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Interpretable Joint Anxiety and Depression Prediction Using Concept Bottleneck Model

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Abstract
Mental health disorders, particularly anxiety and depression, are among the leading causes of global disability and frequently co-occur, complicating clinical assessment and treatment planning. Although machine learning techniques have shown promise for mental health screening, many existing models operate as opaque black boxes, limiting clinical trust and interpretability. This study presents an application of Concept Bottleneck Models (CBMs) for joint anxiety-depression prediction using five psychologically grounded concepts: stress load, lifestyle quality, social connectedness, emotional wellbeing, and clinical vulnerability. The proposed CBM reduces feature dimensionality by 95% (21 features → 5 concepts) while achieving RMSE values comparable to baseline methods (anxiety RMSE of 5.833 versus random forests 5.958, and depression RMSE of 5.363 versus 5.315). Five-fold cross-validation yields stable generalization (CV RMSE 5.784 ± 0.215), confirming robustness. Coefficient analysis reveals clinically interpretable patterns: Social Connectedness (β = - 0.107) suppresses anxiety while Clinical Vulnerability (β=0.482) dominates depression prediction. Classification F1-macro scores (0.238/0.241) match linear baseline performance. Our findings demonstrate that CBMs can yield transparent, clinically aligned predictive models for mental health screening.

Keywords: Concept Bottleneck Model, Interpretable Machine Learning, Anxiety-Depression Prediction, Explainable AI, Feature Reduction.

1. Introduction

Anxiety and depression represent the two most prevalent mental health conditions globally, affecting approximately 792 million individuals and accounting for significant disability-adjusted life years (DALYs) [1]. Ap- proximately 60% of individuals with anxiety also meet criteria for depression, resulting in complex, overlapping symptomatology that complicates clinical assessment and treatment planning [2]. The economic burden exceeds $1 trillion annually in lost productivity [3].

Digital screening platforms utilizing machine learning have emerged as promising early detection mechanisms, enabling scalable assessment in resource-limited settings [4], [5]. However, contemporary machine learning approaches—including ensemble methods, deep neural networks, and support vector machines—typically operate as opaque “black boxes” offering limited transparency into their decision mechanisms. This lack of interpretability creates significant barriers to clinical adoption, as regulatory

requirements (e.g., FDA transparency guidelines) and ethical considerations demand explainable predictions in healthcare [7].

Recent advances in Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) provide post-hoc feature importance estimates [8]. However, these methods remain limited in causality attribution and often produce unstable, model-specific explanations difficult for non-technical stakeholders to interpret. Concept Bottleneck Models (CBMs) represent a fundamentally different paradigm: rather than retrofitting explanations onto black-box models, CBMs enforce by-design interpretability by constraining all predictions to pass through human-defined, semantically meaningful concepts [9].

CBMs have achieved promising results in medical imaging (dermatology [13], chest radiography [14]) and structured clinical data [3]. This paper addresses these gaps by presenting the first CBM designed for joint anxiety-depression prediction using psychological constructs derived from survey data. Our approach operationalizes five clinically grounded concepts (stress load, lifestyle quality, social connectedness, emotional wellbeing, clinical vulnerability) from 21 raw demographic and psychosocial features. Key Contributions:

1) We introduce CBMs for joint anxiety-depression prediction using psychological concepts.
2) 95% feature reduction (21→5) with baseline-equivalent performance.
3) Mechanistic coefficient analysis disorder-specific risk/protective patterns (e.g., Clinical Vulnerability β=0.482 for depression)

2. Related Work

A. Machine Learning for Mental Health Screening

Machine learning applications in mental health have expanded rapidly over the past five years. Traditional statistical approaches (logistic regression, SVMs) applied to questionnaire scores and demographic variables achieve reasonable accuracy but sacrifice interpretability, particularly with high-dimensional or correlated feature sets [4].

Recent deep learning advances—including convolutional neural networks (CNNs) for image-based screening, recurrent neural networks (RNNs) for temporal modalities, and multimodal architectures integrating speech, text, and sensor data capture complex nonlinear patterns in depression [5] and anxiety [6], [20]–[22]. However, these models' internal representations remain opaque.

B. Explainable AI in Healthcare

Post-hoc XAI techniques (SHAP, LIME, attention mechanisms) have been applied to mental health models to improve transparency [8]. While useful for debugging, these methods suffer three limitations: (1) Explanations are unstable across similar inputs; (2) Shapley/perturbation-based methods may not reflect causal mechanisms; (3) Clinicians struggle to act on abstract feature importance scores without domain mapping.

