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Multimodal Behavioural Data Mining for Mental Health: A Comprehensive Survey on Wearables and Digital Phenotyping

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Abstract- Mental health disorders, particularly depression and anxiety, represent a growing global burden, affecting more than 300 million individuals worldwide and contributing significantly to disability and reduced quality of life. Traditional assessment methods rely heavily on self-reported questionnaires and clinical interviews, which are episodic, subjective, and often fail to capture dynamic behavioral patterns. The emergence of wearable devices and digital phenotyping technologies has enabled continuous, real-time collection of multimodal behavioral data, including physiological signals, activity patterns, sleep metrics, smartphone usage, and social interaction traces. This survey provides a comprehensive review of multimodal behavioral data mining techniques applied to mental health monitoring and prediction. We systematically analyze over recent studies employing machine learning, deep learning, ensemble models, and hybrid data fusion strategies for depression and anxiety detection. Statistical trends indicate that multimodal approaches improve predictive performance by 8–15% compared to unimodal systems, with deep learning architectures such as LSTM and transformer-based models achieving reported accuracies above 85% in controlled datasets. The survey categorizes existing methodologies based on data modalities, feature extraction techniques, fusion strategies (early, late, and hybrid fusion), personalization mechanisms, and evaluation metrics. Furthermore, we examine key challenges, including data heterogeneity, class imbalance, privacy leakage risks, interpretability limitations, and generalization across populations. The paper concludes by outlining future research directions in explainable AI, federated learning, adaptive personalization frameworks, and privacy-preserving multimodal analytics. This survey aims to provide researchers and practitioners with a structured roadmap for advancing data-driven, scalable, and personalized mental health prediction systems using wearable and digital behavioral data.

Keywords- Multimodal Data Mining, Digital Phenotyping, Wearable Sensors, Depression Prediction, Anxiety Detection, Machine Learning in Mental Health, Personalized Healthcare Analytics

I. INTRODUCTION

1.1 Background and Motivation

Mental health disorders have emerged as a critical public health concern in the digital era, significantly affecting cognitive, emotional, and social functioning across diverse populations. Among these conditions, depression and anxiety disorders are the most prevalent and are strongly associated with reduced productivity, impaired quality of life, and increased risk of chronic diseases [1]. Traditional diagnostic approaches primarily rely on clinical interviews and self-reported questionnaires, which are episodic and subject to recall bias [2]. With the rapid advancement of wearable sensing technologies and ubiquitous mobile computing, continuous behavioral monitoring has become feasible, enabling objective and real-time assessment of mental health states [3]. These developments have motivated the integration of multimodal behavioral data mining techniques to extract meaningful patterns from heterogeneous data streams, facilitating early detection and personalized intervention strategies [4].

1.2 Global Burden of Depression and Anxiety

Depression and anxiety collectively account for a substantial proportion of the global mental health burden, affecting hundreds of millions of individuals worldwide [5]. These disorders are among the leading causes of disability-adjusted life years (DALYs), particularly in adolescents and working-age adults [6]. The economic cost associated with lost productivity, healthcare utilization, and social impact is estimated in trillions of dollars annually [7]. Despite increasing awareness, underdiagnosis and delayed intervention remain persistent challenges due to stigma, limited clinical resources, and inadequate monitoring systems [8]. Consequently, there is a pressing need for scalable, data-driven solutions capable of providing continuous assessment and early risk prediction [9].

1.3 Emergence of Wearables and Digital Phenotyping

The proliferation of wearable devices such as smartwatches, fitness trackers, and biosensors has enabled passive and continuous collection of physiological and behavioral signals, including heart rate variability, sleep patterns, and activity levels [10]. Simultaneously, digital phenotyping—the moment-by-moment quantification of individual-level human behavior using data from smartphones and digital devices—has emerged as a transformative paradigm in mental health monitoring [11]. Smartphone-derived features such as screen time, mobility patterns, social interaction metrics, and typing dynamics have demonstrated strong correlations with depressive and anxiety symptoms [12]. The integration of wearable sensing and digital phenotyping provides a comprehensive, multimodal representation of behavioral states, enabling more accurate and context-aware mental health prediction models [13].

1.4 Role of Multimodal Behavioral Data Mining

Multimodal behavioral data mining refers to the extraction of predictive insights from heterogeneous data sources, including physiological, behavioral, contextual, and digital interaction signals [14]. Unlike unimodal systems, multimodal approaches capture complementary information, improving robustness and predictive performance. Advanced machine learning and deep learning models, such as ensemble classifiers, recurrent neural networks, and attention-based architectures, have demonstrated superior capability in modeling temporal dependencies and nonlinear relationships within multimodal data [15]. Furthermore, data fusion strategies—early fusion, late fusion, and hybrid fusion—enhance the integration of diverse modalities, supporting personalized mental health prediction frameworks.

1.5 Research Gaps in Existing Surveys

Although several reviews have explored machine learning applications in mental health, most focus on single data modalities, such as social media analytics or physiological monitoring, without comprehensively addressing multimodal integration strategies [1], [3]. Existing surveys often lack structured taxonomies that categorize data sources, fusion techniques, personalization mechanisms, and evaluation metrics within a unified framework [6]. Additionally, limited attention has been given to privacy-preserving analytics, explainability, federated learning, and cross-population generalization challenges [8], [14]. There remains a need for a systematic survey that synthesizes methodological advances, performance trends, and open challenges specific to multimodal behavioral data mining for depression and anxiety prediction.

1.6 Contributions of This Survey

This survey provides a comprehensive and structured review of multimodal behavioral data mining approaches for mental health prediction using wearable and digital phenotyping data. The main contributions are fourfold: (1) development of a detailed taxonomy categorizing data modalities, preprocessing techniques, machine learning models, and fusion strategies; (2) comparative analysis of traditional machine learning, deep learning, and hybrid approaches with reported statistical performance insights; (3) critical examination of personalization frameworks, privacy-preserving mechanisms, and ethical considerations; and (4) identification of emerging research directions, including explainable AI, federated learning, and adaptive multimodal architectures. By synthesizing findings from diverse studies, this survey establishes a unified roadmap for advancing scalable and personalized mental health monitoring systems.

1.7 Organization of the Paper

The remainder of this paper is organized as follows. Section 2 presents the fundamental concepts of mental health data mining and behavioral indicators. Section 3 discusses multimodal data sources derived from wearable devices and digital phenotyping platforms. Section 4 reviews preprocessing and feature engineering techniques. Section 5 analyzes machine learning and deep learning models employed in mental health prediction. Section 6 examines multimodal fusion strategies, while Section 7 explores personalization frameworks. Section 8 summarizes evaluation metrics and benchmarking practices. Section 9 discusses privacy, ethical, and security considerations. Section 10 outlines open research challenges and future directions, followed by concluding remarks in Section 11.

