Workshop 1

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I. Competition Overview

The "Child Mind Institute - Problematic Internet Use" competition is a predictive mental health challenge aimed at identifying problematic internet patterns in children and adolescents. The main objective is to generate predictive models of the relationship between physical activity and fitness data with signals of Problematic Internet Use (PIU), to identify this problematic use in children and adolescents using information from the Child Mind Institute's Healthy Brain Network study.

This challenge addresses a critical current issue around public health: the problematic use of technology by young people, in relation to family dysfunction, substance use, and mental health problems such as anxiety and depression. The competition, supported by Dell Technologies and NVIDIA, aims to generate tools so that clinicians can identify at-risk youth and promote healthier digital habits.

A. Dataset Structure

The information set comes from the Healthy Brain Network, the most important study on child/adolescent brain and behavior in the United States, based on a community recruitment model that offers mental health and learning assessments to thousands of families.

Critical System Components:

- **Training Set:** 3,960 unique participants with tabulated data from more than 80 attributes.
- **Target Variable:** Severity Impairment Index (SII) derived from the Internet Addiction Test (IAT), categorized into 4 ordinal levels (0: None, 1: Mild, 2: Moderate, 3: Severe)
- **Critical Missing Data:** approximately 30% of missing data in Severity Impairment Index (SII), constituting a semi-supervised learning problem.
- **Actigraphy Time Series:** Wrist accelerometer data with X, Y, Z, ENMO, and ambient light measurements in parquet format.

Available Data Categories:

- Demographic and physical data (body mass index [BMI], height, body mass, blood pressure).
- Physical fitness assessments (FitnessGram, endurance, grip strength).
- Bioelectrical impedance analysis.
- Internet addiction test (PCIAT).
- Sleep disturbance scales.
- Internet usage patterns.

Class Distribution: The class structure is distributed as 58.26% at level 0; 26.28% at level 1; 13.82% at level 2; 1.24% at level 3, showing a strong imbalance in the categorical variable of interest.

B. Significant Constraints

Methodological Constraints:

- **Scoring Metric:** Quadratic Weighted Kappa (Cohen quadratic Kappa) for the ordinal regression task, considering it is an ordinal categorical variable. This metric utilizes three matrices (O, W, E) where $\kappa = 1 - \frac{\sum W \times O}{\sum W \times E}$, penalizing classification errors that are more distant from the correct class more heavily, which is appropriate for ordinal variables with class imbalance.
- **Manual Labeling Prohibition:** Strictly prohibited the use of manual labeling information or human prediction of test data.
- **Competition Format:** Code competition executed entirely within Kaggle notebooks with computational constraints.

Technical and Data Constraints:

- **Extensive Missing Data:** The vast majority of features contain significant missing values, requiring advanced imputation techniques.
- **Temporal Complexity:** Actigraphy data must be treated with specialized processes for multivariate time series tasks.
- **Semi-Supervised Problem:** 30% of the participants do not have known SII scores, which requires the use of semi-supervised machine learning approaches.

Participation and Timeline Constraints:

- **Competition Duration:** Held from September 19 to December 19, 2024.
- **Hardware Limitations:** Memory and execution time in the Kaggle environment.
- **Methodologies Employed:** Participants use approaches based on boosting models (CatBoost, LightGBM and XGBoost), neural networks, and ensemble methods, with 5-fold stratified cross-validation control.

C. Competition Context and Scale

Competition Metrics and Engagement:

- **Prize Pool:** $60,000 in total awards and medal points, demonstrating significant investment in advancing PIU prediction methodologies.

- **Participation Scale:** 15,664 total entrants with 4,483 active participants organized into 3,559 competing teams, reflecting broad international engagement.
- **Submission Volume:** 84,049 total submissions indicating intensive iterative model development and optimization efforts across the participant community.
- **Competition Format:** Merger & Entry format allowing team collaboration and knowledge sharing to foster innovative approaches.
- **Host Organization:** Child Mind Institute, a leading nonprofit research institution specializing in child and adolescent mental health with established expertise in large-scale behavioral studies.

System Complexity Context: The nature of the problem articulates aspects of system complexity in relation to the measurement of psychological constructs, individual variability in physical activity patterns, and limitations of current clinical definitions of PIU. The substantial participation metrics (15,664 entrants, 84,049 submissions) demonstrate the international recognition of problematic internet use as a critical public health challenge, with the competition serving as a catalyst for advancing predictive modeling methodologies in pediatric behavioral health assessment and establishing new benchmarks for multi-modal data integration in clinical decision support systems.

