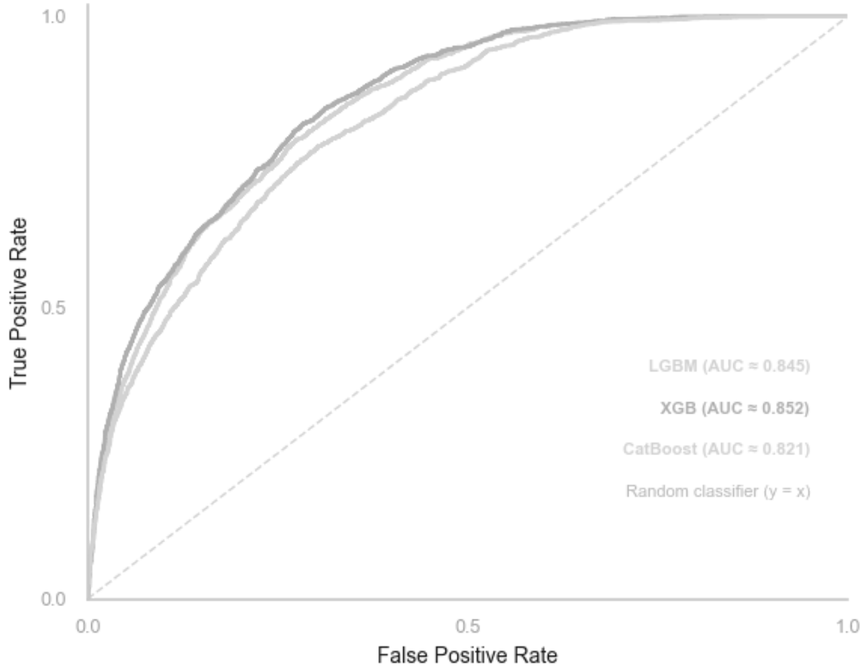


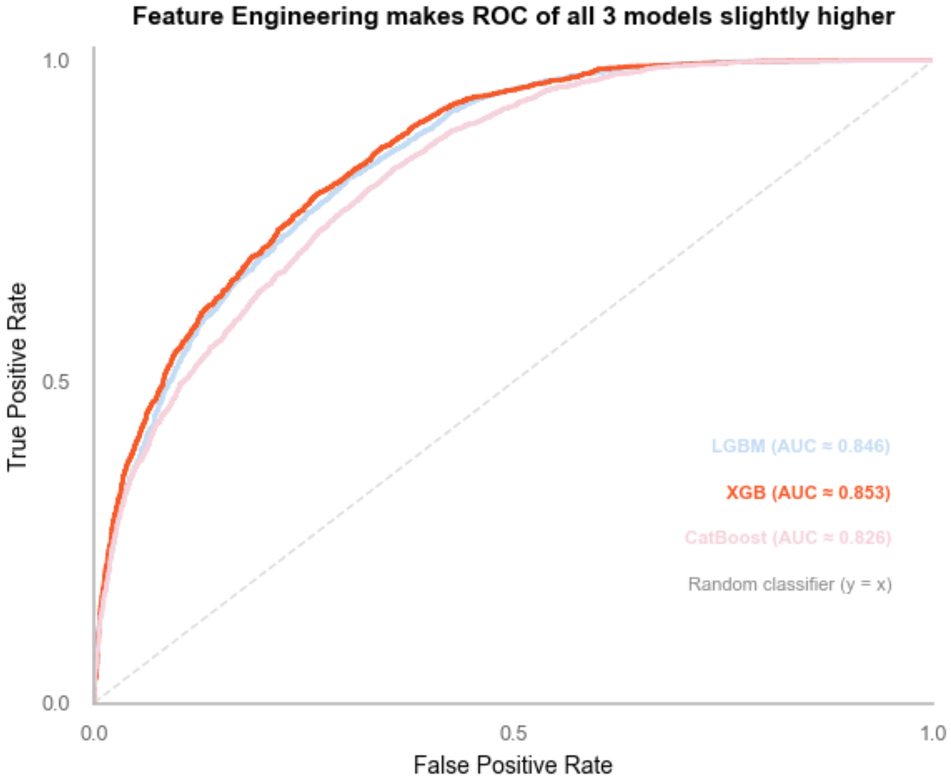
Àfter data cleaning, XGBoost and CatBoost stable and better, however, LGBM faces downgrade in training