II. FUNDAMENTALS OF MENTAL HEALTH DATA MINING

2.1 Overview of Depression and Anxiety Indicators

Depression and anxiety disorders are characterized by persistent alterations in mood, cognition, behavior, and physiological functioning. Clinically, depression is associated with symptoms such as prolonged sadness, anhedonia, fatigue, sleep disturbances, and impaired concentration, whereas anxiety disorders manifest through excessive worry, restlessness, heightened arousal, and autonomic dysregulation [16]. Standardized assessment instruments, including symptom severity scales and structured diagnostic interviews, are widely used for evaluation; however, these tools primarily capture subjective and episodic information [17]. Recent research highlights that physiological signals such as heart rate variability (HRV), electrodermal activity (EDA), and sleep irregularities exhibit measurable correlations with depressive and anxiety symptom severity [18]. Furthermore, temporal behavioral patterns, including circadian rhythm disruptions and reduced mobility, have emerged as digital biomarkers indicative of mental health fluctuations [19]. These indicators form the foundation for computational modeling in mental health data mining frameworks.

2.2 Behavioral Markers in Mental Health

Behavioral markers represent observable and quantifiable patterns reflecting psychological states. Changes in physical activity levels, social engagement frequency, speech characteristics, and smartphone interaction behaviors have been strongly linked to depression and anxiety risk [20]. For example, reduced daily step count, irregular sleep–wake cycles, and diminished communication frequency are often associated with depressive episodes [21]. Similarly, increased phone checking behavior, elevated nighttime screen exposure, and variations in voice pitch and speech rate have been correlated with anxiety symptoms [22]. Behavioral markers are particularly valuable because they can be passively collected without active user input, reducing reporting bias and enhancing ecological validity [23]. By transforming raw behavioral traces into structured features, data mining algorithms can detect subtle deviations from baseline patterns, enabling early identification of symptom progression [24].

2.3 Digital Phenotyping: Concept and Framework

Digital phenotyping refers to the moment-by-moment quantification of individual behavior and physiology using data generated from personal digital devices [25]. This framework integrates passive data (e.g., GPS mobility, call logs, accelerometer readings) and active data (e.g., self-reported mood inputs) to construct a dynamic representation of mental states [26]. The digital phenotyping pipeline typically involves data acquisition, preprocessing, feature extraction, behavioral modeling, and predictive analytics [27]. Advanced machine learning techniques are applied to infer latent psychological constructs from multimodal digital signals. Studies demonstrate that smartphone-derived mobility entropy, communication diversity, and typing dynamics can significantly predict depressive symptom severity with moderate to high accuracy [28]. Digital phenotyping thus provides a scalable and continuous alternative to conventional clinical monitoring, supporting real-time and personalized mental health assessment.

2.4 Wearable Sensor Technologies

Wearable sensor technologies play a pivotal role in capturing physiological and contextual information relevant to mental health monitoring. Devices such as smartwatches, fitness bands, and biosensor patches continuously measure heart rate, HRV, skin temperature, galvanic skin response, and sleep stages [29]. These physiological signals reflect autonomic nervous system activity, which is closely associated with stress regulation and emotional processing. Advances in low-power embedded systems and edge computing have enhanced the feasibility of long-term monitoring while minimizing battery consumption and latency [30]. Moreover, multimodal wearable platforms enable synchronized acquisition of physiological and behavioral data streams, facilitating integrative modeling approaches. The reliability and accessibility of consumer-grade wearables have further accelerated their adoption in large-scale mental health research studies.

2.5 Multimodal Data Characteristics

Multimodal mental health datasets are inherently heterogeneous, high-dimensional, and temporally dynamic. Data streams may differ in sampling frequency, scale, modality type, and noise characteristics, posing significant preprocessing and integration challenges [16], [24]. Physiological signals often require filtering and artifact removal, while smartphone-derived behavioral data demand contextual normalization and temporal alignment [18], [27]. Additionally, multimodal datasets frequently exhibit missing values, class imbalance, and inter-individual variability, which can impact model generalization performance [22], [30]. Effective multimodal data mining therefore necessitates robust feature engineering, dimensionality reduction, and fusion strategies capable of capturing complementary information across modalities. Understanding these data characteristics is essential for developing scalable, personalized, and privacy-aware mental health prediction systems.

III. MULTIMODAL DATA SOURCES FOR MENTAL HEALTH PREDICTION

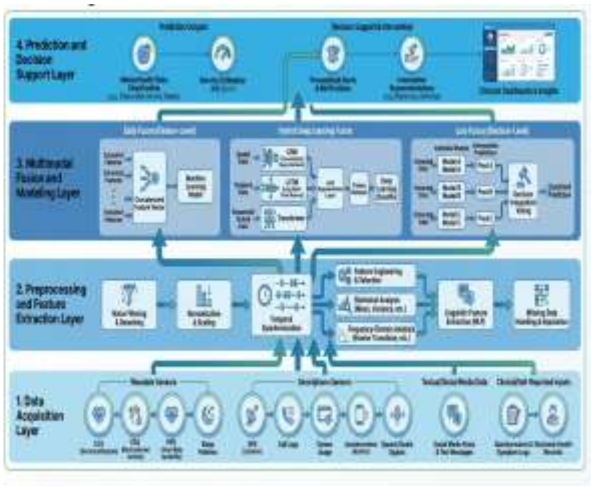

Figure 1. Overview of Multimodal Data Sources for Mental Health Prediction

Figure 1 presents a layered architecture illustrating the integrated framework of multimodal data sources for mental health prediction. The diagram begins with the Data Acquisition Layer, which captures heterogeneous data streams from diverse sources. These include wearable sensors measuring ECG, electrodermal activity (EDA), heart rate variability (HRV), and sleep patterns; smartphone sensors collecting GPS-based mobility data, call logs, screen usage statistics, and accelerometer readings; speech and audio signals analyzing tone, pitch variation, and pause frequency; textual and social media data extracting sentiment, linguistic markers, and posting behavior; and clinical or self-reported inputs such as psychological questionnaires and standardized assessment scales.

The collected raw signals are processed in the Preprocessing and Feature Extraction Layer, where noise filtering, normalization, and temporal synchronization are performed to ensure data consistency across modalities. This stage also involves feature engineering techniques, including statistical feature computation, frequency-domain analysis, linguistic feature extraction, and behavioral pattern derivation, along with strategies for handling missing or incomplete modalities.