II. Systems Analysis

A. Sysytems Analysis

The predictive framework integrates heterogeneous physiological and behavioral signals to estimate the severity of problematic internet engagement among children and adolescents. Continuous wrist actigraphy recordings—capturing ENMO magnitudes, axis-specific acceleration, and time-of-day patterns—are summarized into features such as activity intensity, activity bouts, and nocturnal inactivity that serve as objective proxies for daily movement and sleep. These sensor-derived descriptors are complemented by structured fitness assessments and bioelectrical measures that index cardiometabolic state, as well as by self- and parent-reported questionnaire data that document screen time, psychosocial indicators, and the Parent-Child Internet Addiction Test (PCIAT) used to derive the target ordinal label.

Interactions among these observable quantities produce interpretable behavioral phenotypes: low average daily activity and prolonged sedentary bouts frequently co-occur with elevated self-reported screen exposure, and disrupted sleep metrics derived from actigraphy often mediate associations between inactivity and compulsive digital behaviors. Demographic context—age, sex, socioeconomic status, and school grade—modulates these relationships by shaping device access, parental supervision, and normative peer behavior, while the temporal relationship between data collection windows and questionnaire administration (e.g., the number of days recorded prior to PCIAT completion) is essential for disentangling antecedent from consequent patterns.

Model performance signals and human adjudication form an operational feedback loop that iteratively improves prediction quality. Quantitative diagnostics such as class-specific confusion analysis and weighted kappa statistics identify systematic misclassification, prompting re-examination of feature definitions (for example, how non-wear intervals and battery outages are handled) and possible label noise. Clinical or parental review of flagged cases, together with longitudinal follow-up that records post-prediction changes in activity and screen habits, provides empirical evidence to recalibrate model parameters and to refine risk thresholds for targeted interventions.

Uncertainty and measurement bias permeate the pipeline and thus dictate robust methodological choices. Missingness arising from non-wear, incomplete questionnaires, and uneven representation across socioeconomic strata introduces stochastic variability that can confound causal inference; consequently, temporally aware feature engineering, explicit missingness indicators, uncertainty-sensitive algorithms, and interpretable feature-attribution techniques are warranted. By acknowledging these data limitations while leveraging the complementary strengths of actigraphy, fitness metrics, and psychometric instruments, the system attains both predictive utility and actionable insights for intervention design within the competition's socio-technical setting.

B. Complexity and Sensitivity

Measurement and contextual variability, together with the inherent complexity and sensitivity of behavioral systems, constitute primary constraints on the validity of predictions in this competition. The pipeline ingests high-dimensional, multimodal signals—continuous wrist actigraphy (ENMO, axis accelerations, time-of-day patterns), structured fitness metrics, and psychometric reports—whose nonlinear interactions and context-dependent effects generate emergent patterns. Consequently, small perturbations such as brief device artifacts, minor timing offsets, or transient behavioral anomalies can be amplified by system sensitivity, producing systematic and stochastic distortions in derived features (e.g., activity bouts and sleep proxies).

Heterogeneous individual trajectories (circadian preference, seasonal shifts, cultural norms) and unobserved or comorbid clinical conditions (insomnia, mood disorders, chronic fatigue) act as moderators or confounders that may mask or mimic signals associated with problematic Internet engagement. Socioeconomic disparities and device access further modulate exposure and parental supervision, creating representation bias, while label noise from self- or parent-reported instruments undermines criterion validity. Operational limitations—computational capacity for processing long time series, data retention and privacy constraints—and the potential for deliberate or inadvertent manipulation of inputs add additional vectors of variability. Moreover, sociotechnical feedback, in which predictions alter subsequent behavior, produces adaptive dynamics and nonstationarity that complicate longitudinal interpretation.

Mitigation therefore requires methodological and governance provisions that explicitly address complexity and sensitivity. Analytical strategies should combine temporally aware feature engineering, explicit signal-quality indicators, conservative imputation rules, and treatment of missingness as potentially informative, with routine sensitivity analyses and stress testing to quantify propagation of small perturbations. Model selection must balance expressive capacity for nonlinear dependencies with interpretability and calibrated uncertainty estimates; uncertainty-sensitive algorithms, anomaly detectors, and human-in-the-loop adjudication for high-risk cases reduce the likelihood of harmful decisions. Stratified evaluation, subgroup audits, inclusion of clinical proxies, continuous monitoring, scheduled recalibration, privacy-preserving data handling, and transparent documentation of limitations are all necessary to sustain validity and ethical use within this inherently complex and sensitive socio-technical system.