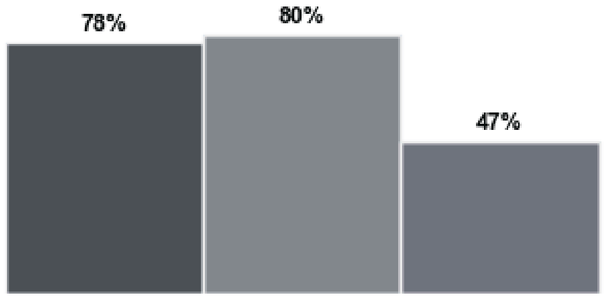


After feature engineering





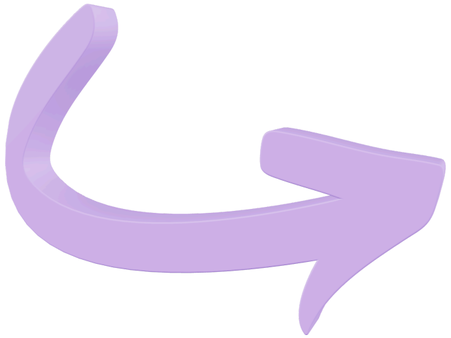
After feature engineering



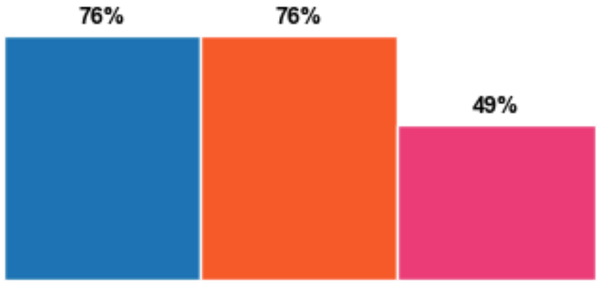
Missed Severe (FN)

False Flagged (FP)

LGBM | XGB | CatBoost



Diagnotic Risk continually reduces in LBGM and XGB models after feature engineering.

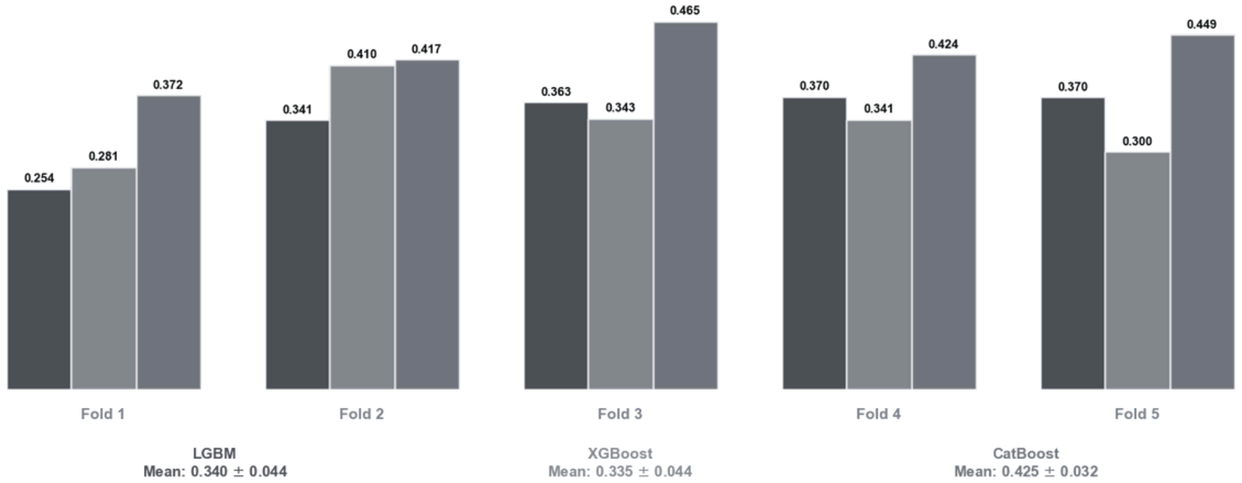


Missed Severe (FN)

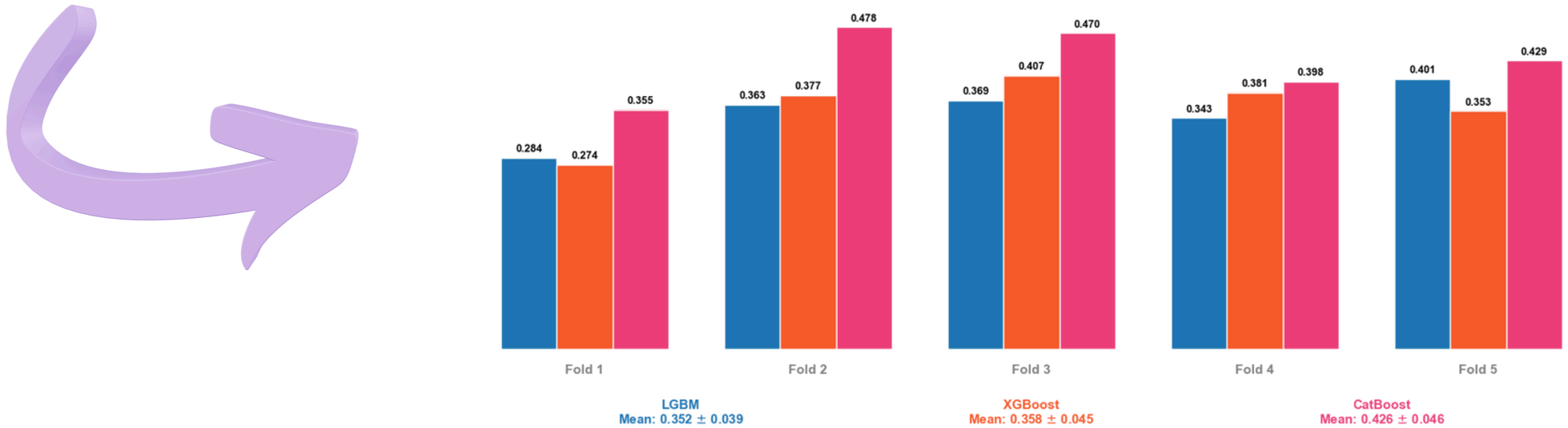
False Flagged (FP)

