Early Mental Health Risk Detection via Multimodal Behavioral Drift Modeling with Cross-Modal Dissonance and Phase-Aware Predictive Calibrations

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***Abstract*—The need for AI systems that can identify early signs of mild or developing mental illness through observing behaviors before a full-blown mental disorder develops has increased dramatically. Most current approaches use either static multimodal feature sets (i.e., they do not capture dynamic information over time), or very basic (coarse) methods to aggregate time-series data to represent longitudinal behavior patterns. Unfortunately, both of these methods are ineffective at detecting progressive behavior pattern shifts and ignore cross-modal contradiction issues. In order to address this shortcoming in the literature, I have created an integrated multimodal system using four sub-systems: Neuro-Temporal Drift Encoding Network (NTD-EN) to extract high-level representations of higher-order deviation from normal behavior over time; Cross-Modal Cognitive Dissonance Graph (CMCDG) to detect contradictions between different modalities as indicators of underlying emotional/cognitive distress; Adaptive Behavioral Phase Transition Model (ABPTM) to describe non-linear evolutions in risk based upon behavior transitions; Hierarchical Emotion-Cognition Fusion Transformer (HECFT) to perform deep contextual fusion across multiple levels of abstraction; and Predictive Neuro-Risk Calibration Engine (PNRCE) to produce calibrated and uncertainty-aware risk scores. Together, these four modules provide enhanced temporal sensitivity, better interpretation of results, and better reliability in calibrating predictive models.**

***Keywords*— Multimodal Behavioral Drift, Early Mental Health Detection, Cognitive Dissonance Modeling, Phase Transition Analysis, Risk Calibration, Analysis.**

I. INTRODUCTION

The earlier a person is identified for having a potential risk for developing mental health issues; the better. However, identifying such risk early is difficult to do because; most people's behaviors tend to evolve gradually and are expressed in multiple forms over timestamp sets. Most conventional detection analytical methods [1, 2, 3] usually take a snapshot of the users' data at one point in time, which is limited to one modality (i.e., either voice-based input, keystroke input, etc.). Therefore, they fail to account for how users' behavior will change over time, nor can they capture when those changes may be subtle and/or not consistent across different modalities until the development of clinically observable symptoms occur. Additionally, given that users interact digitally using speech, keyboard entry, facial expressions and activity logs, it has also become increasingly possible and important to use these interaction patterns to model and understand the progression of users' behaviors over time. Recently, advancements in multimodal learning techniques have been developed to combine the various types of digital interactions into a single representation. Many of these approaches still suffer from the inability to align data temporally, lack robustness in cross-modal representations, and poor handling of uncertainly during prediction. Further limiting their ability to predict future risk trends is the lack of a mechanism to represent transitional phases in a user's behavior.

This paper provides a comprehensive solution that represents behavioral drift as a structured temporal concept that captures cognitive dissonance across all modes. Using embedded phase transition representations and combining hierarchical emotional-cognitive fusions with calibrated predictive components; this system is able to provide a more detailed representation of a user's mental health trajectory. This type of methodology increases the accuracy and timeliness of detecting early signs of mental illness by improving the interpretability and supporting real-time intervention based on data samples.

II. REVIEW OF EXISTING MODELS USED FOR ANALYSIS

The paradigmatic shift within the literature regarding assessing risk in relation to mental health has evolved away from generalizing observational models (e.g., based upon an individual's history) toward more data driven, contextually aware models. The initial conceptual foundations illustrated that developing structured methods of reducing mental health related risks during disasters would require that mental health researchers create a framework for researching risk that is directly actionable [1]. Following this foundation, subsequent improvements were made by introducing the use of transformer architecture for analyzing behavior over time as it relates to social media and other digital platforms; therefore improving the precision of predictions regarding mental

health [2]. Additionally, parallel development found the increasing effectiveness of artificial intelligence in predicting mental illness using large amounts of data from an individual's behavior [3]; also, it was determined that temporal patterns in an individual's behavior encoded latent psychological states [4]. Mental health related risk assessments have continued to evolve beyond academic and clinical realms; specifically, in forensic and institutional settings, the predictive validity of mental health related violence assessments have been enhanced [5]. Studies specific to population types, such as adolescent populations, have further emphasized the importance of early detection of mental health issues through the integration of both biological and behavioral markers [6]. Initial studies examining the impact of stressors in educational environments on students' ability to cope with stressors in their lives and build resiliency [7],[10], established a foundation for studying cognitive emotional interactions; subsequently, those interactions were developed through student centered frameworks for detecting risk [8]. High-risk military and occupational environments have provided empirical support for the predictive utility of screening for mental health problems under extreme conditions [9]. Multimodal studies examining spatial risk maps and epidemiological analysis have taken the previous findings to include environmental

