

Applicability of AI in identifying early signs of depression and anxiety through digital behaviours and language patterns in teens

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ABSTRACT

Early identification of depression in adolescents remains one of the most pressing challenges in global public health, given the condition's rising prevalence and its long-term impact on development, education, and overall wellbeing. Despite growing awareness, most existing screening approaches rely on broad, one-size-fits-all models that treat the adolescent population as a single, homogeneous group. This overlooks the reality that risk factors for depression can vary considerably across subgroups defined by demographic, social, behavioural, or clinical characteristics. As a result, few current methods offer targeted or subgroup-specific estimates of depression risk, limiting their precision and practical usefulness in real-world screening contexts. The present study seeks to address this gap by identifying the specific characteristics that place adolescents at elevated risk of depression, rather than relying solely on generalized risk indicators. Building on these characteristics, the study aims to define meaningful subgroups within the adolescent population and construct subgroup-specific predictive models. These models are designed and optimized to more accurately detect adolescents who are currently experiencing a high risk of depression, taking into account the distinct patterns and risk profiles present within each subgroup. By moving beyond generalized screening tools toward more tailored, subgroup-based approaches, this study aims to improve early detection efforts and ultimately support more effective, timely mental health interventions for at-risk youth. The analysis found several strong predictors of anxiety, including parental education level, alcohol use, and social security status. Anxiety was also linked to personal and family histories of mental illness, along with related factors like a family or personal history of depression. These findings suggest that mental health interventions should account for social and family circumstances, not just clinical ones. The authors recommend using larger samples in future research to make the models more reliable. Overall, the study shows that AI can be a useful tool for early anxiety detection in young people and emphasizes the need to consider multiple, interconnected factors when assessing and treating this condition.

Key words: Machine learning, Adolescent depression, Adolescent anxiety, Pre-empting mental health problems, Digital phenotyping, AI, Potential

1. Introduction

Depression is a common mental disorder affecting more than 300 million people worldwide and is the leading cause of illness and disability in teenagers. Teenage, typically defined as a period from an age of 12 years to 19, has been widely identified as the critical developmental period when depression or symptoms of depression begin as it is when a person's mind is most vulnerable. It has become a very widespread occurrence to see depression and or anxiety present in many teenagers. Depression negatively affects teenagers' cognitive and social functioning and can even lead to self-harm behaviours and suicide. Teenage depression is therefore a grave challenge for both the mental wellbeing of adolescents and socioeconomic development in general.

Depression and anxiety in teenagers are too often ruled out for "children" being dismissive or simply not understanding the gravity of the terms and problems they may be facing. Therefore, it is all too common for depression in teenagers to be overlooked compared to that in adults and the under-diagnosis of this leads to a substantial proportion of depressed teens to not receive timely intervention and can lead to fatal outcomes.[1]

An approach to tackling the growing pressure on teenagers' mental health is through early identification. Early identification of mental health problems in teens, particularly through recognising the early signs of depression, when linked to timely intervention, has consistently been associated with improved prognoses, modifiable disorder trajectories, and better long-term outcomes. As rates of adolescent depression continue to increase, there is a growing need for approaches that can identify individuals at risk before symptoms become severe or crises emerge. Detecting depression at an earlier stage provides greater opportunities for timely assessment, access to appropriate support, and interventions that may reduce symptom severity, improve recovery, and lessen the long-term impact of depression on educational, social, and emotional development.

Artificial intelligence (AI) has emerged as a promising tool to support the early identification of depression in adolescents by analysing large and complex datasets more efficiently than traditional approaches. AI systems can integrate information from multiple sources, including behavioural patterns, speech and language, social media activity, wearable devices, and electronic health records, to identify subtle indicators of depression that may not be readily apparent during routine clinical assessment. Machine learning (ML), a subset of AI, enables these systems to learn patterns from existing data and generate predictions about an individual's

likelihood of experiencing depression. By recognising complex interactions between biological, psychological, and social factors, AI has the potential to enhance screening, support clinical decision making, and facilitate earlier intervention for adolescents at risk.[2]

Digital phenotyping is an approach that uses digital technologies to understand real time data about an individual's behaviours, experiences, and daily activities. This information is then collected through sensors and electronic activity records, such as GPS location data, or else through user input, like completing surveys or cognitive tasks. The larger the volume and complexity of the data the better the working of digital phenotyping. This is well suited to artificial intelligence (AI), which in turn identifies patterns that may not be visible with the use of conventional analysis. Digital phenotyping has been used in a number of applications with respect to mental health. This includes early screening and diagnosis, monitoring symptoms or relapse, and personalised treatment. Research has indicated the manner in which raw sensor data can be changed into clinically acceptable insights. This is first done by collecting digital data, then extracting features and combining them into behavioural markers, for example, social withdrawal and then relating these landmarks to mental health conditions like depression and anxiety.