LGBM | XGB | CatBoost

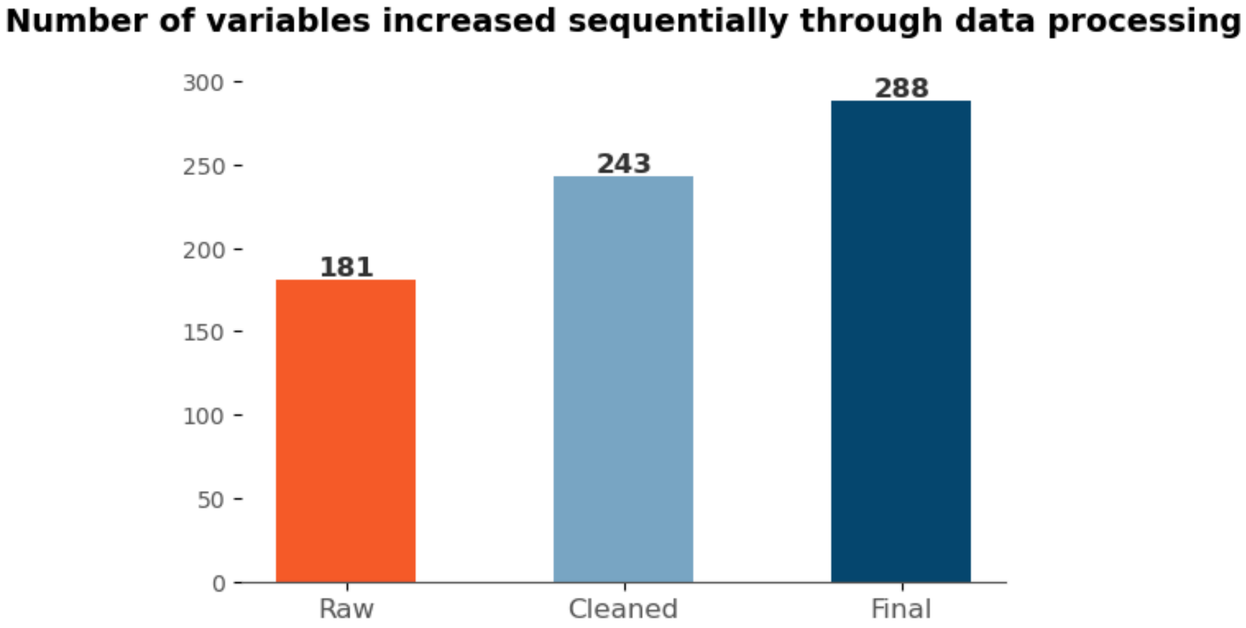
After feature engineering

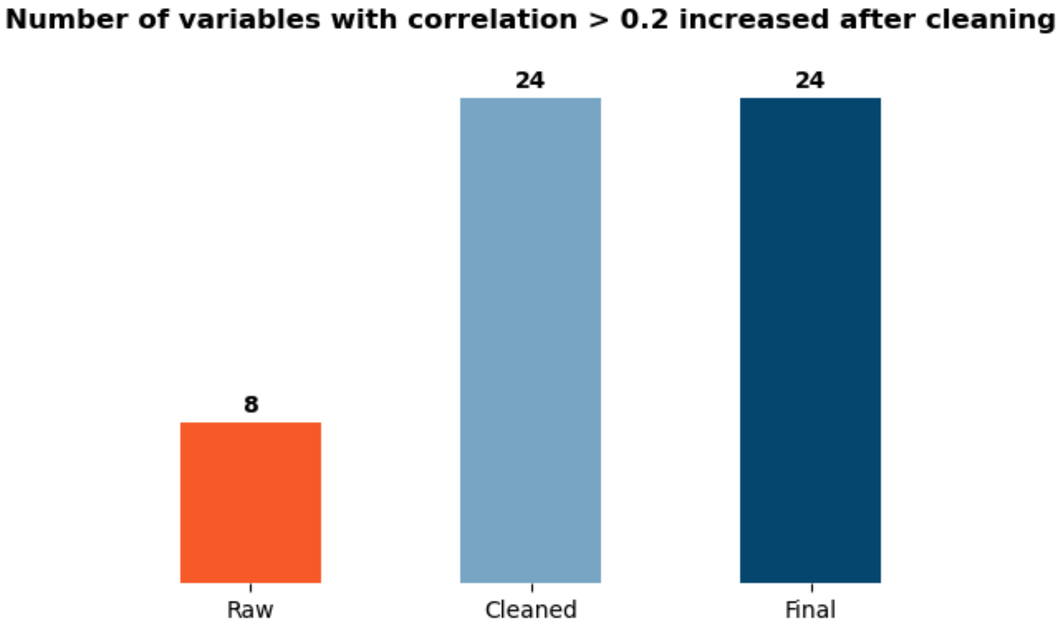


Affter feature engineering, all of 3 models more stable and better