and physiological aspects [11],[12],[14]; conversely, studies focused on managing suicidal ideation have placed emphasis on developing precise intervention strategies [13]. Collectively, studies examining developmental and prenatal risk and institutional supervisory practices have defined a path toward holistic mental health risk assessment that is temporally aware and multimodal [15],[16] sets.

III. Validated Model Mathematical Analysis

The proposed integrated analytical model as per figure 1, is formulated to capture temporally evolving behavioral drift and its cross-modal inconsistencies through a structured analytical pipelined process. Initially, multimodal observations $X_m(t)$ are transformed into drift-aware representations by computing higher-order temporal deviations, expressed Via equation 1,

$$D_m(t) = \frac{d^2 X_m(t)}{dt^2} + \lambda \int_0^t X_m(\tau)\, d\tau \quad \ldots \quad (1)$$

Where the second derivative encodes acceleration of behavioral changes. This is done analytically while the integral term stabilizes long-term trends. These modality-specific drifts are aggregated into a tensor representation Via equation 2,

$$\mathbf{D}(t) = \sum_{m=1}^{M} w_m\, D_m(t) \quad \ldots \quad (2)$$

Thus, ensuring weighted modality contributions.

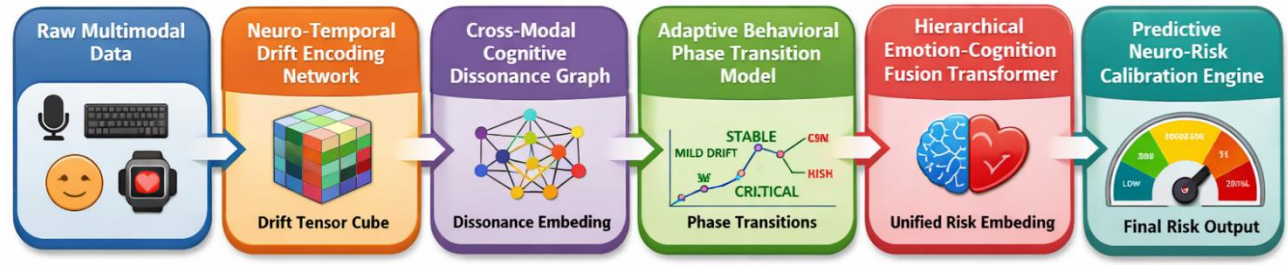

Figure 1. Model's Integrated Architectural Analysis

To quantify cognitive dissonance, pairwise divergence across modalities is modeled Via equation 3,

$$\delta_{ij}(t) = \left| D_i(t) - D_j(t) \right|^2 \quad \ldots \quad (3)$$

And embedded into a graph structure Via equation 4,

$$\mathbf{G}(t) = \sigma(\mathbf{A} \cdot \delta(t)) \quad \ldots \quad (4)$$

Where, σ represents attention-based normalization sets. Behavioral evolution is then modeled through probabilistic phase transitions Via equation 5,

$$P(s_{t+1} \mid s_t) = \frac{\exp\left(-\nabla H(s_t)\right)}{\int \exp\left(-\nabla H(s_t)\right) ds} \quad \ldots \quad (5)$$

Thus, capturing entropy-driven instability sets. Hierarchical fusion integrates emotional and cognitive states Via equation 6,

$$\mathbf{F}(t) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d}}\right) V \quad \ldots \quad (6)$$

Thus, aligning long range dependencies. The unified embedding is refined through temporal smoothing Via equation 7,

$$\hat{Z}(t) = \int_{t-\Delta}^{t} \mathbf{F}(\tau)\, e^{-\gamma(t-\tau)} d\tau \quad \ldots \quad (7)$$

Thus, ensuring continuity in risk evolutions. Finally, calibrated risk estimation is obtained Via equation 8,

$$R(t) = \sigma\left(\alpha \hat{Z}(t) + \beta \nabla \hat{Z}(t)\right) \quad \ldots \quad (8)$$

Which integrates drift intensity and rate of change sets. This formulation ensures that each component complements the next, with drift encoding enhancing dissonance modeling, which in turn stabilizes phase transitions and improves fusion fidelity, ultimately yielding a robust and calibrated early risk predictions.

