KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 10 December 2025
Revised 09 February 2026
Accepted 14 February 2026
Published online 10 March 2026

Journal of Adolescent and Youth Psychological Studies

Open peer-review report

E-ISSN: 2981-2526

Predicting Adolescent Depressive Relapse via LSTM Modeling of Smartphone Telemetry

Elena. Stoyanova[1], Rachid. El Amrani[2*], Rezki. Hmeyada[3]

[1] Department of Psychology, Sofia University, Sofia, Bulgaria
[2] Department of Social Psychology, Mohammed V University, Rabat, Morocco
[3] Faculty of Letters and Human Sciences, Mohamed V University, Rabat, Morocco

*** Corresponding author email address**: rachid.elamrani@um5.ac.ma

Editor	Reviewers
Nadereh Saadati Department of Psychology and Counseling, KMAN Research Institute, Richmond Hill, Ontario, Canada nsaadati@kmanresce.ca	**Reviewer 1:** Nouhayla Hafidi High Institute of Human Sciences, Tunis Al Manar University, Tunis, Tunisia. Email: nouhayla.hafifi@gmail.com **Reviewer 2:** Marwa Onsy The American University in Cairo, New Cairo, Egypt. Email: marwa_onsy@aucegypt.edu

1. Round 1

1.1. Reviewer 1

Reviewer:

The methodological design—a prospective, multi-center cohort of remitted adolescents followed for 18 months with continuous telemetry and bi-weekly PHQ-A assessments—is a major strength, yet the reporting of sample characteristics and follow-up completeness is incomplete in the current text (e.g., missing or corrupted numerical values on p.5), and these omissions must be corrected to allow readers to fully assess selection bias, attrition, and generalizability.

The predictive performance of the LSTM model is framed in terms of AUC-ROC, sensitivity, specificity, and F1-score, but the actual numerical values and their uncertainty (e.g., 95% confidence intervals or bootstrapped ranges) are not visible in the provided excerpt; for a paper that primarily claims predictive utility, it is essential to present these metrics clearly, compare them against simpler baselines (e.g., logistic regression with summary features, random forests, or even PHQ-A trajectories alone), and consider calibration metrics (e.g., calibration plots, Brier score) to support claims about clinical usefulness.

The authors rightly highlight ethical and privacy safeguards (IRB approval, adherence to the Declaration of Helsinki, explicit avoidance of capturing keystroke content), which is commendable in adolescent digital phenotyping research; however, the manuscript should expand its treatment of ethical issues by detailing data storage and encryption procedures, governance of access to individual-level risk predictions, opt-out mechanisms during the 18-month monitoring, and how the potential psychological burden of continuous surveillance on adolescents was assessed or mitigated.

The article convincingly argues for the conceptual suitability of LSTM networks for temporal modeling of relapse risk, yet it would be valuable to more clearly situate this work within the broader machine learning literature by discussing alternative sequence models (e.g., temporal convolutional networks, transformers, or survival models with time-varying covariates), clarifying why LSTM was chosen over these options, and whether any benchmarking against alternative architectures was attempted.

From a clinical implementation standpoint, the paper currently stops short of specifying how the predicted 14-day relapse probabilities would be integrated into real-world care pathways—there is little discussion of actionable risk thresholds, acceptable trade-offs between false positives and false negatives, alert fatigue for clinicians, or how these predictions could be aligned with stepped-care interventions—so the discussion should include a more concrete proposal or at least scenarios for clinical deployment.

Authors uploaded the revised manuscript.

1.2. Reviewer 2

Reviewer:

The description of the passive sensing framework is rich and convincingly ties specific telemetry features (mobility, accelerometer, nocturnal use, keystroke dynamics) to core depressive phenomenology (social withdrawal, circadian disruption, psychomotor retardation); nonetheless, the paper should provide a more structured, possibly tabular, mapping of each raw sensor stream to derived features, units, aggregation windows, and clinical interpretation to facilitate replication and cross-study comparison.

The LSTM modeling pipeline is described at a high level (multivariate daily sequences, dropout, Adam optimizer, binary cross-entropy, train/validation/test split), but key details needed for reproducibility and rigorous evaluation are missing, including exact architecture (number of layers and units per layer), sequence length used as input, hyperparameter tuning strategy, handling of class imbalance, and whether any nested cross-validation or temporal cross-validation was employed to mitigate overfitting on a single cohort.

While the results section suggests clinically meaningful behavioral changes in the 14-day pre-relapse window (reduced mobility and activity, increased nocturnal device use, lengthened inter-key intervals) and indicates statistical significance, the absence of precise effect sizes, confidence intervals, and exact p-values in the text, along with missing entries referenced in Tables 1 and 2, impairs the reader's ability to gauge the robustness and practical magnitude of these associations; these quantitative details should be reported explicitly and consistently.

Authors uploaded the revised manuscript.

2. Revised

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

JAYPS
Adolescent and Youth Psychological Studies
E-ISSN: 2981-2526