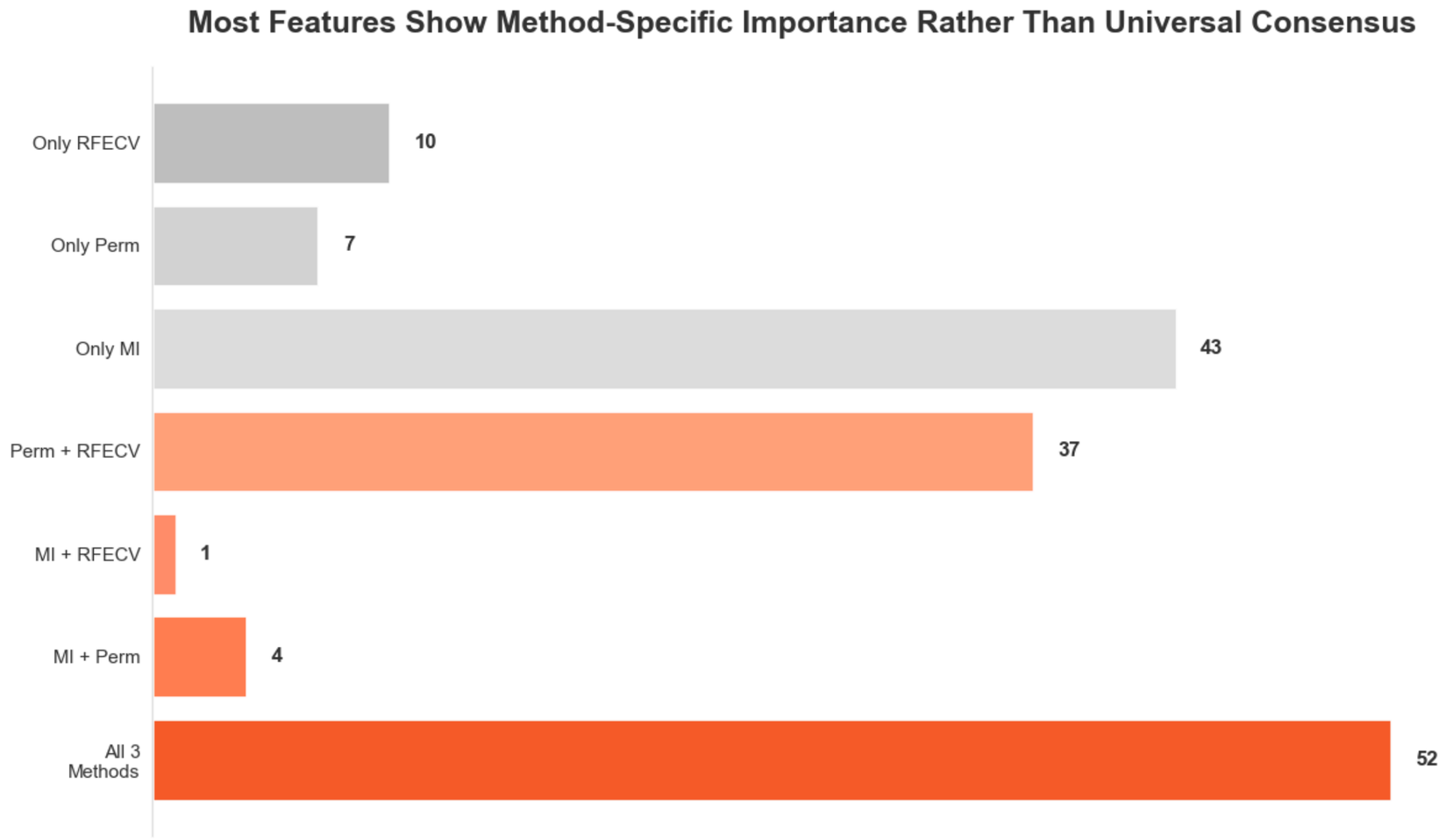


After Data Transform

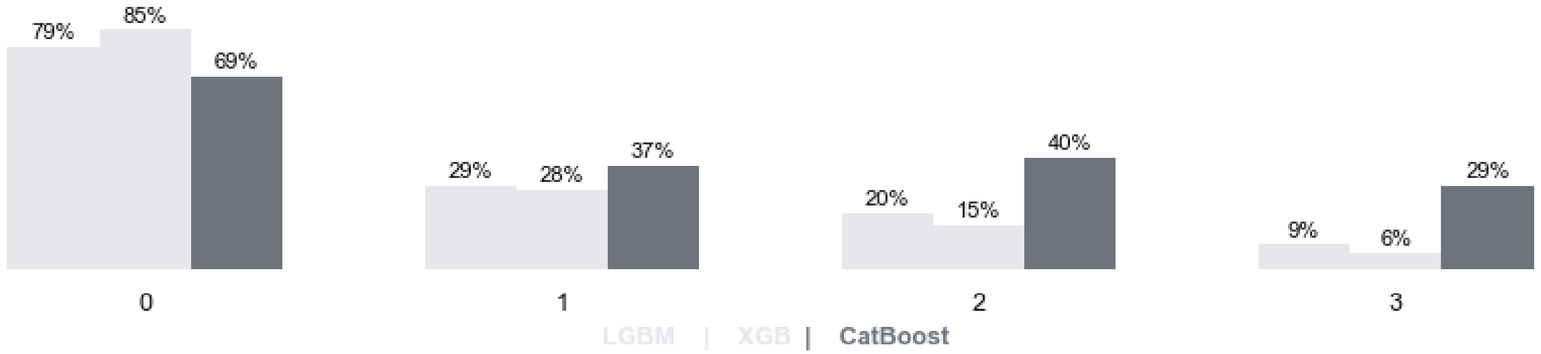




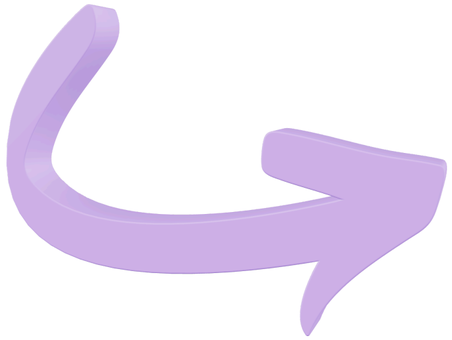
Feature Selection Results (n_features_choose = 100, for each method)