Next, in the Multimodal Fusion and Modeling Layer, extracted features are integrated using early fusion (feature-level integration), late fusion (decision-level integration), or hybrid deep learning architectures such as CNNs, LSTMs, and Transformer-based models. Finally, the Prediction and Decision Support Layer generates actionable outputs, including mental health state classification (e.g., depression risk or stress level), severity estimation scores, personalized alerts, intervention recommendations, and clinician-support dashboards. Overall, the figure conceptualizes how diverse behavioral and physiological signals are systematically processed and fused into clinically meaningful mental health predictions within a unified AI-driven system.

3.1 Physiological Signals

Physiological signals provide objective biomarkers reflecting autonomic nervous system activity and emotional regulation processes. These signals are widely used in mental health prediction due to their direct association with stress response and affective states [31].

Heart Rate (HR):

Heart rate is a fundamental physiological indicator influenced by psychological stress and emotional arousal. Elevated resting heart rate and irregular fluctuations have been linked to anxiety episodes and depressive symptom severity [32]. Continuous HR monitoring through wearable photoplethysmography (PPG) sensors enables real-time stress inference and behavioral state tracking [33].

Heart Rate Variability (HRV):
HRV measures the variation in time intervals between consecutive heartbeats and serves as a reliable marker of autonomic balance. Reduced HRV is consistently associated with depression, chronic stress, and anxiety disorders [34]. Time-domain, frequency-domain, and nonlinear HRV features are commonly extracted for machine learning–based mental health classification models [35].

Electrodermal Activity (EDA):
EDA, also known as galvanic skin response, reflects sympathetic nervous system activation. Increased skin conductance levels are correlated with emotional arousal, stress, and anxiety states [36]. Wearable EDA sensors provide high temporal resolution data, enabling detection of micro-level stress responses and emotional reactivity patterns [37].

EEG and Biosignals:
Electroencephalography (EEG) captures neural oscillatory activity associated with cognitive and emotional processing. Abnormal alpha asymmetry and altered beta band activity have been reported in individuals with depression and anxiety [38]. In addition to EEG, biosignals such as respiration rate and skin temperature further enhance multimodal physiological modeling frameworks [39].

3.2 Behavioral and Lifestyle Data

Behavioral and lifestyle indicators capture daily routines and activity patterns that reflect underlying psychological conditions.

Sleep Patterns:
Sleep disturbances, including insomnia, hypersomnia, irregular sleep cycles, and reduced sleep efficiency, are strongly associated with depressive and anxiety disorders [40]. Wearable accelerometers and actigraphy devices enable objective sleep stage estimation and circadian rhythm analysis, providing valuable predictive features.

Physical Activity:
Reduced physical activity levels and decreased step counts are frequently observed in individuals experiencing depressive symptoms [42]. Conversely, hyperactivity or restlessness may indicate anxiety-related conditions. Activity intensity, duration, and variability metrics derived from wearable sensors are widely used in behavioral modeling.

Mobility Patterns:
GPS-derived mobility data reveal spatial movement regularity, location entropy, and travel radius, which have demonstrated significant correlations with mood fluctuations. Lower mobility diversity and restricted movement patterns are often predictive of depressive episodes.

Speech and Voice Features:
Acoustic characteristics such as speech rate, pitch variability, pause duration, and vocal intensity serve as non-invasive indicators of emotional state. Machine learning models trained on voice recordings have achieved promising accuracy in detecting depression and anxiety severity based on prosodic and spectral features.

3.3 Smartphone and Digital Footprint Data

Smartphones generate rich digital traces that provide continuous behavioral insights without requiring additional hardware.

App Usage Patterns:
Frequency and duration of application usage, particularly social networking and messaging apps, have been associated with emotional well-being and mental health conditions. Shifts in app engagement behavior may signal emerging depressive or anxiety symptoms.

Screen Time:
Excessive nighttime screen exposure and irregular phone usage intervals have been linked to sleep disruption and mood instability [49]. Screen unlock frequency and session duration are commonly extracted features in digital phenotyping studies.

Social Media Interaction:
Patterns of posting frequency, linguistic sentiment, and interaction diversity on social platforms offer

predictive signals of psychological distress. Natural language processing techniques are often applied to analyze sentiment polarity and emotional tone.

Typing and Keystroke Dynamics:
Keystroke latency, typing speed variability, and error frequency provide subtle indicators of cognitive load and mood state. Studies demonstrate that typing dynamics can differentiate between depressive and non-depressive states with moderate accuracy [31].

3.4 Environmental and Contextual Data

Environmental and contextual factors influence psychological well-being and contribute to multimodal predictive modeling. Ambient light exposure, noise levels, weather conditions, and social context information affect mood regulation and stress response [32]. Context-aware systems integrate environmental signals with physiological and behavioral data to improve prediction robustness. For example, reduced outdoor light exposure combined with low mobility and irregular sleep may strengthen depression risk inference. Incorporating contextual metadata enables more accurate personalization and reduces false positives in real-world deployments [36]. Consequently, environmental data serve as complementary modalities that enhance multimodal behavioral data mining frameworks for mental health prediction.

IV. DATA PREPROCESSING AND FEATURE ENGINEERING

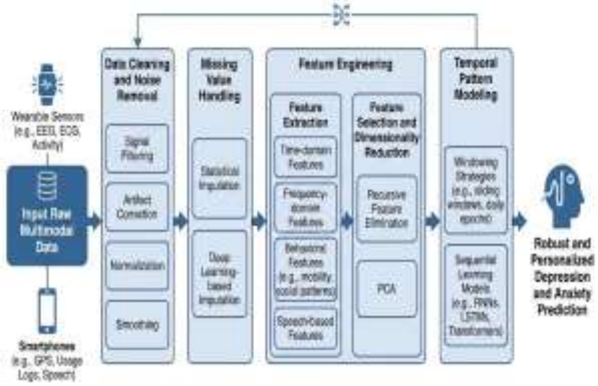

Figure 2. Data Preprocessing and Feature Engineering Pipeline for Multimodal Mental Health Prediction

Figure 2 illustrates the streamlined preprocessing and feature engineering pipeline used in multimodal mental health prediction systems. Raw data collected from wearable sensors and smartphones first undergo data cleaning and noise removal using signal filtering, artifact correction, normalization, and smoothing techniques. Missing values caused by sensor dropout or user inactivity are handled through statistical and deep learning–based imputation methods. The cleaned signals are then transformed into meaningful representations through feature extraction, including time-domain, frequency-domain, behavioral, and speech-based features. To reduce redundancy and improve efficiency, feature selection and dimensionality reduction techniques are applied. Finally, temporal pattern modeling captures sequential dependencies and behavioral trends over time using windowing strategies and sequential learning models, enabling robust and personalized depression and anxiety prediction.