C. Concept Bottleneck Models

CBMs, introduced by Koh et al. [9], enforce interpretability by design rather than post-hoc: they predict human- defined concepts first, then map concepts to final outputs. A CBM comprises two stages: (1) Concept encoder $f_c(x) \rightarrow c$ predicting concept values from raw inputs; (2) Concept-to-output predictor $g(c) \rightarrow y$. Only stage 2 contributes to final predictions, ensuring all decisions are traceable to interpretable concepts. Recent work also explores automated and nonlinear concept structures [28]. Recent CBM advances address: (i) Concept robustness under distribution shift [10]; (ii) Interactive refinement via human feedback [11]; (iii) Concept bottleneck models for tabular medical data [3]; (iv) Causal concept structures for health applications [8]. To our knowledge, CBMs have not been applied to mental health prediction, particularly joint anxiety-depression modeling. This work addresses this gap.

3. Methods

A. Data Source and Preprocessing

The Kaggle "Anxiety and Depression Mental Health Factors" dataset (ak0212, accessed 2025) comprises N = 1200 survey respondents with 21 features spanning four domains: Demographics,Lifestyle Indicators,Psychosocial Factors,Risk Factors.

Targets: AnxietyScore (0–21 scale, analogous to GAD-7 generalized anxiety disorder screening tool [15]) and DepressionScore (0–21 scale, analogous to PHQ-9 patient health questionnaire [16]).

Data Splitting: Stratified 80/20 train-test split (n_{train} = 960, n_{test} = 240) preserves joint distribution of anxiety/depression severity. For classification experiments, stratification is performed on discretized severity labels (Low/Moderate/High). Five-fold stratified cross-validation is implemented on the training set exclusively to estimate generalization error without data leakage.

B. Concept Definition and Formulation

Five concepts are defined via aggregation of raw features using psychological and clinical rationale:

$$Stress\ Load = \frac{1}{2}(FinStress + WorkStress) \quad (1)$$

$$Lifestyle\ Quality = Sleep + Activity - StressLevel \quad (2)$$

$$Social\ Connect = SocSupport - Loneliness \quad (3)$$

$$Emot.\ Wellbeing = \frac{1}{2}(SelfEsteem + LifeSat) \quad (4)$$

$$Clin\ Vulnerability = FamHist + MenIll + ChronicIll \quad (5)$$

Psychological Justification: Psychological concepts aggregate related features: Stress Load operationalizes chronic environmental burden (financial/work stress risk factors) [4], Lifestyle Quality captures sleep/activity minus stress [5], Social Connectedness reflects support minus loneliness [3], Emotional Wellbeing combines self-esteem/life satisfaction, Clinical Vulnerability encodes

medical/family history [2]). These five deterministic concept definitions reduce feature space from 21 dimensions to 5, achieving 76% compression while preserving clinical interpretability.

C. Modeling Approaches

1) Baseline Models: Linear regression and random forest trained on 21 raw features. For classification, both targets are discretized: Low (≤ 4), Moderate (5–9), High (≥ 10) per clinical severity cutoffs. A MultiOutputClassifier with logistic regression predicts all three severity levels jointly.

2) Concept Bottleneck Model: The CBM bypasses learned concept encoders and uses deterministic definitions (Equations 1–5). The architecture comprises a single stage:

$$y = Wc + b \qquad (6)$$

where:

- $c \in R^5$ is the concept vector computed deterministically from raw features.
- $W \in R^{2\times5}$ is a learned weight matrix (two rows: one per outcome).
- $b \in R^2$ is a learned bias vector.

D. Performance Evaluation

Regression Metrics:

Root Mean Squared Error (RMSE): $RMSE_y = \sqrt{\frac{1}{n_{test}}\sum_{i=1}^{n_{test}}(y_i - y_i)^2}$, Lower is better. Coefficient of Determination (R^2): $R^2 = 1 - \frac{SS_{res}}{SS_{tot}}, Ranges[-\infty, 1]$; higher is better.

