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Deep Neural Network Modeling of Adolescent Generalized Anxiety Using Attentional Bias, Physiological Arousal, Worry Severity, and Parent–Child Conflict

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1. Round 1

1.1. Reviewer 1

Reviewer:

A major reporting concern is the pervasive absence of numerical values (sample size, age range, percentages, means/SDs, correlations, accuracy, AUC, layer sizes, importance weights) throughout the Methods and Results sections as they are currently presented; whether this is a formatting issue or not, from a publication standpoint the paper must include all exact numerical parameters (e.g., N, age range, cutoffs, learning rate, dropout value, performance indices with confidence intervals) in the text and tables, as this is crucial for transparency, interpretability, and reproducibility.

The Discussion is theoretically well-informed and integrates the findings with contemporary models of worry, intolerance of uncertainty, and family dynamics; nonetheless, it tends to emphasize theoretical consonance at the expense of critical appraisal of the model's limitations, such as potential overfitting, the restricted number of predictors, the possibility that simpler models (e.g., regularized logistic regression, random forests) could perform comparably, and the risk of conflating statistical prediction with causal inference; incorporating a more explicit comparison with conventional models and a sober reflection on the clinical interpretability of "black box" predictions would improve the balance.

The limitations section correctly notes the cross-sectional design, self-report bias, screening-based GAD classification, and limited generalizability to Chilean adolescents, but it could go further by addressing methodological limitations specific to the machine-learning approach, including class imbalance (if present), potential data leakage, lack of external validation, and the fact that model performance might not replicate in non-laboratory, real-world settings; explicitly acknowledging these ML-specific constraints will enhance the transparency and trustworthiness of the study.

Authors uploaded the revised manuscript.

1.2. Reviewer 2

Reviewer:

The Methods section offers an appropriate general description of the cross-sectional predictive design, sampling strategy, and measures, but it remains insufficiently detailed on several key points: the exact age range and distribution, total N and participation rate, handling of potential clustering at the school/class level, and any power or sample size considerations for training a DNN; adding these details would significantly strengthen the methodological rigor and allow readers to judge whether the model is adequately powered relative to the number of parameters.

The description of the deep neural network architecture is promising but not yet adequate for replication: while you note three hidden layers with unspecified numbers of neurons, use of ReLU, dropout, Adam, and binary cross-entropy, important implementation details are missing, including the exact number of input features, hidden layer sizes, dropout rate, learning rate, batch size, initialization scheme, number of epochs and patience parameter for early stopping, and any regularization beyond dropout; these should be fully specified, ideally with a succinct model schematic and/or code-like pseudo-description.

The choice of a simple train–test random split is reasonable as a starting point, but relying solely on a single split to report model performance (accuracy and AUC) raises concerns about overfitting, sampling variability, and optimistic bias; I strongly recommend adding k-fold cross-validation or repeated cross-validation, reporting performance distributions (means and standard deviations or confidence intervals), and clearly distinguishing between training, validation, and test sets to provide a more robust estimate of generalization.

The feature importance analysis using Garson's algorithm is an interesting attempt at explainability, yet the paper needs to justify this choice more explicitly and clarify its limitations in the context of modern XAI methods: Garson's method was originally proposed for simpler feedforward networks and may not fully capture complex non-linear interactions; discussing alternative or complementary approaches such as permutation importance, SHAP values, or Integrated Gradients—and explaining why Garson's algorithm was selected—would enhance the credibility and interpretive depth of the explainability component.

Authors uploaded the revised manuscript.

2. Revised

Editor's decision after revisions: Accepted.
Editor in Chief's decision: Accepted.

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