C. Chaos and Randomness

Within the competition's socio-technical milieu, several hallmarks of chaos theory are evident or reasonably anticipated. The prediction task ingests temporally dense, multimodal signals (actigraphy, questionnaires, fitness metrics) whose interactions are intrinsically nonlinear; consequently, the mapping from input space to the ordinal problematic-use label exhibits sensitivity to initial conditions. Minor differences in timing (e.g., when actigraphy sampling begins relative to questionnaire administration), brief anomalous events (a single night of atypical wakefulness), or slight sensor artifacts can produce disproportionate changes in model inputs and, through nonlinear feature interactions, substantial shifts in predicted risk. This property limits long-horizon predictability and mandates probabilistic forecasting rather than deterministic classification.

Feedback loops within the system instantiate dynamic reinforcement that aligns with chaotic dynamics. Positive feedback—whereby increased screen exposure degrades sleep and self-regulation, which in turn fosters more screen use—can produce runaway trajectories that amplify small perturbations into sustained problematic states. Negative feedbacks (for example, corrective interventions that increase activity and thereby reduce screen time) can stabilize trajectories, but the presence of delays and hysteresis in human behavior means that such stabilizing influences may produce oscillations or transient overshoots rather than monotonic recovery. These interacting loops, especially when coupled with temporal lags, create conditions favorable to complex, hard-to-predict temporal patterns.

From a dynamical systems perspective, the population of participants can be conceptualized as occupying a behavioural phase space with multiple attractors: relatively healthy engagement, intermittent risky use, and entrenched problematic use. Bifurcations—qualitative changes in system behavior triggered by parameter shifts such as sudden increases in device availability, epidemic-scale social changes, or policy interventions—may move individuals or subpopulations from one basin of attraction to another. Moreover, measurement noise and unobserved heterogeneity can give rise to strange or fractal-like attractors in the empirical phase portrait, producing highly irregular trajectories that challenge simple linear intuition.

Noise and stochasticity interact with deterministic nonlinear dynamics to produce noise-induced transitions and nonstationarity. Random shocks (illness, family stressors, the viral adoption of a new application) can precipitate abrupt departures from prior trajectories, while persistent changes in the environment alter the underlying data distribution on which models were trained. Because noise both obscures and can catalyze transitions between behavioral regimes, robust analysis requires explicit uncertainty quantification, sensitivity analyses, and stress-testing to understand how small perturbations propagate through the pipeline.

Practically, recognizing these chaotic features implies several methodological and governance responses: favor ensemble and probabilistic models with calibrated uncertainties; report prediction intervals and not only point labels; implement routine sensitivity and adversarial perturbation tests; monitor model performance continuously and schedule recalibration to accommodate nonstationarity; and retain human-in-the-loop adjudication for high-impact decisions. Such measures acknowledge the limits of predictability imposed by chaos while enabling ethically responsible use of model outputs in intervention design and deployment.

D. Conclusion

The analysis indicates that the multimodal predictive system—combining temporally dense actigraphy, structured fitness metrics, and psychometric reports—offers meaningful capacity to detect behavioral phenotypes associated with problematic Internet use and to support early, targeted interventions. Its principal strengths lie in objective, time-resolved sensor data that complement self-report instruments, enabling rich temporal and circadian features, and in a flexible modeling architecture (ordinal formulations, ensembles, temporally aware networks) that can exploit complementary signal modalities while admitting human-in-the-loop adjudication and recalibration.

However, the system also exhibits important limitations rooted in complexity, sensitivity, and data quality. Non-wear intervals, battery failures, missing questionnaires, label noise and socioeconomic representation biases reduce inferential validity and can produce systematic misclassification. Nonlinear interactions and feedback loops mean that small perturbations or external shocks can be amplified, imposing intrinsic limits on long-horizon predictability and increasing the risk of false positives and negatives. To mitigate these weaknesses, the deployment posture must prioritize robust data governance, explicit uncertainty quantification, routine sensitivity and stress testing, stratified fairness audits, continuous monitoring with scheduled recalibration, and human oversight for high-impact decisions—thereby balancing the system's predictive utility with ethical and operational safety.