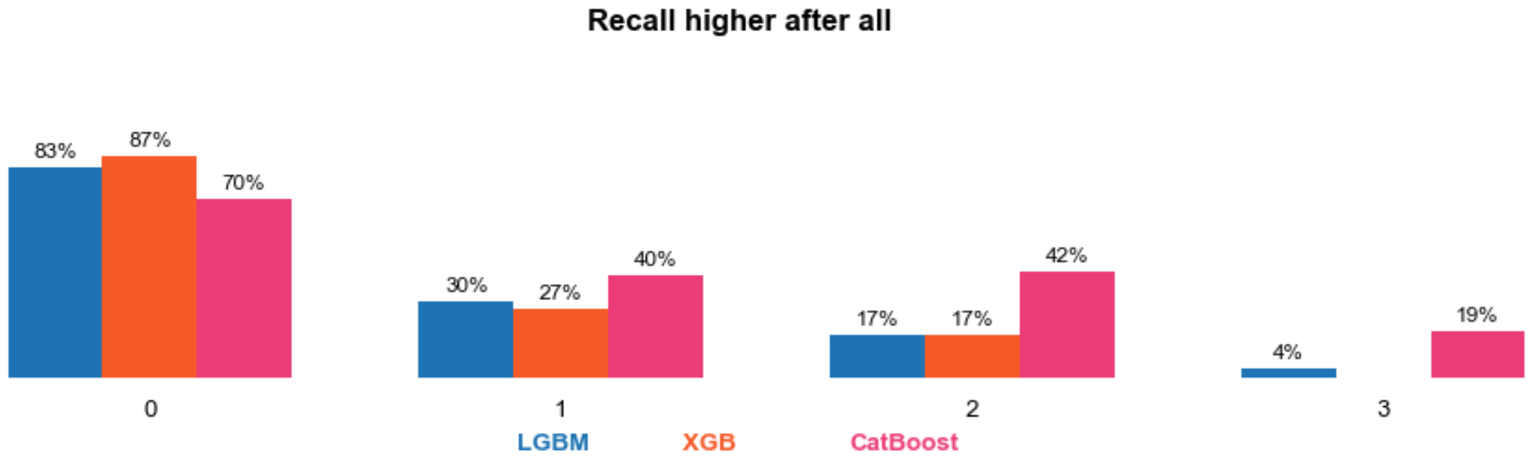


Final model after all the data preparation flow



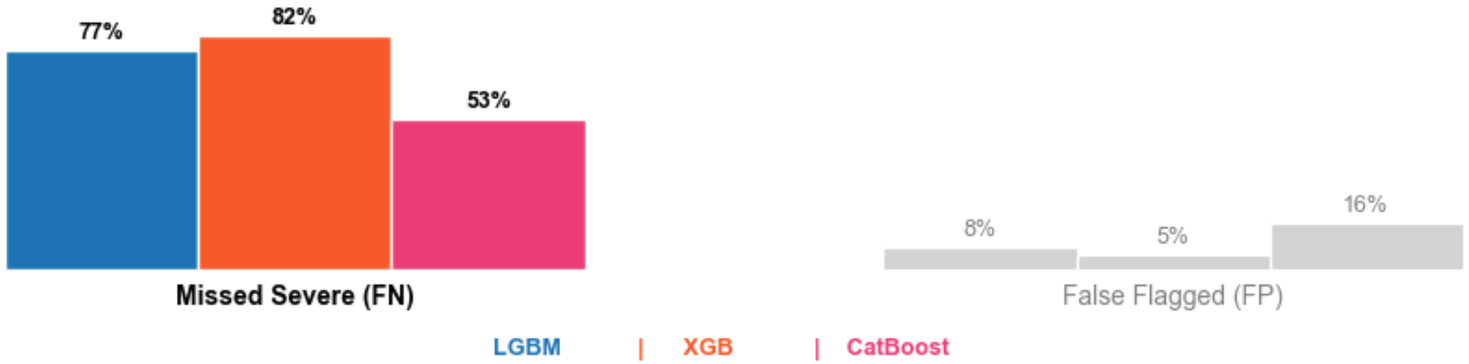
Raw training



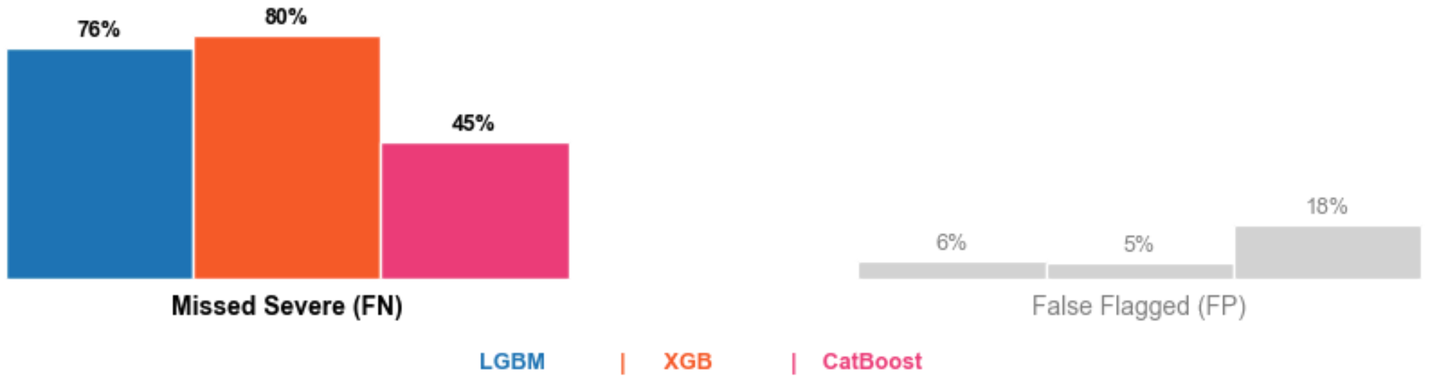