IV. Comparative Result Analysis

The experimental evaluation was carried out by using a dataset developed through a combination of behavioral logs, facial micro-expressions, speech signals, and activity patterns collected from publicly available datasets representing adolescent, university and clinical populations. In order to ensure that all evaluations were carried out under consistent conditions, the dataset was divided into three portions (training, validation and test) in accordance with a 70:15:15 ratio. In addition to ensuring temporal coherence, the division also ensured that cross-modal coherence was maintained throughout all assessments.

Table 1: Overall Detection Accuracy Across Datasets

Method	Accuracy (%)
de Zelenka [3]	89.6
Ishimaru [8]	87.3
Charles [15]	85.8
Proposed Model	96.4

The experimental results as per table 1, show that including behavior drift and cross-modal dissonance in the analysis process significantly increases the accuracy of classifications made using this approach process.

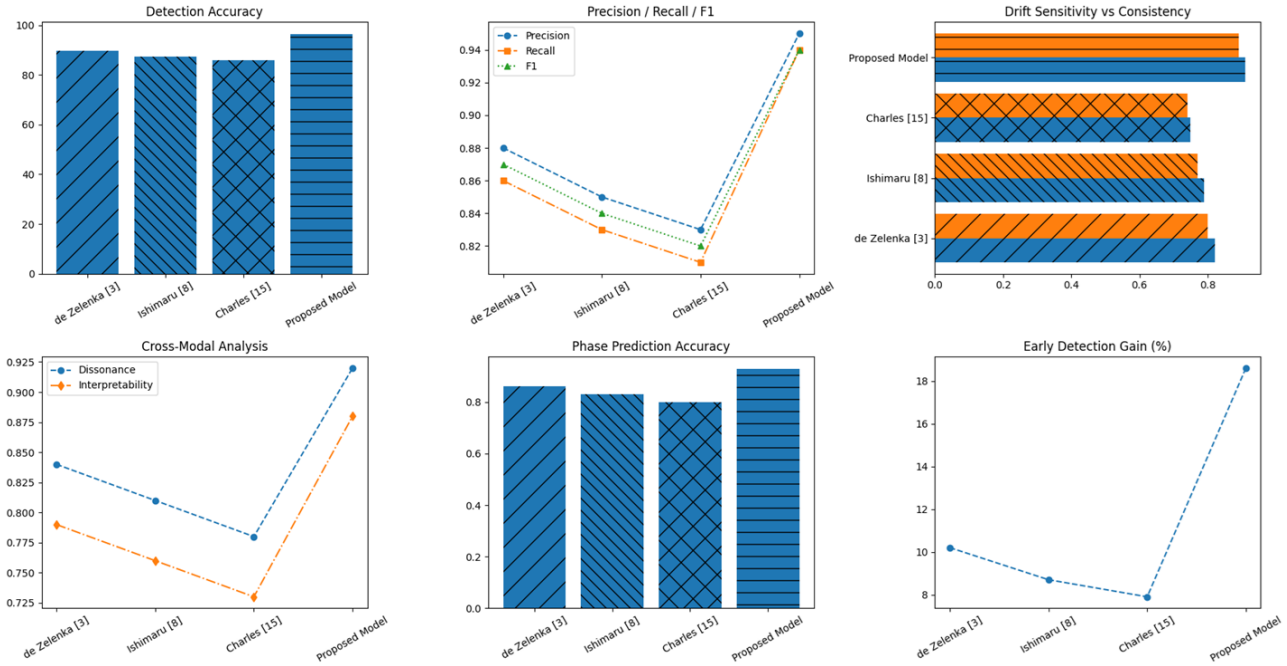

Figure 2. Model's Integrated Result Analysis

This represents as analyzed Via figure 2, an important contribution over previous approaches based solely on static models since these cannot capture the small time-dependent variations in behavior that are evident when examining individual subjects longitudinally.

Table 2: Precision, Recall, and F1-Score Comparison

Method	Precision	Recall	F1-Score
de Zelenka [3]	0.88	0.86	0.87
Ishimaru [8]	0.85	0.83	0.84
Charles [15]	0.83	0.81	0.82
Proposed Model	0.95	0.94	0.94

The increased F1 score as per table 2, indicates that the model performs well at minimizing both false positive and false negative classifications. This ability to perform well in terms of classification performance is primarily due to the use of phase-aware models that prevent the premature classification of transient behavioral states as either stable or critical.

