

A Multimodal Machine Learning Approach to Adolescent Loneliness Using Social Disconnection, Parasocial Relationships, Emotional Inhibition, Family Cohesion, and Digital Isolation

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E d i t o r

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R e v i e w e r s

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1. Round 1

1.1. Reviewer 1

Reviewer:

The Introduction repeatedly emphasizes “multimodal machine learning” as a conceptual contribution, yet the manuscript does not clearly define what constitutes “multimodality” in this study. For example, the paragraph beginning with “Despite growing scholarly attention to adolescent loneliness and digital wellbeing...” discusses integration of subjective and objective indicators, but the authors should provide a clearer theoretical rationale explaining why psychosocial self-report variables and digital behavioral metrics are conceptually complementary modalities rather than simply heterogeneous predictors.

The sentence “Adolescent loneliness is inherently multidimensional and likely influenced by intricate combinations of emotional inhibition, social disconnection, family dynamics, parasocial engagement, and behavioral technology use patterns” would benefit from explicit reference to a guiding theoretical framework. Currently, the manuscript lacks a unifying theoretical model (e.g., socioecological theory, compensatory internet use theory, attachment theory, interpersonal acceptance-rejection theory) that explains why these particular predictors were selected and how they are expected to interact.

The paragraph discussing parasocial relationships (“Although parasocial engagement may temporarily satisfy emotional needs for companionship and validation...”) oversimplifies the literature by emphasizing primarily maladaptive implications.

Contemporary parasocial relationship research suggests both adaptive and maladaptive functions depending on identity development, social context, and emotional regulation capacities. The authors should include a more balanced conceptualization and explain why parasocial relationships were hypothesized to positively predict loneliness in this specific adolescent sample.

In the “Study Design and Participants” section, the authors state that “school counselors and administrative staff collaborated with the research team to facilitate participant recruitment and parental coordination.” However, there is no description of institutional review board approval, ethical clearance number, parental consent procedures, adolescent assent procedures, or data privacy protections related to digital monitoring applications. Considering that minors’ digital activity was monitored, ethical transparency must be substantially expanded.

The description of the digital monitoring protocol lacks sufficient methodological precision. The sentence “behavioral indicators were collected using secure screen-time tracking software installed voluntarily by participants” raises major concerns regarding reproducibility. The authors should specify the name of the monitoring software, compatibility across operating systems, sampling intervals, passive versus active tracking procedures, and whether participants could manually disable monitoring features during the observation period.

The inclusion criterion “having regular access to the internet and digital devices” is insufficiently operationalized. The authors should define what constitutes “regular access,” particularly because digital inequality and socioeconomic disparities may significantly influence online behavior patterns, loneliness, and the resulting machine learning predictions.

The manuscript states that “participants with more than 15% missing data” were excluded from analysis. However, the authors do not report how many participants were excluded specifically for missingness versus invalid response patterns. A participant flow diagram or attrition breakdown should be provided to improve transparency.

The Measures section describes the UCLA Loneliness Scale, Social Connectedness Scale-Revised, and other instruments adequately; however, psychometric evidence for the present sample is absent. The manuscript repeatedly references prior validation studies but fails to report Cronbach’s alpha coefficients, McDonald’s omega values, confirmatory factor analysis indices, or measurement invariance analyses for the current dataset. These statistics are necessary because machine learning performance is highly dependent on measurement quality.

The “Digital Social Disconnection Questionnaire” appears to be insufficiently described and may represent a novel or adapted instrument. The manuscript does not provide information regarding its developers, validation process, sample items, factor structure, or psychometric properties. Since this variable emerged as the strongest predictor in the SHAP analysis, its measurement validity must be rigorously documented.

The reporting of the machine learning models in Table 2 lacks critical technical detail. For example, the authors do not report hyperparameters for Random Forest, XGBoost, Support Vector Machine, or Multilayer Perceptron models. Without this information, the study is not reproducible. The manuscript should include either a supplementary appendix or a methodological table detailing hyperparameter configurations, optimization ranges, and final selected values.

The SHAP-based feature importance analysis is described narratively, but the manuscript does not provide sufficient visual or quantitative detail regarding SHAP distributions, interaction values, or local versus global interpretability analyses. The figure should include axis labels, magnitude scales, and confidence intervals where applicable. Additionally, the authors should discuss whether feature importance stability was evaluated across folds or subsamples.

Authors uploaded the revised manuscript.

1.2. Reviewer 2

Reviewer:

The Data Analysis section contains several methodological inconsistencies. The manuscript reports the use of “accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and mean squared error indices depending on the prediction task,” but only classification metrics are ultimately reported in Table 2. The mention of mean

squared error implies regression modeling, yet no regression-based machine learning results are shown. The authors should clarify whether both classification and regression frameworks were tested.

The sentence “The dataset was divided into training (70%), validation (15%), and testing (15%) subsets using stratified sampling procedures” requires further explanation regarding class balancing procedures. If loneliness was dichotomized, the authors should report class distribution, prevalence ratios, and whether imbalance correction techniques such as SMOTE, class weighting, or oversampling were applied.

The manuscript states that “feature engineering procedures included dimensionality reduction through principal component analysis, recursive feature elimination, and feature importance ranking using SHAP values.” This sequence is methodologically ambiguous because SHAP values are generally computed after model fitting rather than during feature engineering. The authors should present a stepwise analytical pipeline clarifying the order of preprocessing, feature selection, dimensionality reduction, and model interpretation procedures.

The Findings section reports that “preliminary data screening demonstrated acceptable normality for all psychological variables,” yet the study’s main analyses are based primarily on nonparametric machine learning methods that do not require normality assumptions. The inclusion of normality statistics appears disconnected from the central analytical strategy and should either be justified or removed.

Table 1 reports strong intercorrelations among several predictors, including social disconnection and digital isolation ($r = 0.66$). Although the manuscript states that multicollinearity thresholds were not exceeded, no VIF or tolerance statistics are provided. Given the overlap between these constructs, multicollinearity diagnostics should be explicitly reported.

Authors uploaded the revised manuscript.

2. Revised

Editor’s decision after revisions: Accepted.

Editor in Chief’s decision: Accepted.