Adolescent Mental Health Assessment Based on Affective Computing Technology

Shuyi Jia[1], Yanming Ren[1], Xiwang Fan[2], Minghao Wang[3], Hua Shi[4] *, Pei Sun[1] *

[1] Faculty of Health and Wellness, City University of Macau

[2] Shanghai Pudong New Area Mental Health Center, School of Medicine, Tongji University

[3] SituTech Co. Ltd.

[4]Chinese PLA Center for Disease Control and Prevention

* peisun@cityu.edu.mo, placdc@139.com

Abstract: *Adolescent mental health has become an important concern in schools and society, yet current assessment approaches still rely mainly on self-report questionnaires and clinician-administered interviews, which are limited in objectivity, scalability, and suitability for repeated monitoring. This study examined the feasibility of adolescent mental health assessment based on affective computing technology, with particular attention to its potential for student wellbeing assessment and early support in educational contexts. Using a cross-sectional diagnostic design, 383 adolescents aged 10–19 years were recruited from community and clinical settings in Shanghai, including 189 participants with clinically diagnosed major depressive disorder and 194 healthy controls. Participants completed a gamified "Whac-A-Mole" task on an online platform while facial videos were recorded by a 720p webcam at 16 frames per second. Forty visual behavioural features were extracted and used to train a Random Forest classifier. The model achieved an AUC of 0.813 on the internal test set and 0.886 on the external cohort. The findings support the feasibility of using affective computing and gamified interaction to develop more sensitive, scalable, and youth-friendly approaches to adolescent mental health assessment.*

Keywords: adolescent mental health, affective computing, student wellbeing, machine learning, gamified assessment

1. Introduction

Adolescent mental health has become an increasingly important concern in both schools and society. In educational settings, emotional and psychological difficulties may affect students' wellbeing, learning engagement, school adjustment, and developmental outcomes. At the same time, youth mental health problems have shown a marked rise over the past decade, which has intensified the need for effective and scalable approaches to early identification and support (Twenge et al., 2019).

Current assessment approaches still rely mainly on self-report questionnaires and clinician-administered interviews. Although these methods remain valuable, they are often constrained by subjectivity, social desirability bias, reliance on professional interpretation, and limited suitability for repeated and process-oriented monitoring. These limitations make it difficult to capture the dynamic nature of adolescent mental health and to support early identification in a timely and youth-friendly manner. Because psychological problems are shaped by interacting social and individual factors, more sensitive and multi-layered approaches to assessment are needed (Kinderman, 2005; McGorry & van Os, 2013).

Recent advances in affective computing offer a promising direction for improving adolescent mental health assessment. By analysing multimodal behavioural signals such as facial expressions, gaze patterns, head movements, and valence–arousal dynamics, affective computing makes it possible to derive more objective, fine-grained, and non-invasive indicators of emotional states. Prior work has shown that video-based and multimodal approaches can support depression detection, but many existing systems have been developed for adults, constrained laboratory settings, or data sources that are less suitable for adolescent engagement and broader application (Ray et al., 2019; Wang et al., 2025).

Against this background, the present study examined the feasibility of adolescent mental health assessment based on affective computing technology. Specifically, it investigated whether visual behavioural indicators extracted from a gamified task could be used to distinguish adolescents with depression from healthy controls. Framed for GCCCE, the study also considers the potential of affective computing as a technology-enhanced approach to student wellbeing assessment and early support in educational contexts.

2. Method

2.1. Participants

This study adopted a cross-sectional diagnostic design. A total of 437 adolescents aged 10–19 years were initially recruited from community and clinical settings in Shanghai between March 2024 and August 2025. Participants with depressive symptoms were referred from the Shanghai Pudong Mental Health Center and met the DSM-5 diagnostic criteria for major depressive disorder (MDD) without comorbid psychiatric conditions. Healthy controls were recruited from local schools and screened to exclude major emotional or psychiatric disorders.

After excluding participants with low task adherence or poor data quality, the final dataset comprised 383 adolescents, including 189 participants with MDD and 194 healthy controls. All participants provided written informed consent, and parental or guardian consent was additionally obtained for those under 18 years of age. The study protocol was approved by the Ethics Committee of the Shanghai Pudong Mental Health Center.

2.2 Gamified task and data collection

To elicit relatively spontaneous affective and attentional responses, participants completed a gamified “Whac-A-Mole” task delivered on an online platform. Cartoon moles appeared randomly on the screen, and participants were instructed to tap them as quickly as possible. The task was designed to create an engaging and low-pressure context that encouraged natural behavioural expression. During task performance, facial videos were recorded using a 720p webcam at 16 frames per second.

2.3. Feature extraction and classification

From the recorded videos, 40 visual behavioural features were extracted, including facial action units, gaze metrics, head pose indicators, and valence–arousal dynamics. These features were then used to train a Random Forest classifier for depression screening. Model performance was evaluated through internal testing and independent external validation. This design allowed the study to assess both the discriminative value of the extracted features and the robustness of the model across cohorts.