Passive data collection is important for mental health as it is a continuous, unobtrusive monitoring which reduces dependence on self-reported information, as this can be influenced by recall bias. By using AI and machine learning techniques, these objectives, along with real time data can reveal subtle behavioural changes that could be related to depression which otherwise may have been missed through traditional clinical assessments. This supports the fact that early identification leads to timely intervention.[3]

2. Literature review

Roughly half of all lifetime mental health disorders emerge before age 14, and three-quarters by age 25, yet adolescent depression and anxiety remain chronically underdiagnosed and undertreated relative to their prevalence (Sharma et al., 2025). This mismatch between epidemiological burden and clinical detection has made adolescence a priority population for a growing body of research applying artificial intelligence and machine learning (ML) to mental health screening. The appeal is straightforward: traditional detection pathways rely on adolescents or caregivers recognizing symptoms and seeking care, a process that is slow, unevenly distributed across socioeconomic groups, and *vulnerable to the very stigma and self-concealment that characterize internalizing disorders in youth*. AI-based approaches promise something different—continuous, passive, or data-driven identification of risk that does not depend on a young person first naming their own distress. However, “AI for early detection of adolescent depression and anxiety” is not a single research program; it is a coat covering

markedly different data sources, modelling strategies, and operational definitions of what “**early**” and “**detection**” actually mean. This review synthesizes recent studies to characterize where the empirical evidence is genuinely strong, where the field is relying on convenience rather than validated signal, and where meaningful disagreements between studies expose unresolved questions about what pre-emptive AI screening should actually be built on.

[Beames et al. (2024), published in *Heliyon*, offers the most methodologically disciplined account of what has actually been attempted in the passive-sensing subfield. Their scoping review screened 6,946 initial records down to 35 eligible studies examining how smartphone sensor data—GPS coordinates, Wi-Fi association logs, accelerometer readings, call logs, and app-usage patterns has been used to detect or predict depression and anxiety in young people aged 12 to 25. The results are notable less for what they reveal about model performance than for what they reveal about researcher behaviour: GPS and/or Wi-Fi association logs appeared in 74% of the included studies, accelerometer data in 40%, and phone lock/unlock status in roughly a third, while sleep-related and circadian-movement features were comparatively underused, appearing in only about a quarter and a tenth of studies respectively. Of the behavioural constructs derived from this raw sensor data, mobility and sociability patterns. How far someone travels, how many distinct locations they visit, how routine or erratic their movements are—showed the most consistent associations with depression and anxiety symptoms across studies.

This is a valuable but double-edged finding. On one hand, it lends empirical weight to a long-standing clinical intuition that social withdrawal and behavioural disengagement are core, observable markers of internalizing distress, and it demonstrates that these markers can, in principle, be captured passively without self-report. On the other hand, Beames and colleagues are explicit that this is a *scoping review rather than a performance meta-analysis* (definition): it maps which sensors researchers have used, not which sensors work best. The dominance of GPS and accelerometer data in this literature is at least partly an artifact of ease of collection rather than a demonstrated predictive superiority, and the near-universal reliance on prospective longitudinal observational designs (97% of the sample)—while methodologically appropriate—means the field still has very little experimental or causal evidence to draw on.[3]

[Where Beames et al. maps a possibility space, Tabares Tabares et al. (2024) tests a concrete classification problem. Their study applied three supervised ML algorithms—Support Vector Machine, K-Nearest Neighbours, and Random Forest—to PHQ-9 and GAD-7 questionnaire. This data was collected from adolescents, with the primary aim of classifying anxiety severity. Using cross-validation, the Random Forest model achieved 91% accuracy (higher than other comparable studies). The confusion-matrix and ROC-curve analyses indicated strong discriminative performance except for some difficulty in distinguishing mild-severity cases.