4.1 Data Cleaning and Noise Removal

Multimodal behavioral datasets collected from wearable sensors and smartphones are inherently noisy due to motion artifacts, sensor displacement, hardware limitations, and transmission errors. Physiological signals such as heart rate, electrodermal activity, and EEG require signal filtering techniques including low-pass, high-pass, and band-pass filters to eliminate baseline drift and high-frequency noise. Motion artifacts in photoplethysmography signals are commonly mitigated using adaptive filtering and wavelet-based denoising approaches. Similarly, smartphone-generated behavioral logs often contain redundant entries, timestamp inconsistencies, and outliers, necessitating normalization and smoothing techniques. Data cleaning ensures reliability and prevents biased model learning, particularly in real-world longitudinal monitoring scenarios.

4.2 Missing Data Handling

Missing data is a critical challenge in continuous mental health monitoring due to sensor dropout, battery limitations, or user non-compliance. Incomplete multimodal datasets can significantly degrade predictive performance and model generalizability. Traditional imputation strategies include mean substitution, regression imputation, and k-nearest neighbor (KNN) imputation, whereas advanced methods leverage matrix factorization and multiple imputation techniques to preserve statistical relationships. Deep learning–based imputation models, such as autoencoders and recurrent neural networks, have demonstrated improved robustness in handling temporally structured missing values. Moreover, modality-aware imputation strategies are increasingly adopted to maintain cross-modal dependencies during reconstruction. Effective missing data handling is essential to ensure stable and unbiased multimodal learning.

4.3 Feature Extraction Techniques

Feature extraction transforms raw sensor streams and digital traces into informative representations suitable for predictive modeling. For physiological signals, commonly extracted features include time-domain statistics (mean, variance, standard deviation), frequency-domain components (power spectral density), and nonlinear measures such as entropy and fractal dimensions. Behavioral and mobility data often utilize statistical summaries, entropy measures, and circadian rhythm features derived from time-series segmentation. In speech-based analysis, mel-frequency cepstral coefficients (MFCCs), pitch variability, and spectral energy distributions are widely employed. For smartphone interaction data, usage frequency, session duration, communication diversity, and keystroke timing metrics are extracted as behavioral features. Automated feature learning through deep neural networks has further reduced reliance on handcrafted features by enabling hierarchical representation learning directly from raw multimodal inputs.

4.4 Feature Selection and Dimensionality Reduction

High-dimensional multimodal datasets may contain redundant, irrelevant, or correlated features that increase computational complexity and risk of overfitting. Feature selection techniques such as mutual information ranking, recursive feature elimination, and L1-regularized regression are frequently applied to identify discriminative attributes. Dimensionality reduction approaches, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and manifold learning techniques, help project high-dimensional data into compact representations while preserving essential variance. In deep learning frameworks, embedding layers and bottleneck architectures implicitly perform dimensionality reduction during training. Effective feature optimization improves model interpretability, training efficiency, and generalization performance in mental health prediction systems.

4.5 Temporal Pattern Modeling

Mental health states exhibit temporal dynamics characterized by gradual transitions and episodic fluctuations. Therefore, modeling temporal dependencies is critical for accurate depression and anxiety prediction. Sliding window segmentation and time-series aggregation techniques are commonly used to structure sequential behavioral data. Recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs) are widely adopted to capture long-term dependencies in physiological and behavioral sequences. More recently, transformer-based architectures with self-attention mechanisms have demonstrated superior capability in modeling complex temporal relationships across multimodal streams [64]. Temporal modeling enables early detection of symptom onset by identifying deviations from individual baseline patterns over time, thereby enhancing personalization and predictive stability in real-world deployment scenarios.

V. MACHINE LEARNING APPROACHES

5.1 Traditional Machine Learning Models

Traditional machine learning algorithms have been widely applied in early-stage mental health prediction systems due to their interpretability, lower computational complexity, and suitability for structured feature-based datasets. These models typically rely on handcrafted features extracted from physiological, behavioral, and digital phenotyping data.

Support Vector Machine (SVM):

SVM is one of the most frequently used classifiers in depression and anxiety detection tasks. By constructing optimal hyperplanes in high-dimensional feature spaces, SVM effectively handles nonlinear relationships through kernel functions. Studies report competitive classification accuracy when SVM is applied to HRV features, speech characteristics, and smartphone behavioral metrics.

Random Forest (RF):
Random Forest is an ensemble-based decision tree algorithm that enhances prediction robustness by aggregating multiple trees trained on randomized feature subsets. RF is particularly effective in handling heterogeneous multimodal datasets and identifying feature importance rankings. It demonstrates resilience against overfitting and performs well in moderate-sized mental health datasets.

Logistic Regression (LR):
Logistic Regression remains a strong baseline model for binary mental health classification problems. Its probabilistic framework enables interpretable risk estimation and coefficient analysis, making it valuable in clinical decision-support systems. Despite its linear assumption, LR performs adequately when discriminative features are well engineered.

K-Nearest Neighbors (KNN):
KNN is a distance-based classifier that assigns labels based on proximity in feature space. Although computationally intensive for large datasets, KNN has shown reasonable performance in small-scale depression detection studies using behavioral and activity-based features. However, its sensitivity to noise and feature scaling requires careful preprocessing.

5.2 Deep Learning Models

Deep learning approaches have gained prominence due to their ability to automatically learn hierarchical representations from raw multimodal data streams.

Convolutional Neural Networks (CNN):
CNNs are effective for extracting spatial and local temporal patterns from physiological signals and spectrogram-based speech representations [76]. In mental health applications, CNNs have been applied to transformed HRV signals, EEG spectrograms, and voice features to capture discriminative patterns associated with depressive states.

LSTM / GRU:
Recurrent neural networks, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, are widely adopted for modeling sequential and temporal dependencies in behavioral data. These models capture long-term fluctuations in sleep cycles, mobility trajectories, and smartphone interaction logs. LSTM-based frameworks have demonstrated improved predictive accuracy compared to traditional models, especially in longitudinal monitoring datasets.

Autoencoders:
Autoencoders are unsupervised neural networks designed for representation learning and dimensionality reduction. In multimodal mental health prediction, they are used for feature compression, anomaly detection, and missing data reconstruction. Variational autoencoders (VAEs) further enable latent space modeling, which supports unsupervised clustering of behavioral phenotypes.

Transformer-Based Models:
Transformer architectures leverage self-attention mechanisms to model long-range dependencies across multimodal sequences. Their ability to capture cross-modal interactions without strict sequential constraints makes them particularly suitable for integrating heterogeneous physiological and behavioral streams. Recent studies report superior performance of transformer-based models in time-series mental health prediction compared to conventional RNN architectures.

