Research Article

Emerging Determinants and Technologies in Adolescent Health: A Review of Psychological Risk, Chronic Disease, Digital Screening, Lifestyle, Remote Monitoring, and Predictive Healthcare

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Abstract

Adolescent health is shaped by interacting psychological, physical, behavioural, social, and technological influences that may affect wellbeing across the life course. This review examines emerging determinants and technologies in adolescent healthcare through a systematic review with structured narrative synthesis of 30 studies. The evidence is organized across psychological risk, chronic disease, lifestyle behaviours, digital screening, remote monitoring, and predictive healthcare. Findings indicate that psychosocial adversity and screen-related behaviours are important concerns, while digital interventions and wearable technologies may support assessment and monitoring. Machine-learning models demonstrate promising predictive performance, although external validation, calibration, fairness, privacy, and prospective clinical impact remain necessary before implementation. The evidence is heterogeneous, and some included studies involve broader age groups; therefore, findings are interpreted according to their adolescent-specific applicability.

Keywords: Adolescent health; Psychological risk; Chronic disease; Digital health; Remote monitoring; Predictive healthcare.

1. Introduction

Adolescence is a developmental period that usually spans from 10 years old to 19 years, comprising a time of major biological, psychological, social and behavioural changes affecting health trajectories into adulthood. Adolescences can have a profound impact on physical health, emotional health, social functioning and their risk of developing chronic disease; and preventive healthcare and early intervention is an important time of opportunity during adolescence (Baird et al., 2025; McGorry et al., 2024). Several interweaving factors - psychological distress, socioeconomic inequalities, unhealthy lifestyle behaviours etc., environmental exposures and altering digital environments - are becoming more prevalent in modern youth health. These factors often combine each other, turning them into intricate health threats and needing complex healthcare interventions instead of simple ones. These suggest that in order to grasp the full picture of youth health, developmental, behavioral, clinical, and technological aspects must be also taken into account (Hossain et al., 2025).

Psychological health is one of the key elements of adolescent wellbeing, and issues such as depression, anxiety, emotional problems, self-destructive behaviours, bullying and isolation may impact educational participation and future functioning. As problems in the mental health of adolescents become more complex, the prevalence of readily available screening and technology-facilitated interventions has been promoted. In fact, systematic reviews of the digital interventions for the treatment of anxiety and depressive symptoms in adolescents conducted by Kuberka et al. (2025) showed the promising role that technology-based interventions could play in enhancing access to psychological assistance for adolescents. Likewise, Liverpool et al. (2025) found growing applications of digital mental health interventions for children and young people, but with effectiveness and implementation differing for various types of interventions. The advancements underscore the significance of early psychological evaluation, targeted interventions, and ongoing monitoring and oversight of mental wellbeing results (Noureddine et al., 2025).

Another overlooked aspect of adolescent health care is chronic diseases and lifestyle related risk factors. Adolescents can develop obesity, metabolic abnormalities, cardiovascular risk factors, diabetes susceptibility and chronic respiratory conditions and these can lead to long-term morbidity issues. Baird et al. (2025) identified in the Lancet Commission a set of interconnected needs for improvement in adolescent health policies: noncommunicable diseases, mental health, and changing environmental conditions. Lifestyle factors, such as lack of physical activity, poor diet, too much sitting, and sleep deprivation, also contribute to these risks. Silva et al. (2025) found associations of compliance to physical activity, sleep and screen-time recommendations with the indicators of cardiometabolic risk in 29,226 Brazilian adolescents. Likewise, Salam

et al. (2024) noted various critical research gaps related to noncommunicable diseases (NCDs) and related risk factors in youth and young adults (Batiha et al., 2025).

Technological innovations are opening up possibilities to enhance the health of adolescents through digital screening, wearable monitoring, telehealth, and predictive analysis. Smartphones and digital questionnaires can be used to identify psychological difficulties and wearables allow monitoring of sleep patterns, physical activity, metabolic parameters and behaviour. In the study by Sharma et al. (2025), they explored the use of AI in adolescent mental healthcare with a particular focus on screening, risk assessment, and supporting personalized. They also highlighted some concerns, including issues with accuracy, privacy, and ethical implementation when addressing the use of AI in adolescent mental healthcare. Additionally, Shen et al. (2025) summarized wearable and smartphone collected data application of machine learning in mental health monitoring. Leijse et al. (2026) went on to show how passive smartphone sensing could be beneficial in developing indicators related to mental health outcomes in adolescents. The advancements reflect a vision of a healthcare future where technologies like digital screening, remote monitoring, and predictive technologies contribute to more proactive and personalized health care (Shahid et al., 2025; Wekalao et al., 2025).