Prepared training

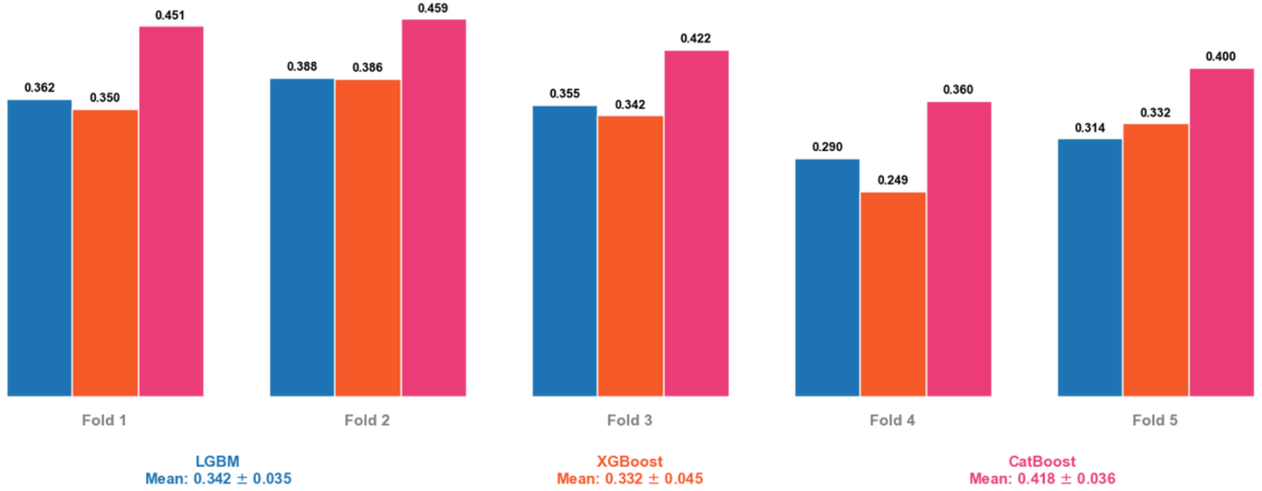
Final model after all the data preparation flow



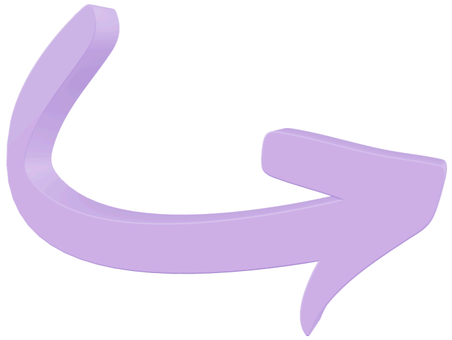
Diagnotic Risk reduces after all.