3. Results

The model demonstrated promising classification performance. On the internal test set, the area under the curve (AUC) reached 0.813. On the independent external cohort, the model achieved an AUC of 0.886, with accuracy, precision, recall, and F1-score of 0.812, 0.841, 0.761, and 0.799, respectively. Key discriminative indicators included AU6, AU12, gaze yaw variability, and valence fluctuation. These findings suggest that affective-computing-derived visual behavioural features collected during a brief gamified task can provide meaningful information for identifying depression-related differences in adolescents.

Table 1.

Participant characteristics by group

Characteristic	Depression group (n = 189)	Healthy control group (n = 194)
Age range, years	10–19	10–19
Age, mean (SD)	17.09 (3.89)	14.06 (0.76)
Male, n (%)	50 (26.9)	113 (58.2)
Female, n (%)	136 (73.1)	81 (41.8)
Middle School Year 1, n (%)	0 (0.0)	185 (95.4)
Secondary School Year 1, n (%)	75 (40.3)	9 (4.6)
Secondary School Year 2, n (%)	111 (59.7)	0 (0.0)

Note. Participant values are taken from the uploaded manuscript's sample characteristics table.

Table 2.

Summary of task design, extracted features, and model performance

Category	Measure	Value
Experimental paradigm	Task	Gamified "Whac-A-Mole" task
Data acquisition	Video recording	720p webcam, 16 fps
Feature set	Number of visual features	40
Feature set	Feature domains	Facial action units, gaze, head pose, valence–arousal
Classification model	Primary classifier	Random Forest
Internal test set	AUC	0.813
External cohort	AUC	0.886
External cohort	Accuracy	0.812
External cohort	Precision	0.841
External cohort	Recall	0.761
External cohort	F1-score	0.799

Note. AUC = area under the receiver operating characteristic curve. Performance values are taken from the uploaded manuscript.

4. Discussion

The findings support the feasibility of using affective computing technology to develop more sensitive, scalable, and youth-friendly approaches to adolescent mental health assessment. Rather than serving as a replacement for clinical diagnosis, this approach may function as a complementary tool for early screening, risk identification, and repeated monitoring. The present study therefore contributes to ongoing efforts to expand mental health assessment beyond single-point self-report measures and toward richer behavioural data streams.

The use of a gamified task is also noteworthy. Gamification has been shown to enhance engagement and motivation in digital tasks, which may be particularly valuable when working with adolescent populations (Hamari et al., 2014; Mekler et al., 2017). In the current study, the gamified task provided an engaging and less stigmatizing context while still enabling the extraction of meaningful visual behavioural markers.

From an educational technology perspective, the study highlights the potential of integrating artificial intelligence, behavioural data, and gamified interaction into student wellbeing assessment. In school-based or youth-oriented digital support environments, such approaches may complement traditional screening tools and contribute to earlier and more accessible support. Future work should further examine privacy protection, ethical governance, interpretability, and longitudinal validation, as well as the adaptation of these tools for school-based support systems and other educational contexts.

5. Conclusion

This paper reports an empirical proof of concept for adolescent mental health assessment based on affective computing technology. Using a gamified video-based task and a Random Forest classifier, the study shows that visual behavioural features can differentiate adolescents with depression from healthy controls with promising accuracy and generalizability. More broadly, the work suggests that affective computing may contribute to technology-enhanced, multimodal, and youth-friendly approaches to student wellbeing assessment and early support.

References

American Psychiatric Association. (2022). *Diagnostic and statistical manual of mental disorders* (5th ed., text rev.). Author.

Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. In Proceedings of the Annual Hawaii International Conference on System Sciences (pp. 3025–3034). IEEE. https://doi.org/10.1109/HICSS.2014.377

Kinderman, P. (2005). A psychological model of mental disorder. Harvard Review of Psychiatry, 13(4), 206–217. https://doi.org/10.1080/10673220500243349

McGorry, P., & van Os, J. (2013). Redeeming diagnosis in psychiatry: Timing versus specificity. The Lancet, 381(9863), 343–345. https://doi.org/10.1016/S0140-6736(12)61268-9

Mekler, E. D., Brühlmann, F., Tuch, A. N., & Opwis, K. (2017). Towards understanding the effects of individual gamification elements on intrinsic motivation and performance. Computers in Human Behavior, 71, 525–534. https://doi.org/10.1016/j.chb.2015.08.048

Ray, A., Kumar, S., Reddy, R., Mukherjee, P., & Garg, R. (2019). Multi-level attention network using text, audio and video for depression prediction. In Proceedings of the 9th International Audio/Visual Emotion Challenge and Workshop (pp. 81–88). ACM. https://doi.org/10.1145/3347320.3357697

Twenge, J. M., Cooper, A. B., Joiner, T. E., Duffy, M. E., & Binau, S. G. (2019). Age, period, and cohort trends in mood disorder indicators and suicide-related outcomes in a nationally representative dataset, 2005–2017. Journal of Abnormal Psychology, 128(3), 185–199. https://doi.org/10.1037/abn0000410

Wang, L., Wang, C., Li, C., et al. (2025). AI-assisted multi-modal information for the screening of depression: A systematic review and meta-analysis. npj Digital Medicine, 8, Article 1–14. https://doi.org/10.1038/S41746-025-01933-3