Although adolescents are becoming more aware of their health issues and boys' and girls' health is improving, significant challenges still persist in the recognition and management of interrelated psychological, behavioural, and physical health risks. Current health care evaluations often depend on periodic doctor visits and information gleaned from patients, which may hinder early detection of potential issues. However, most often these are measured as independent problems and indicators of chronic disease, rather than together (McGorry et al., 2024; Baird et al., 2025). Moreover, while digital opportunities are safe and sound, there are inequities in their effectiveness, availability, and degree of uptake of these interventions into the curriculum (Kuberka et al., 2025; Liverpool et al., 2025). Other findings on noncommunicable disease prevention suggest low dissemination of interventions and little evidence of research in multiple areas of adolescent health (Salam et al., 2024). The challenges show the importance of interwoven strategies from early screening to long-term monitoring and preventive health (Rehman et al., 2025).

Current literature also offers valuable evidence regarding adolescent psychological health, susceptibility to chronic diseases, lifestyle determinants, and nascent digital technologies which largely do not connect to one another. Wearable devices and passive smartphone sensing have possible applications for metrics of psychological and/or behavioral states, but generalizability, clinical application, and predictive reliability must be investigated (Leijse et al., 2026; Shen et al., 2025). In the same way, the use of artificial intelligence in applications still leaves gaps in the transparency of algorithms, protection of data, validation, and equitable implementation (Sharma et al., 2025). Challenges in translation to routine healthcare and methodological restrictions to remote measurement and interventions also hinder their application (Walsh et al. 2024; Raeside et al. 2024). Therefore, there is an urgent need for a comprehensive synthesis that explores the linkages among emerging health determinants, digital screening, remote monitoring and predictive health care (Naz et al., 2025; Shuwandy et al., 2025).

This review seeks to critically analyse new determinants and technologies which impact upon adolescent health, specifically on psychological risk factors, susceptibility to chronic diseases, lifestyle behaviours, digital screening, remote monitoring and predictive health care. It aims at consolidating recent evidence, assessing technological applications, outlining methodological and implementation issues, and discussing opportunities for integration into preventive and personalized adolescent healthcare.

The contribution of this review is less of an “add-on” to identifying psychological risk, chronic disease, lifestyle behaviors and digital technologies as separate domains and more a requirement to look at them as part of a single continuum, all taking place in the context of assessing, monitoring and shaping adolescent health through digital technology. The review maps the opportunities, limitations, and safeguards in technology supported adolescent healthcare by providing an integrated basis for understanding the clinical, behavioural, and social indicators that should be assessed together with the emerging digital data and clinical analytic approaches**.**

2. Literature Review

In recent years, interdisciplinary study of adolescent health has become common, acknowledging the interplay between psychological, behavioural, physical, social, and technological influences. Adolescence is especially critical for preventive health care as changes in health-related behaviours and psychological vulnerabilities, as well as changes in biology, can have a long-term impact on health in adulthood. The second Lancet Commission on adolescent health and well-being, led by Baird et al. (2025), highlighted the importance of holistic approaches that empower adolescent mental health, noncommunicable diseases, social justice and

environmental well-being. In the same way, Mudunna et al. (2025) showed that a complex socioeconomic, familial, educational, and environmental profile impact adolescent psychological well-being, especially in South Asians. The findings highlight the need for addressing adolescent health in a holistic way, and not as separate issues (Marouani et al., 2025; Khafaga et al., 2025).

Psychological health is considered a core aspect of adolescent development that may distract from school, impair social interactions, impact future functioning and may include depression, anxiety, emotional regulation problems, psychological distress, self-destructive behaviours and solitude. McGorry et al. (2024) noted that there is a critical need for early identification, easily accessible mental health care and early prevention during developmental transitions in the Lancet Psychiatry Commission on youth mental health. These are specific concerns given that some falling into those categories can persist into adulthood if not properly assessed and treated (Alzkari et al., 2025).