Visual Representation

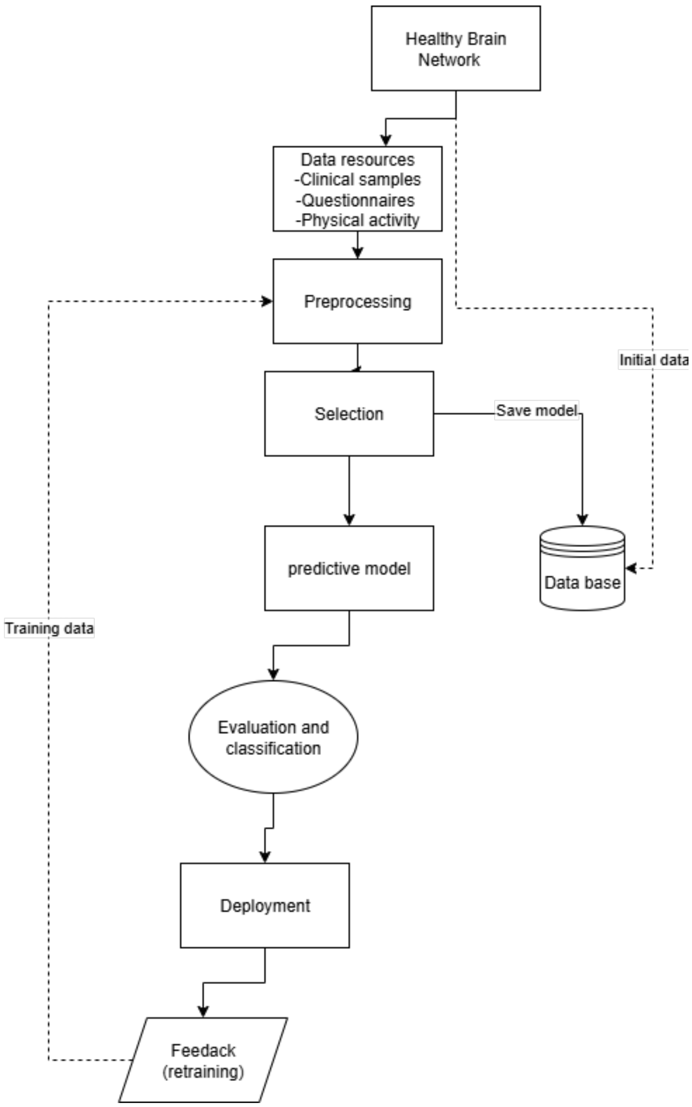

Fig. 1. System Architecture

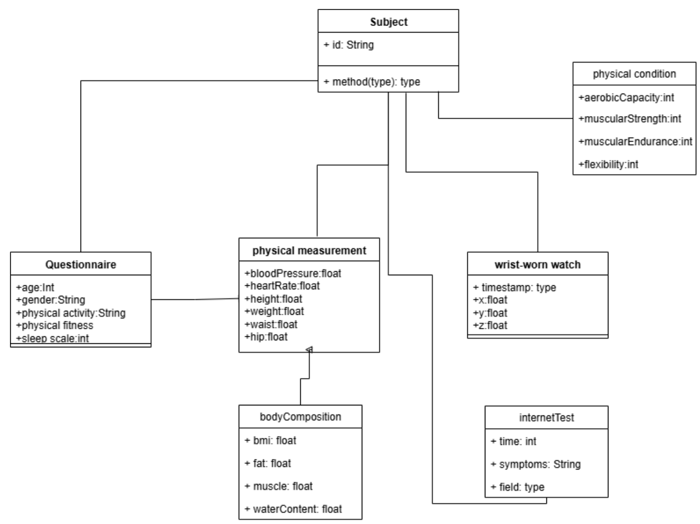

Fig. 2. Element Relationship Map

References

[1] Child Mind Institute, "Child Mind Institute — Problematic Internet Use," *Kaggle Competition Platform*, 2024. [Online]. Available: https://www.kaggle.com/competitions/child-mind-institute-problematic-internet-use

[2] Child Mind Institute, "Healthy Brain Network Dataset," *Data Repository*, 2024. [Online]. Available: https://data.healthybrainnetwork.org

[3] A. Dennis, B. H. Wixom, and D. Tegarden, *Systems Analysis and Design: An Object-Oriented Approach with UML*, 6th ed. Hoboken, NJ: John Wiley & Sons, 2019.

[4] S. H. Strogatz, *Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering*, 2nd ed. Boulder, CO: Westview Press, 2018.

[5] D. J. Kuss et al., "Problematic internet use in children and adolescents: associations with psychiatric disorders and impairment," *PMC*, vol. 7251845, Oct. 2019.