The more analytically interesting contribution, however, is not the accuracy figure but the predictor set the model surfaced as significant: parental education level, alcohol consumption, and social security (health insurance) affiliation all emerged as meaningful contributors to anxiety classification, alongside the more expected variable of personal and family history of depression and mental illness. This finding pushes back against a purely symptom-centric or biomedical framing of adolescent anxiety detection—the model is not simply learning to recognize a cluster of self-reported symptoms but picking up on the socioeconomic and familial relations surrounding those symptoms. *Tabares Tabares and colleagues themselves argue for a multidimensional assessment approach that incorporates social and family context alongside clinical variables.*[4]

[5]Mardini et al. (2025), published in JMIR Mental Health, deferred from Tabares Tabares as their data was on a larger scale and they used real world clinical data rather than questionnaires. The sample size was 52054 adolescents from the age group 10-17.

According to them the model had a minimal impact on predictive performance. This directly complicates the socioeconomic-context narrative that Tabares Tabares et al.'s smaller-scale findings seemed to support. Two studies, both explicitly interested in the role of social and demographic context in adolescent anxiety and depression prediction, arrive at meaningfully different conclusions about how much that context actually contributes once a sufficiently large individual-level clinical dataset is available. One plausible reading is that individual-level demographic and clinical variables *already capture most of the socioeconomic signal that block-level SDoH data would otherwise provide*, rendering the added complexity of neighbourhood-level linkage somewhat redundant on a larger scale. Mardini and colleagues are appropriately cautious, calling for future work that incorporates individual-level (rather than block-level) SDoH data and validates the models across more varied populations before drawing firm conclusions.[5]

This study shifts focus to high school students specifically, building a machine-learning model that uses common stress related variables to predict emotional well-being. Rather than diagnosing depression or anxiety directly, it looks at the everyday pressures students face and how these connect to their overall mental state. The authors emphasise on the practical application of their theory. They argue that AI-driven prediction tools could aid teachers and school counsellors at an early stage. This would help in identifying students that require support well before issues become severe, indicating how predictive modelling can move beyond clinical settings into everyday school environments where early intervention is often most effective. [6]

3. Research gap and methodology

This paper would analyse the manner in which AI technology helps in detecting signs of depression in teenagers. To what extent would this help in pre-empting from digital behaviour and language patterns that the teenager is suffering from depression and anxiety.

The methodology adopted would be of the mixed method type where both quantitative and qualitative methods would be adopted from authentic secondary sources. The quantitative data would be explained in a qualitative fashion from known sources.

4. Analysis on the role of AI and similar technology in grasping signs of anxiety in teenagers through their digital behaviour and language patterns

Table 1: Comparison of research with respect to digital behaviour and language patters in identifying anxiety among teenagers

Researcher	Year	Sample size	Numeric
Mardini et al.	2025	52,054 adolescents aged 10-17	The dataset included 12,572 anxiety cases and 7,812 depression cases. XGBoost achieved AUC=.80 for anxiety and AUC=.81 for depression
Leijse et al.	2026	45 studies; 2,939 participants; 663 effect sizes	A meta-analysis found a small but statistically significant overall relationship between passive smartphone sensing and adolescent mental-health outcomes ($r=.12$). r being correlation
Brady et al.	2026	39 external studies	AUC of .708. 74% of studies identified existing diagnoses rather than predicting future onset, showing current limitations.

Li et al. / McNeilly et al.	2023	83 adolescents	354,278 messages; 90 days; 3,384 person-days; average 89.55 messages/day (SD=82.92). SD being standard deviation positive emotion: $r=-.29$, $p=.007$; negative emotion: $r=.35$, $p=.001$ p is probability
Kadirvelu et al.	2026	103 adolescents	92 passive smartphone features; 14 days of smartphone data; SDQ-high-risk balanced accuracy .71; insomnia .67; suicidal ideation .77; eating-disorder risk .70 SDQ being Strength and difficulties questionnaire
Weib et al.	2024	278 adolescents	Anxiety symptoms: 108/278 (40.30%); depression symptoms: 101/278 (37.69%); ML anxiety: AUROC=.83; ML depression: AUROC=.77; sleep disturbance: anxiety OR=2.12, depression OR=1.80 AUROC being area under the Reciever Operating Characteristic curve
Macleod et al.	2021	122 youth	2 weeks of passive smartphone sensing; depression: stationary time $r=.293$, $p=.003$, mobility $r=-.271$, $p=.006$; anxiety: stationary time $r=-.249$, $p=.01$, mobility $r=.234$, $p=.02$, screen use $r=.203$, $p=.049$

Ren et al.	2023	22 adolescents	1,145 EMAs: 15 weeks; anxiety prediction: AUC=.71, accuracy=67%; anger: AUC=.74, accuracy=71%; sadness: AUC=.66, accuracy=65% Ecological momentary assessments
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5. Use of technology as a tool and instrument for treatment of depression and anxiety