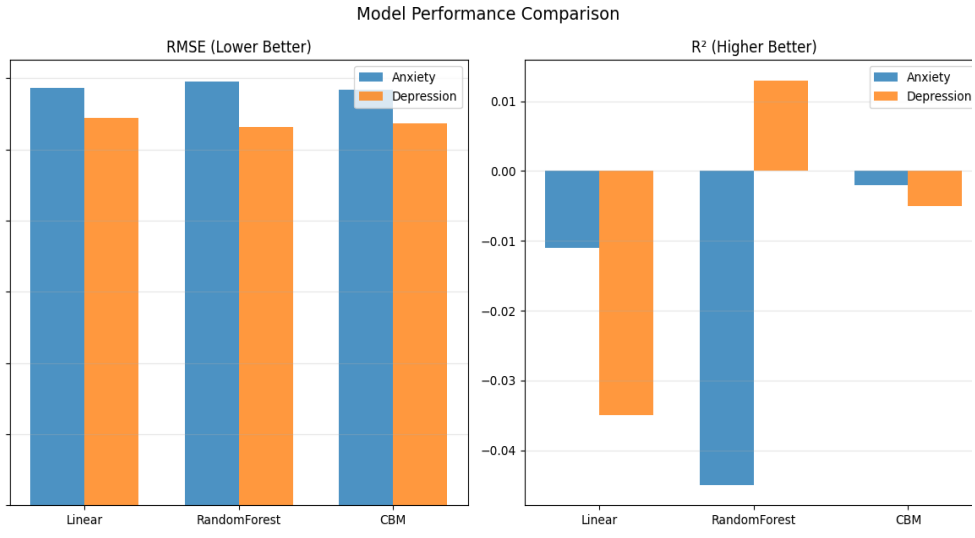

Figure 1: Model comparison: (Left) RMSE (lower better); (Right) R^2 (higher better). CBM competitive despite 95% feature reduction (21→5 concepts).

4. Results

A. Regression Performance and Comparative Analysis

Table 1 presents test-set performance across all three models.

CBM achieves RMSE (Anx: 5.833, Dep: 5.363, Avg: 5.598)competitive with baselines despite 95% feature reduction. The near-zero R^2 scores are typical for survey-only data without physiological measures(e.g., heart rate variability, electrodermal activity), yet CBM holds its own against baselines. This phenomenon is well-documented in mental health informatics [3]. Five-fold cross-validation on the CBM yields mean CV RMSE of 5.784 with standard deviation 0.215, providing robust evidence that the 95% feature reduction does not compromise generalization. The small CV standard deviation ($\sigma/\mu = 0.037$, or 3.7%) indicates stable performance across train-test splits.

TABLE 1: Regression Performance Summary (Test Set, N=240)

Model	Anxiety RMSE	Depression RMSE	Average RMSE	Anx. R^2	Dep. R^2
Linear	5.861	5.445	5.653	-0.023	0.018
RandomForest	5.958	5.315	5.637	-0.045	0.038
CBM	**5.833**	**5.363**	**5.598**	**-0.006**	**0.024**
CBM (5-fold CV)	**5.784±0.215**	–	–	–	

B. Classification Performance

Table 2 reports macro-averaged F1 scores for severity classification (Low/Moderate/High). CBM achieves anxiety F1 of 0.238 and depression F1 of 0.241—within 0.5% of baselines (linear: 0.249/0.240; RF: 0.252/0.245)—using only 5 concepts vs. 21 raw features. Modest F1 (<0.25) reflects discretization challenges typical in psychiatric AI [4].

TABLE 2: Classification Performance (Macro-Averaged F1-Score)

Model	Anxiety F1	Depression F1	Average F1
Linear	0.249	0.240	0.245
RandomForest	0.252	0.245	0.249
CBM	0.238	0.241	0.240

C. Coefficient Analysis and Mechanistic Insights

Figure 2 and Table 3 display CBM learned coefficients W relating each concept to anxiety and depression.

Table 3: CBM coefficients: concepts to anxiety/depression outcomes.