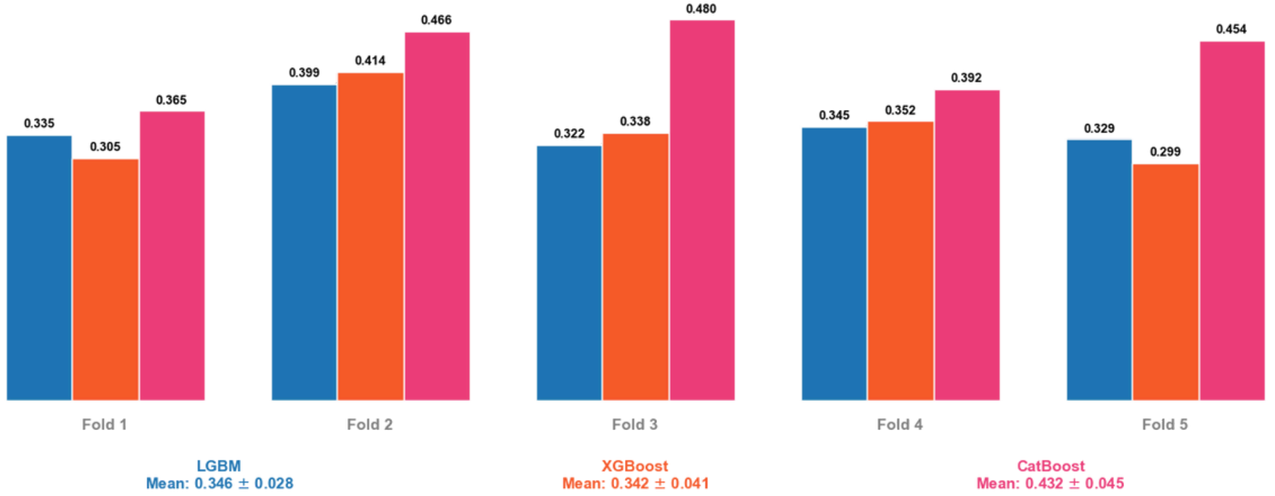
Final model after all the data preparation flow