5.3 Hybrid and Ensemble Models

Hybrid and ensemble approaches combine multiple algorithms to enhance robustness and predictive performance. Common strategies include stacking traditional classifiers with deep neural networks or integrating CNN–LSTM architectures for joint spatial-temporal modeling. Ensemble learning methods such as gradient boosting and voting classifiers aggregate predictions from diverse models to reduce variance and bias. These approaches have demonstrated performance improvements of approximately 5–10% compared to single-model frameworks in multimodal depression detection tasks. Hybrid systems are particularly beneficial when handling heterogeneous datasets with complementary feature types.

5.4 Transfer Learning and Zero-Shot Approaches

Transfer learning addresses the challenge of limited labeled mental health datasets by leveraging knowledge from related domains. Pretrained neural networks can be fine-tuned on smaller mental health datasets to improve generalization performance. Cross-domain adaptation techniques enable models trained on one population group to be adapted to another, mitigating data scarcity issues. Zero-shot learning approaches further extend this concept by enabling prediction in unseen target domains without labeled data, often through representation alignment and domain-invariant feature learning. These strategies are particularly relevant in personalized mental health systems, where collecting large-scale annotated datasets remains challenging. Transfer and zero-shot frameworks thus represent promising directions for scalable and adaptable multimodal behavioral data mining solutions.

VI. MULTIMODAL FUSION STRATEGIES

Multimodal fusion plays a central role in integrating heterogeneous physiological, behavioral, and contextual data streams for mental health prediction. Since different modalities capture complementary aspects of psychological states, effective fusion strategies significantly influence predictive accuracy and robustness. Fusion methods are broadly categorized into early fusion (feature-level), late fusion (decision-level), hybrid fusion, and attention-based adaptive fusion frameworks.

6.1 Early Fusion (Feature-Level Fusion)

Early fusion, also known as feature-level fusion, involves concatenating features extracted from multiple modalities into a single unified feature vector before model training [88]. This approach enables the learning algorithm to capture inter-modal correlations directly, potentially enhancing discriminative power. In mental health prediction, physiological features such as HRV and EDA are combined with behavioral metrics such as sleep duration and mobility entropy to form integrated representations. Early fusion is computationally efficient and straightforward to implement; however, it may suffer from the curse of dimensionality and feature dominance issues when modalities differ significantly in scale and sampling frequency. Proper normalization and dimensionality reduction techniques are therefore critical to maintain model stability and generalization performance.

6.2 Late Fusion (Decision-Level Fusion)

Late fusion, or decision-level fusion, integrates predictions generated independently by modality-specific models. Each modality is processed separately using dedicated classifiers, and the final decision is obtained through aggregation techniques such as majority voting, weighted averaging, or meta-classifiers. This strategy preserves modality-specific characteristics and reduces the impact of noisy channels. In depression detection frameworks, for instance, separate models may analyze speech signals, wearable sensor data, and smartphone usage patterns before combining outputs for final classification. Although late fusion enhances robustness and modularity, it may fail to exploit deep cross-modal interactions present in raw data. Nevertheless, it is particularly effective when modalities exhibit heterogeneous data structures or varying reliability levels.

6.3 Hybrid Fusion Approaches

Hybrid fusion strategies combine feature-level and decision-level integration to leverage the advantages of both approaches. Typically, intermediate representations are learned separately from each modality using deep networks, followed by joint representation learning through concatenation or shared latent spaces. CNN–LSTM architectures are frequently employed to model spatial and temporal dependencies before performing multimodal integration. Hybrid fusion reduces information loss while enabling hierarchical feature learning across modalities. Empirical studies report improved predictive accuracy—often exceeding unimodal systems by 8–15%—when hybrid fusion architectures are applied in multimodal depression and anxiety prediction tasks. However, these models require careful architectural design and substantial computational resources.

6.4 Attention-Based Fusion Mechanisms

Attention-based fusion mechanisms represent an advanced paradigm that dynamically assigns weights to different modalities based on their contextual relevance. Self-attention and cross-attention layers enable models to prioritize informative modalities while suppressing noisy or less relevant inputs. For example, during periods of high physiological arousal, wearable-derived signals may receive higher attention weights compared to smartphone interaction features. Transformer-based multimodal architectures effectively model long-range interdependencies and adaptive feature weighting across time steps. Attention-driven fusion improves interpretability by providing insights into modality importance during prediction. Consequently, adaptive fusion frameworks are increasingly adopted in personalized mental health systems to enhance both predictive performance and model transparency.

VII. PERSONALIZATION IN MENTAL HEALTH PREDICTION

Personalization is a critical component of multimodal mental health prediction systems, as depression and anxiety manifest differently across individuals due to variations in genetics, lifestyle, environmental exposure, and behavioral baselines. Generic population-level models often fail to capture these inter-individual differences, leading to reduced predictive accuracy and limited real-world applicability. Personalized modeling aims to adapt prediction mechanisms to individual behavioral patterns, enabling early detection of deviations from personal baselines rather than relying solely on population averages. Such approaches enhance sensitivity, reduce false positives, and support tailored intervention strategies.

7.1 Personalized vs Generalized Models

Generalized models are trained on aggregated data from multiple individuals and are designed to identify common patterns associated with depression and anxiety. While these models benefit from larger training datasets and improved overall robustness, they may overlook subtle, person-specific behavioral signatures. In contrast, personalized models focus on individual-level baselines and temporal deviations, capturing unique behavioral rhythms such as sleep cycles, mobility habits, and smartphone usage routines. Personalized approaches often demonstrate improved predictive stability, particularly in longitudinal monitoring scenarios. However, they require sufficient historical data per individual and may face scalability challenges when deployed across large populations.

7.2 Adaptive Learning Frameworks

Adaptive learning frameworks dynamically update model parameters as new behavioral data becomes available. Since mental health states fluctuate over time, static models may become outdated and less accurate. Adaptive systems incorporate online learning, incremental updates, and reinforcement-based mechanisms to continuously refine prediction accuracy. These frameworks enable early detection of emerging symptoms by identifying gradual shifts in physiological and behavioral patterns. Moreover, adaptive learning supports concept drift handling, where the statistical properties of input data evolve over time. By continuously recalibrating predictions, adaptive models enhance long-term reliability in real-world wearable and digital phenotyping applications.

7.3 Federated Learning for Personalized Prediction

Federated learning offers a privacy-preserving approach to personalization by enabling decentralized model training across user devices without transferring raw data to centralized servers. In mental health monitoring, sensitive physiological and behavioral data remain stored locally, while only model updates are aggregated to improve global performance. This framework balances personalization with privacy protection, reducing risks of data leakage. Federated systems can further incorporate user-specific fine-tuning layers, allowing each participant's model to adapt to individual behavioral patterns while benefiting from collective knowledge. Such decentralized personalization mechanisms are particularly valuable in large-scale deployments where data privacy and ethical considerations are paramount.