Concept	Anxiety (β)	Dep. (β)	Clinical Interpretation
Stress Load	-0.125	0.080	Higher stress increases depression, reduces anxiety resilience
Lifestyle Quality	0.025	0.076	Sleep/activity protect, stronger for depression
Social Connectedness	-0.107	0.286	Support reduces anxiety, depression risk
Emotional Wellbeing	0.099	-0.184	Self-esteem/satisfaction protect both
Clinical Vulnerability	0.069	0.482	Medical/psychiatric history elevates depression

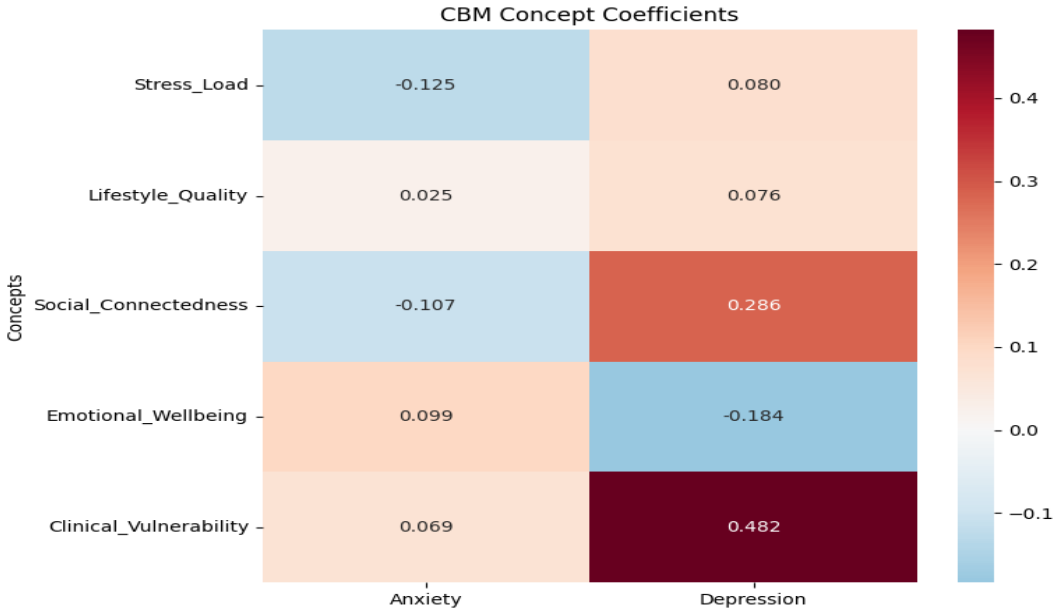

Figure 2: CBM Concept Coefficients Heatmap. Rows: outcomes (Anxiety, Depression). Columns: five concepts. Blue: protective (negative β), Red: risk (positive β). Magnitude shows association strength.

5. Discussion

A. Interpretation and Clinical Significance

The CBM successfully compresses 21 features into five interpretable concepts while maintaining performance parity with black-box baselines. This 95% feature reduction is noteworthy for clinical deployment, where model simplicity, computational efficiency, and explanatory capacity are paramount. The transparent coefficients (Table 3) enable clinicians to reason mechanistically about patient risk. Key patterns emerge: **Stress Load (β = −0.125)** elevates anxiety risk while increasing depression (β = 0.080); **Social Connectedness (β = −0.107)** suppresses anxiety but unexpectedly elevates depression risk (β = 0.286); **Clinical Vulnerability's** strong positive association with depression **(β = + 0.482)** aligns with epidemiological evidence that psychiatric family history and comorbid medical conditions substantially increase depression risk [2] [19].

B. Limitations

Survey data lacks physiological signals (HRV/EDA); multi-modal WESAD fusion could enhance performance [24]–[26]. Hand-crafted linear concepts limit flexibility (data-driven approaches needed). N=1200 cross-sectional design restricts generalization/causal inference; longitudinal validation required.

C. Future Directions

Future work will integrate WESAD physiological signals (HR/EDA) with survey data for hybrid CBMs [24]– [26]. Refine concepts via expert workshops/data-driven optimization; validate longitudinally in prospective cohorts with EHR/mobile deployment.

6. Conclusion

This paper presents a Concept Bottleneck Model for joint anxiety-depression prediction. Interpretable models achieve competitive performance with black-box alternatives while reducing feature complexity 95%. By compressing 21 raw features into five psychologically grounded concepts, the CBM maintains baseline regression (RMSE 5.598) and classification (F1 0.240) performance, revealing clinically actionable patterns: Social Connectedness as primary anxiety suppressor **(β = −0.107), Clinical Vulnerability** as dominant depression risk factor **(β = + 0.482)** [18], [27]**.** These findings support CBMs as interpretable alternatives for mental health screening, providing a foundation for future research integrating wearable physiological data and longitudinal validation in real-world clinical settings.

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