Raw training

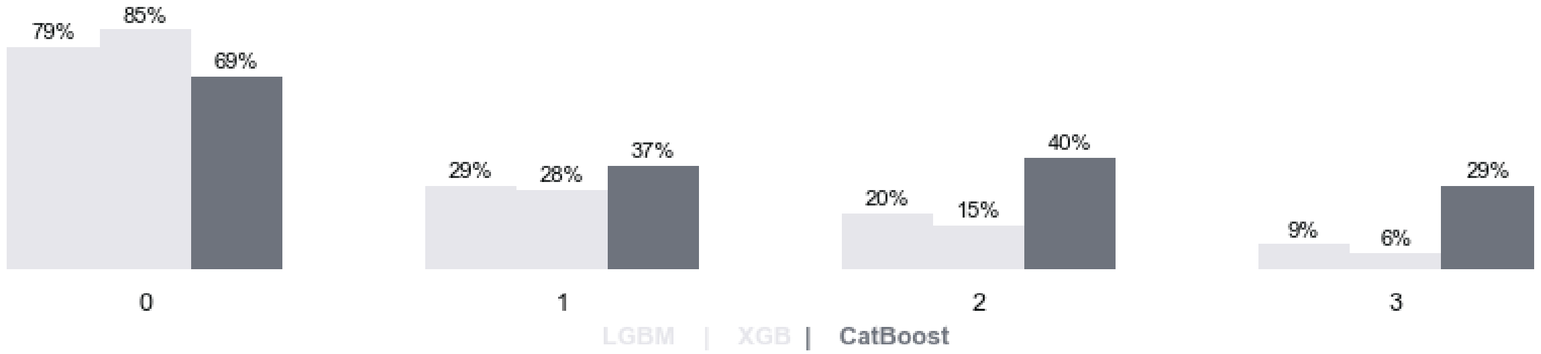


After all, model is better

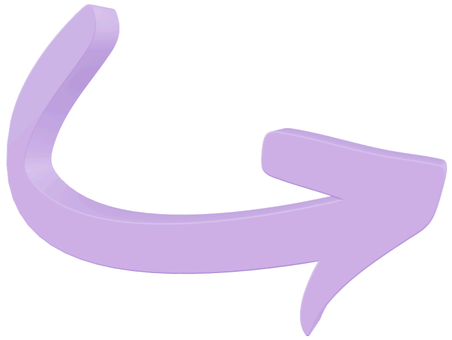


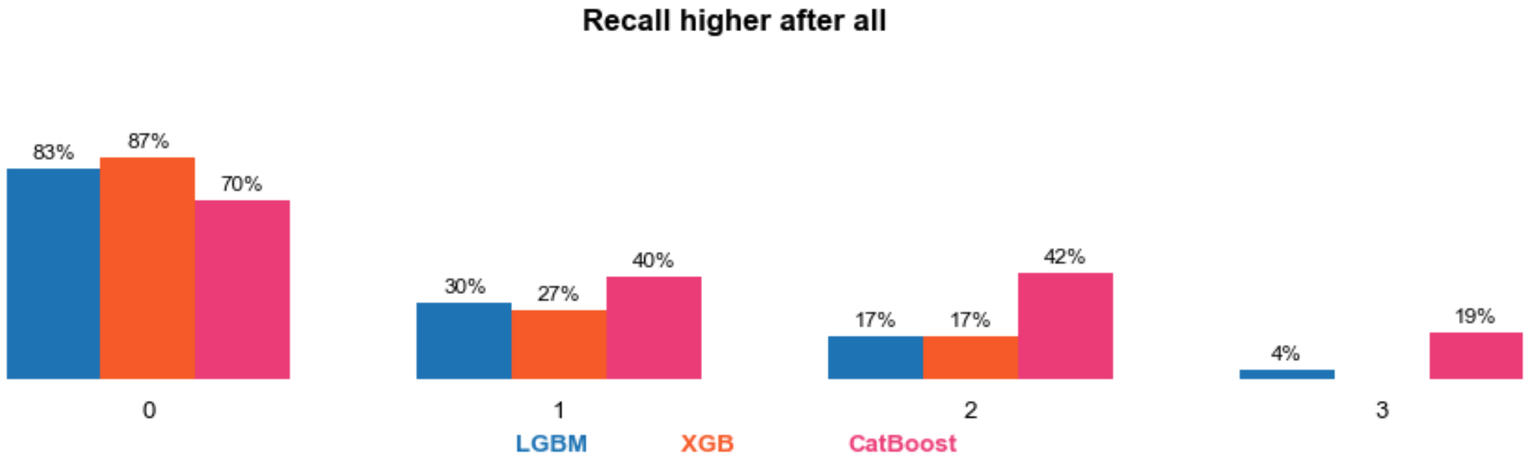
Prepared training

Final model after all the data preparation flow



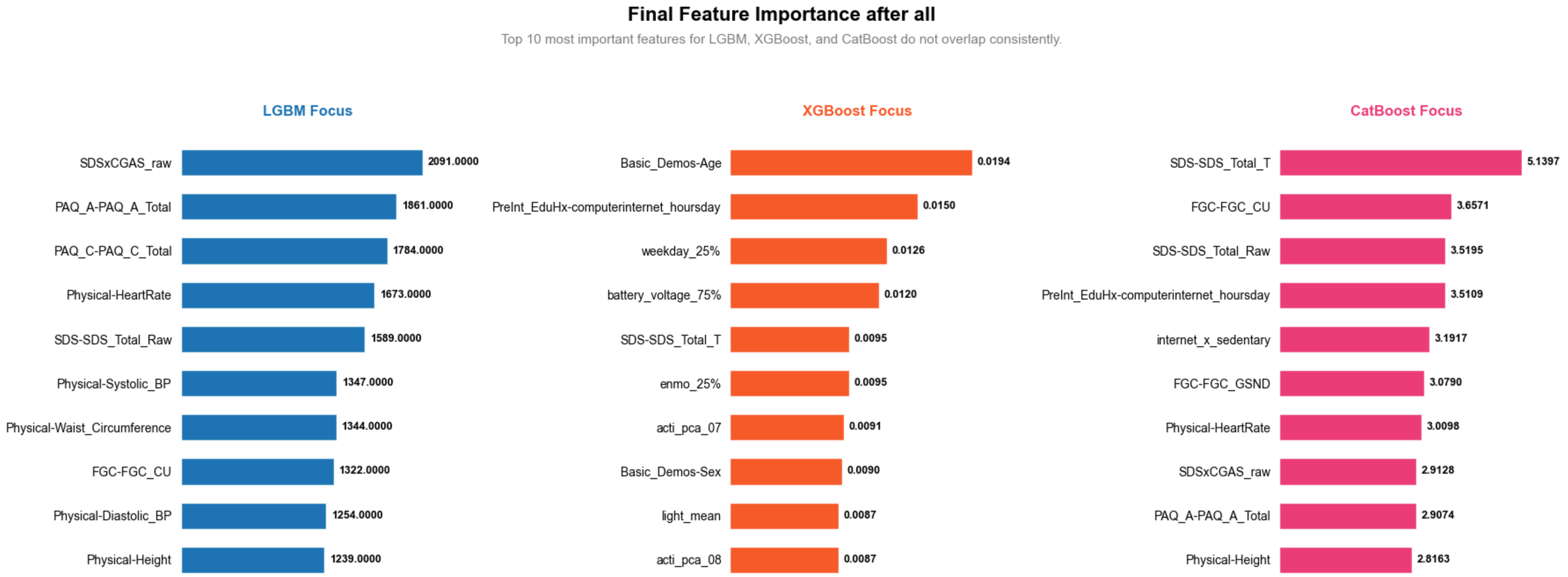
Raw training





Prepared training

Final model after all the data preparation flow



Thank you for watching our story