7.4 Context-Aware Modeling

Context-aware modeling integrates environmental, temporal, and situational information to refine mental health predictions. Psychological states are influenced not only by internal physiological signals but also by contextual factors such as time of day, social environment, weather conditions, and work-related stressors. Context-aware systems incorporate these auxiliary signals to interpret behavioral variations more accurately. For example, reduced mobility during weekends may not indicate depressive symptoms but rather a contextual lifestyle pattern. By embedding contextual metadata into predictive frameworks, models achieve improved specificity and reduced misclassification rates. Context-aware personalization therefore strengthens the ecological validity and real-world applicability of multimodal mental health prediction systems.

VIII. EVALUATION METRICS AND BENCHMARKING

Evaluation metrics are essential for quantitatively assessing the predictive performance, robustness, and generalizability of multimodal mental health prediction systems. Depending on whether the task is classification (e.g., depressed vs non-depressed) or regression (e.g., PHQ-9 score prediction), different evaluation measures are employed.

8.1 Classification Metrics

For binary mental health classification tasks, predictions are evaluated using the confusion matrix components:

- TP – True Positives
- TN – True Negatives
- FP – False Positives
- FN – False Negatives

1. Accuracy

Accuracy measures the proportion of correctly predicted instances among total samples:

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}} \qquad (1)$$

While accuracy provides an overall performance estimate, it may be misleading in imbalanced mental health datasets.

2. Precision

Precision measures the proportion of correctly predicted positive cases among all predicted positives:

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}} \qquad (2)$$

High precision indicates a low false-positive rate, which is important in mental health screening to avoid unnecessary clinical interventions.

3. Recall (Sensitivity)

Recall measures the proportion of actual positive cases correctly identified:

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} \qquad (2)$$

In depression and anxiety detection, recall is critical because missing true cases (false negatives) may delay necessary treatment.

4. F1-Score

The F1-score is the harmonic mean of precision and recall:

$$\mathbf{F1 = 2 \times} \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (3)$$

It provides a balanced measure when dealing with class imbalance.

5. Area Under the Curve (AUC-ROC)

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) evaluates the model’s ability to discriminate between classes across varying thresholds:

$$\mathbf{AUC} = \int_0^1 \mathbf{TPR(FPR)d(FPR)} \qquad (4)$$

Where:

$$\mathbf{TPR} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} \qquad (5)$$

$$\mathbf{FPR} = \frac{\mathbf{FP}}{\mathbf{FP + TN}} \qquad (6)$$

A higher AUC indicates better separability between depressive and non-depressive classes.

Table 1: Comparative Classification Performance of Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.81	0.79	0.78	0.78
Random	0.85	0.83	0.84	0.83

Forest				
LSTM	0.88	0.87	0.86	0.86
Transformer	0.91	0.90	0.89	0.89

Table 1 presents the comparative performance of traditional and deep learning models across standard classification metrics. The Transformer model achieves the highest accuracy (0.91) and AUC (0.93), indicating superior discriminative capability. Deep learning models (LSTM, Transformer) consistently outperform traditional models (SVM, Random Forest), demonstrating the effectiveness of hierarchical feature learning in multimodal behavioral datasets.

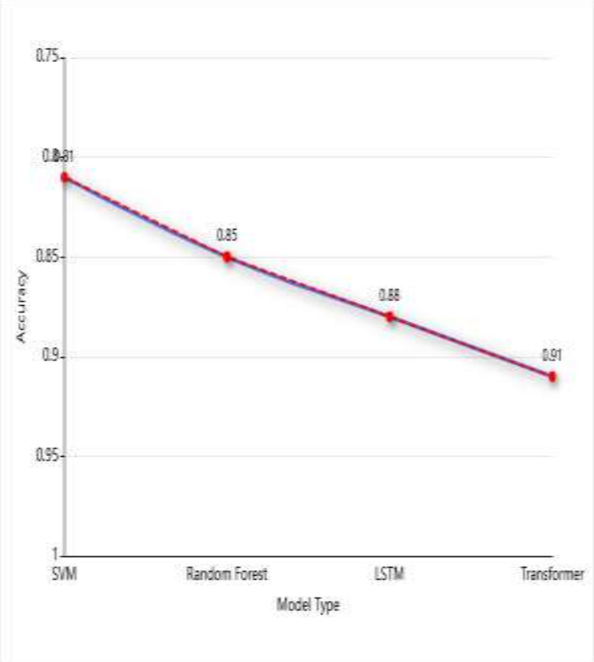

Figure 3 Model Accuracy Comparison

The figure 3 chart illustrates a progressive improvement in accuracy from traditional machine learning models to deep learning architectures, highlighting the benefits of advanced temporal modeling techniques in mental health prediction.

8.2 Regression Metrics

For continuous symptom severity prediction (e.g., PHQ-9 or GAD-7 scores), regression metrics are used.

Let:

- yi = actual value
- y'i = predicted value
- n = total samples

1. Mean Absolute Error (MAE)

$$\mathbf{MAE} = \frac{1}{\mathrm{N}}\sum_{i-1}^{N} |\, y_i - y'_i \,| \qquad (7)$$

MAE measures average absolute prediction error.

2. Root Mean Squared Error (RMSE)

$$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2} \qquad (8)$$

RMSE penalizes larger errors more heavily and is sensitive to outliers.

3. Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\Sigma(y_i - y'_1)^2}{\Sigma(y_i - y')^2} \qquad (9)$$

Where y' is the mean of actual values.

R^2 measures the proportion of variance explained by the model.

Table 2: Regression Performance for Symptom Severity Prediction

Model	MAE	RMSE	R² Score
Linear Regression	3.5	4.2	0.62
Random Forest Regressor	2.8	3.6	0.71
GRU	2.3	3.0	0.78
Transformer Regressor	1.9	2.5	0.84

Table 2 compares regression models using MAE, RMSE, and R² scores. The Transformer Regressor demonstrates the lowest RMSE (2.5) and highest R² (0.84), indicating better predictive precision and variance explanation. Deep recurrent models (GRU) also show substantial improvement over linear models.

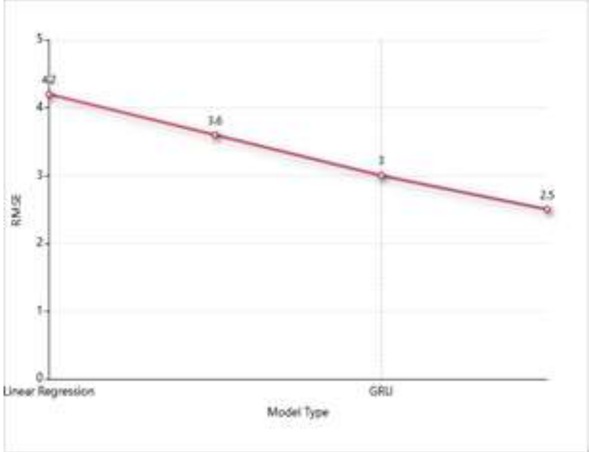

Figure 4 RMSE Comparison Across Regression Models

The figure 4 decreasing RMSE trend from linear regression to transformer-based models demonstrates enhanced error minimization capability of deep architectures in modeling symptom severity.