Researcher	Year	Sample size	Numerics
Pennant et al.	2015	3146 participants	Technology-based CBT: $g=0.47$ (g = effect size).
Välimäki et al.	2017	22 studies, 4,979 participants	Depression: $P=.02$; anxiety: $P<.001$ (P = probability).
Schniering et al.	2022	91 adolescents, ages 12–17	Online CBT: 45 treatment, 46 waitlist; 43.8% vs 20.9% remitted from all anxiety/mood disorders.
Topooco et al.	2019	70 adolescents, mean age 17.5	Internet CBT produced $d=.86$ for depression; clinically significant improvement occurred in 46% of the treatment group compared with 11% of controls (d =

			standardized effect size).
Osborn et al.	2020	103 Kenyan adolescents, ages 13–18	A digital intervention was tested against a study-skills control for depression, anxiety and well-being; outcomes were measured immediately after the intervention and at follow-up.
Kuberka et al.	2025	20 studies; 17 digital interventions	3 interventions were rated quite promising, 6 slightly promising, 4 inconclusive and 7 not promising.
Wang et al.	2026	18 RCTs; 5,821 participants aged 12–25	Digital interventions for anxiety: SMD=.33; depression: SMD=.44; CBT ranked 83.4% for anxiety and 79.3% for depression (SMD = standardized difference).

6. Limitations

The study relies entirely on secondary sources and therefore summarises and analyses existing research rather than taking primary data. The studies that are conducted within this field are highly varied, with some having sample sizes upwards of ten thousand while others in double digits. Many of the studies which suggest the use of present technologies within smartphones and or devices like gyroscopic metre or accelerometer might favour this simply because it's easy to collect as phones regularly hold this data for various uses such as crash detection.

Another limitation might be applicability as the majority of research is conducted within the United States without much input from others apart from a few from Nigeria, China and India.

The ethical aspect is also a limitation as for this model or research to truly be representative it would involve the consent of data by teens for AI models to be able to use and analyse to detect or accurately pre-empt mental health problems.

One of the most important limitations we have is misdiagnosis, as text patterns can sometimes be faked or changed depending on the person and all emotions and aspects may not be able to be captured unless ample field testing has been done to get the model acclimated such as to produce accurate results.

7. Conclusion and the way ahead

This review has shown that artificial intelligence holds real, evidenced potential in identifying signs of depression and anxiety among teenagers, though its role remains closer to early diagnosis than true prevention. Passive sensing studies such as Beames et al. (2024) and Macleod et al. (2021) demonstrate that behavioural signals like mobility, sociability and screen use carry genuine clinical relevance. Predictive modelling studies such as Tabares Tabares et al. (2024) and Mardini et al. (2025) confirm that machine learning can classify anxiety and depression with strong accuracy, though they disagree on how much socioeconomic context adds to that accuracy once clinical and demographic data are already included. Broader reviews such as Brady et al. (2026) and Sharma et al. (2025) reveal that most existing research identifies conditions that already exist rather than forecasting risk before onset. Intervention studies, including Topooco et al. (2019) and Wang et al. (2026), further show that once risk is identified, digital tools such as internet-based CBT can meaningfully reduce symptoms. Taken together, the literature supports a cautious but clear conclusion. AI can detect meaningful patterns in adolescent behaviour and language, but it is not yet a proven tool for prevention in the strict sense of flagging risk before any symptoms appear.

The way forward, therefore, lies not in further isolated studies but in the development of a single, integrated AI model built specifically for adolescent populations. This model should be constructed in clear stages. First, data collection should combine passive smartphone sensing, such as mobility and temperature patterns, with individual level clinical and demographic data, rather than relying on either source alone. Second, feature selection should prioritise variables already shown to carry predictive weight across studies, including social withdrawal, sleep disturbance, and family history of mental illness, while testing rather than assuming the value of social determinants of health. Third, the model should be trained using longitudinal rather than cross sectional data, so that it can be validated against future onset of symptoms and not simply current diagnosis. Fourth, the model should be piloted in school settings, where counsellors and teachers can act on its outputs at an early stage, before symptoms become severe. Finally, the model should be tested across more diverse populations than the current literature allows, since

existing research is concentrated heavily in the United States, China and the United Kingdom. Only through this structured, staged approach can AI move from its current role in detection toward its intended role in genuine, timely prevention.

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