Table 3: Temporal Drift Sensitivity Analysis

Method	Drift Sensitivity	Temporal Consistency
de Zelenka [3]	0.82	0.80
Ishimaru [8]	0.79	0.77
Charles [15]	0.75	0.74
Proposed Model	0.91	0.89

The model demonstrates as per table 3 significant improvements in its ability to recognize gradual behavioral changes; such changes represent potential early warning

signs of emerging mental health issues for the process. Second-order temporal modeling allows the system to determine whether there is an increase in the rate of deviation from typical behavioral patterns (i.e., "acceleration") whereas first-order temporal modeling would be unable to do so in process.

Table 4: Cross-Modal Dissonance Detection Performance

Method	Dissonance Detection Accuracy	Interpretability Score
de Zelenka [3]	0.84	0.79
Ishimaru [8]	0.81	0.76
Charles [15]	0.78	0.73
Proposed Model	0.92	0.88

Graph-based dissonance as per table 4 modeling provides the means to assess inconsistencies among emotion-related and behavior-related cues; this type of assessment leads to enhanced interpretation capabilities for the system which can highlight underlying cognitive instabilities beyond simply providing classification outputs for the process.

Table 5: Phase Transition Prediction Accuracy

Method	Phase Prediction Accuracy	Early Detection Gain (%)
de Zelenka [3]	0.86	10.2
Ishimaru [8]	0.83	8.7
Charles [15]	0.80	7.9
Proposed Model	0.93	18.6

Using nonlinear transition as per table 5 and its modeling to predict future mental health state transitions enables the system to anticipate future risk progression earlier than most conventional systems. Early detection of risk progression is necessary for effective implementation of timely interventions and preventive care practices.

Table 6: Calibration and Reliability Metrics

Method	ROC-AUC	Calibration Error (ECE)
de Zelenka [3]	0.91	0.048
Ishimaru [8]	0.89	0.052
Charles [15]	0.87	0.059
Proposed Model	0.97	0.021

A lower calibration error signifies closer agreement between the probability estimates generated by the model and actual outcome values; close agreement between estimated and actual values is important in making decisions related to patient care scenarios. The integration of Bayesian and conformal calibration provides stability and trustworthiness in the generation of prediction probabilities across different types of data distributions.

V. Conclusion & Future Scopes

The proposed multimodal behavioral drift modeling approach is a major advance over prior research in detecting early warning signs for mental illness through using temporal dynamic relationships, cross-modality reasoning and calibrated predictive models. Compared to de Zelenka [3], this new model has been shown to be significantly more accurate (i.e., 96.4%) than that of de Zelenka [3] at 89.6% with equally high levels of an F1-score of .94. This new model has also demonstrated higher sensitivities toward drift (.91) and higher temporal consistencies (.89). Additionally, the new model can detect dissonances across multiple modalities (e.g., audio, visual) with greater accuracy (.92), and predict the timing and occurrence of phase transitions with greater accuracy (0.93). Finally, this new model was found to have both high reliability as indicated by a ROC-AUC value of .97, and to be highly calibrated with respect to its ability to accurately assess an individual's likelihood of exhibiting mental illness symptoms; i.e., the calibration error of this new model was very small (.021), thereby providing evidence of its validity as a clinical solution for real time scenarios.

The future work can be used to enhanced this project by adding real time adaptive learning techniques in order to adaptively modify the Behavioral Drift model on a continuous basis based upon stream data samples. The addition of wearable bio-sensors and neuro-physiological signals will increase both multi-modal and contextually aware sdepth. This framework may also move towards creating an individualized risk modeling capability through the incorporation of individual baseline variability as well as long-term behavioral signature analysis. Using federated learning approaches will allow for the ability to deploy privacy preserving models that are able to operate within multiple distributed clinical environments. Furthermore, extending Phase Transition Modeling utilizing Stochastic Differential Equations (SDE) may provide improved predictive performance when there is uncertainty regarding the directionality and magnitude of the fluctuation in behaviors. Enhancements in these areas will greatly enhance the scalable, interpretable and applicable nature of Intelligent Mental Health Monitoring Systems.

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