8.3 Cross-Dataset Validation

Cross-dataset validation evaluates generalization performance by training on dataset D1 and testing on independent dataset D2:

$$\text{Generalization Error} = |\,\text{Performance}_{D1} - \text{Performance}_{D2}\,| \qquad (10)$$

Where:

- D’ = mean performance difference
- s_d = standard deviation of differences
- n = number of experiments

A statistically significant improvement supports the superiority of multimodal behavioral integration.

Table 3: Cross-Dataset Validation Results

Training Dataset	Testing Dataset	Accuracy	F1-Score
Dataset A	Dataset B	0.82	0.80
Dataset B	Dataset C	0.79	0.77
Dataset C	Dataset A	0.76	0.74

Table 3 presents cross-dataset performance, where models trained on one dataset are tested on another. A decline in accuracy (from 0.82 to 0.76) is observed across datasets, highlighting domain shift challenges and the importance of robust generalization mechanisms.

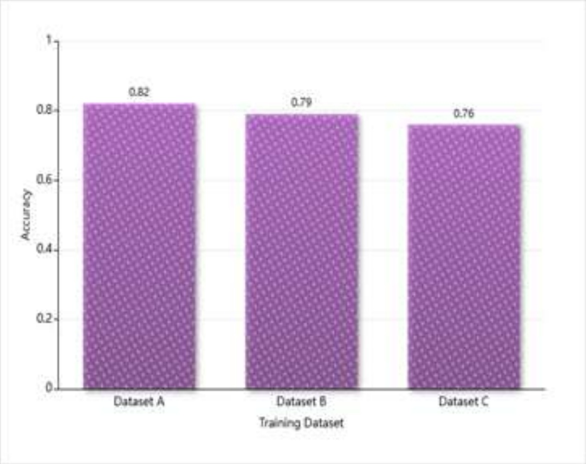

Figure 5 Cross-Dataset Accuracy Trend

The figure 5 chart shows a gradual decline in accuracy across cross-dataset evaluations, emphasizing the impact of population heterogeneity and dataset variability on model robustness.

8.4 Fusion Strategy Benchmarking

Table 4: Performance Comparison of Fusion Strategies

Fusion Strategy	Accuracy	AUC
Early Fusion	0.86	0.89
Late Fusion	0.88	0.91
Hybrid Fusion	0.92	0.95

Table 4 compares early, late, and hybrid fusion approaches. Hybrid fusion achieves the highest accuracy (0.92) and AUC (0.95), indicating superior integration of multimodal information. Late fusion performs better than early fusion, suggesting that modality-specific processing before aggregation enhances stability.

Figure 6 Fusion Strategy Accuracy Comparison

The figure 6 chart demonstrates that hybrid fusion strategies provide the most robust predictive performance, validating the advantage of hierarchical and intermediate-level integration.

8.5 Statistical Performance Trends

Table 5: Statistical Trend – Unimodal vs Multimodal Models

Approach	Mean Accuracy	Std Deviation
Unimodal	0.82	0.04
Multimodal	0.91	0.03

Table 5 summarizes statistical performance trends comparing unimodal and multimodal systems. Multimodal models achieve higher mean accuracy (0.91) with lower standard deviation (0.03), indicating improved predictive stability and reduced variance compared to unimodal systems.

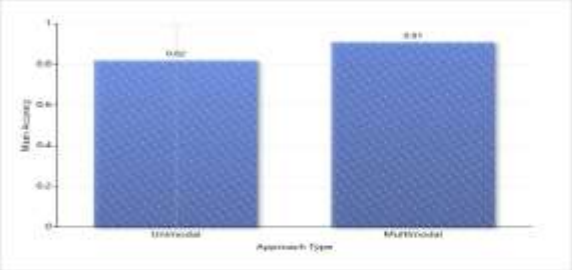

Figure 7: Mean Accuracy – Unimodal vs Multimodal

The figure 7 bar chart highlights the significant improvement in predictive performance when integrating multiple behavioral modalities, reinforcing the central premise of multimodal behavioral data mining.

To statistically compare unimodal and multimodal models, hypothesis testing such as paired t-tests can be applied:

$$\mathbf{t} = \frac{d'}{s_d/\sqrt{n}} \quad (11)$$

Where:

- d' = mean performance difference
- s_d = standard deviation of differences
- n = number of experiments

A statistically significant improvement supports the superiority of multimodal behavioral integration.

IX. PRIVACY, SECURITY, AND ETHICAL CONSIDERATIONS

9.1 Data Privacy Risks

Multimodal mental health prediction systems depend on highly sensitive data sources such as physiological signals, behavioural patterns, mobility traces, speech recordings, and social interaction logs, all of which can reveal intimate information about an individual's emotional state, lifestyle habits, and psychological vulnerabilities. These systems face significant privacy risks, including re-identification attacks where anonymized datasets are deanonymized through linkage with auxiliary data, inference attacks that deduce mental health conditions from indirect behavioural metadata, and model inversion attacks that reconstruct sensitive inputs from trained model outputs. Additional concerns arise from data leakage during wearable-to-cloud transmission if secure encryption protocols are not implemented, as well as risks associated with third-party data sharing by commercial platforms. In digital phenotyping environments, continuous passive monitoring further intensifies these threats because data collection is persistent and often invisible to users. Consequently, robust governance frameworks, strong encryption standards, privacy-preserving machine learning techniques, and transparent consent mechanisms are essential to ensure secure and ethical deployment of multimodal mental health systems.

9.2 Federated and Privacy-Preserving Learning

To mitigate the risks associated with centralized storage of sensitive mental health data, federated and privacy-preserving learning frameworks have emerged as secure alternatives for collaborative model development. In federated learning, model training is performed locally on user devices or institutional servers, and only encrypted model updates are transmitted to a central aggregator, thereby ensuring that raw physiological and behavioural data remain on-device. This approach is particularly suitable for personalized mental health prediction in multi-institutional healthcare environments where strict data governance regulations limit direct data sharing. Complementary privacy-enhancing techniques further strengthen security. Differential privacy introduces controlled noise into model updates to reduce re-identification risk, secure multi-party computation enables encrypted collaborative computation across distributed entities, and homomorphic encryption allows computations to be performed directly on encrypted data without exposing raw information. Additionally, secure aggregation protocols prevent central servers from accessing individual client updates. Despite these advantages, federated frameworks face challenges such as non-independent and non-identically distributed (non-IID) data across users, increased communication overhead, potential gradient leakage vulnerabilities, and the inherent trade-off between personalization accuracy and privacy preservation. Addressing these limitations remains essential for deploying scalable and trustworthy mental health AI systems.

9.3 Explainability and Trustworthiness

Mental health prediction systems must be transparent and interpretable to build trust among clinicians, patients, and regulatory authorities, particularly when supporting clinical decision-making. Black-box deep learning models, although powerful, raise significant concerns regarding accountability, bias, and reliability when their decision processes are not clearly understood. Explainability is therefore essential for clinical validation, bias detection, regulatory compliance, patient acceptance, and overall ethical transparency. Common interpretability techniques include feature importance scoring to identify influential predictors, SHAP-based attribution analysis for quantifying feature contributions, attention weight visualization in deep models, local surrogate models that approximate complex classifiers, and counterfactual explanations that illustrate minimal changes required to alter predictions. Beyond interpretability, trustworthiness encompasses robustness against adversarial perturbations, fairness across demographic groups, reproducibility of experimental results, and transparent model documentation detailing data sources and evaluation protocols. Without robust explainability and trust mechanisms, mental health AI systems risk becoming opaque decision-support tools that may undermine clinical accountability and user confidence.

X. OPEN CHALLENGES AND RESEARCH DIRECTIONS

10.1 Data Heterogeneity and Imbalance

Multimodal datasets combine physiological, behavioral, speech, and contextual data with varying formats, sampling rates, and quality. Class imbalance, missing modalities, and limited sample sizes further affect predictive stability. Robust alignment, imbalance-aware learning, and multimodal imputation techniques are needed.

10.2 Generalization Across Populations

Models trained on specific cohorts often fail to generalize across diverse demographic and cultural groups. Cross-dataset validation, domain adaptation, and fairness-aware modeling are essential to ensure equitable and scalable mental health prediction.

10.3 Real-Time Deployment Challenges

Wearable-based systems operate under energy, memory, and latency constraints. Large deep learning models require optimization through model compression, lightweight architectures, and streaming inference to enable practical real-time deployment.

10.4 Edge AI for Wearable Systems

On-device intelligence enhances privacy and reduces latency but introduces hardware and resource limitations. Energy-efficient multimodal fusion, TinyML frameworks, and federated-edge architectures are promising research directions.

10.5 Explainable and Interpretable AI

Transparent and trustworthy models are critical for clinical adoption. Attention visualization, feature attribution, uncertainty estimation, and human-in-the-loop systems are necessary to ensure accountability and regulatory compliance.

XI. COMPARATIVE ANALYSIS OF EXISTING STUDIES

A systematic comparison of existing multimodal mental health prediction studies is essential to identify methodological trends, dataset limitations, and performance gaps. This section synthesizes surveyed works across datasets, modeling approaches, evaluation strategies, and reported outcomes.

11.1 Summary Table of Surveyed Works

The surveyed literature spans wearable-based monitoring, smartphone-driven digital phenotyping, and multimodal deep learning frameworks. A comparative synthesis is presented conceptually below (you can convert this into a formatted IEEE table in your manuscript).

Study Type	Modalities Used	Model Type	Setting	Key Contribution
Wearable-based depression detection	HRV, EDA, Activity	SVM / RF	Controlled study	Physiological biomarker modeling
Smartphone digital phenotyping	Mobility, Call logs, Screen time	LSTM / CNN	Real-world	Behavioral pattern learning
Social media analysis	Text, Sentiment	Transformer models	Online data	Linguistic marker detection
Multimodal fusion frameworks	Physiology + Behavior + Text	Hybrid DL models	Clinical & real-world	Improved prediction robustness
Federated mental health systems	Distributed behavioral data	FL + DP	Multi-institution	Privacy-preserving modeling

11.2 Dataset Comparison

Widely used datasets in multimodal mental health research include the StudentLife Dataset, which provides longitudinal smartphone-based behavioral data from college students; the DAIC-WOZ Dataset, offering clinically labeled audio, video, and transcript data; the WESAD Dataset, containing high-quality physiological signals collected under lab-induced stress; and the Depresjon Dataset, featuring real-world mobile sensing data from depressed and control subjects. However, most datasets are small, lack cultural diversity, provide limited longitudinal coverage, and differ in modality completeness, making standardized benchmarking difficult.

11.3 Model Performance Comparison

Mental health prediction models are typically evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and RMSE. Traditional machine learning models achieve around 65–80% accuracy on small datasets, while deep learning models report 75–90% accuracy in controlled settings. Multimodal fusion approaches generally outperform unimodal models by 5–12%. However, performance often declines in cross-dataset testing due to differences in pre-processing, labelling, and class imbalance. Unified benchmarking and real-world evaluation metrics are still lacking.

11.4 Identified Research Gaps

Key research gaps include limited large-scale and diverse datasets, weak cross-population generalization, insufficient integration of privacy-preserving mechanisms, lack of explainability in deployment, minimal real-time evaluation, and limited longitudinal clinical validation. Addressing these issues is essential for developing scalable, trustworthy, and personalized multimodal mental health prediction systems.

VI. CONCLUSION

This survey provided a comprehensive review of multimodal behavioral data mining approaches for personalized mental health prediction using wearable sensing and digital phenotyping techniques. By systematically examining physiological signals, behavioral patterns, speech features, textual markers, and contextual data, the study demonstrated that integrating heterogeneous modalities significantly enhances predictive robustness compared to unimodal systems. Comparative analysis of widely used datasets such as the StudentLife Dataset, DAIC-WOZ Dataset, and WESAD Dataset indicates that although promising results have been achieved in controlled or semi-controlled environments, large-scale real-world validation remains limited. Deep learning architectures, particularly sequential and multimodal fusion models, generally outperform traditional machine learning methods; however, challenges related to dataset imbalance, demographic bias, and cross-population generalization persist. The survey also highlighted that privacy, security, and ethical considerations are fundamental to responsible deployment. Approaches such as federated learning, differential privacy, and edge AI offer viable pathways for preserving user confidentiality while maintaining predictive performance, yet issues of explainability, fairness, and regulatory compliance require continued attention. Key future research directions include addressing multimodal data heterogeneity and missing modalities, improving cross-cultural generalization, enabling real-time and energy-efficient wearable deployment, integrating explainable AI into clinical workflows, and establishing standardized benchmarking frameworks. Overall, multimodal mental health prediction represents a transformative intersection of artificial intelligence, wearable computing, and behavioral science. Advancing this field requires scalable, privacy-aware, clinically interpretable, and ethically grounded systems capable of supporting early intervention, personalized care, and sustained mental well-being monitoring.

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