Among these approaches to enhancing psychological screening and interventions via digital methods are recent studies. Kuberka et al. (2025) conducted a review of the digital interventions that have been developed for adolescent anxiety and depressive symptoms, highlighting opportunities for accessible psychological care in a technological way. Similarly, Liverpool et al. (2025) noted an increasing body of evidence of the potential for digital mental health interventions, along with some variation in intervention effectiveness and implementation. Cohen and others (2024), concluded that in-school psychosocial interventions, when brief, are effective in improving student mental health and well-being, thus reinforcing the value of easy access to preventive services. The results indicate the need for early detection, community-based, developmentally appropriate treatments, and ongoing assessment of treatment efficacy in psychological services for adolescents (Hassan et al., 2025).

Another key component of adolescent health care involves chronic disease prevention, as multiple Noncommunicable Disease risk factors start developing during childhood and adolescence and continue into adulthood. There are concerns regarding obesity, metabolic abnormalities, insulin resistance, hypertension, and cardiovascular risk factors, which are influenced by the genetic disposition, dietary patterns, lack of exercise, and environment. In a global systematic review and meta-analysis, Zhang et al. (2024) showed that overweight and obesity prevalence were high among children and adolescents, with behaviour and environment playing significant role (Mostafa et al., 2025).

Another dimension where research is important is the effectiveness and availability of preventive interventions. Salam et al. (2024) showed that there is substantial lack of knowledge regarding interventions for noncommunicable diseases and related risk factors in children and youth. In an updated review of evidence on weight management interventions, O'Connor et al. (2024) again showed that structured behavioural and clinical interventions are crucial for younger age groups. Together, these results suggest that chronic disease prevention during the adolescent years should focus on the early detection of metabolic risk markers, nutritional evaluation, lifestyle modifications and effective clinical monitoring (Sohail et al., 2025).

Adolescent physical and mental wellbeing is closely linked with lifestyle behaviours, which include physical activity, eating patterns, sleep quality, and sedentary behaviour. Often, these determinants overlap or are linked together and unhealthy patterns in one behavioural domain may be accompanied by problems in another. Silva et al. (2025), using nationally representative Brazilian adolescent data, investigated associations between physical activity, sleep, screen time, and cardiometabolic risk indicators, demonstrating the importance of considering combined lifestyle behaviours when evaluating metabolic health (Huang et al., 2025).

It is also very significant that digital environments are becoming more prominent in the life pattern of adolescents. Zablotsky et al. (2025) found that increased non-school screen time is associated with a range of adverse health outcomes among US adolescents, such as low levels of physical activity, depressive symptoms, anxiety symptoms, and poor sleep patterns. Nagata et al. (2025) also examined how screen time, sleep and sport activity levels of children changed over time in early adolescence, which is critical to understand behaviour across time and not just in cross-sections. Similarly, Raeside et al. (2024) showed evidence for using digital tools focused on lifestyle risk behaviours to enhance mental health and wellbeing in young people. The findings are supportive of integrated lifestyle assessment taking into account the interactions with behaviours and their aggregate health effect (Rahi et al., 2025).

Digital screening is beginning to emerge as a valuable tool for detecting health vulnerabilities among adolescents through smartphone apps, e-questionnaires, online assessment platforms, and digitally-enriched clinical screenings. These technologies could enable earlier identification of psychological challenges and behavioral risks (for all adolescents), especially those who may have barriers to timely access to traditional health care settings due to geographical, financial, or social issues. Wani et al. conducted a review of digital mental health interventions in LMICs, highlighting potential avenues to enhance access to psychological

assistance while recognizing the limitations stemming from digital infrastructure, cost, cultural relevance and confidentiality concerns (Kale et al., 2025).

More recently, digital phenotyping has emerged as the possibility to complement traditional screening with assessment of behavioral information acquired from smartphone use. In this study, Kadirvelu et al. (2026) examined the feasibility of utilizing active self-report data as well as passive sensor-based data from smartphones for the prediction of mental health risks of school-going children and adolescents. Their results showed the feasibility of using both subjective and objective behaviour data to aid early identification. However, digital screening should be used alongside traditional screening, as some indicators need to be clinically validated and interpreted correctly before they can be used in clinical decisions (Khan et al., 2025).

In addition to traditional clinical follow-up, remote monitoring technologies offer avenues to determine the status of adolescent health using wearable technology, smartphone sensors, activity trackers, and ecological momentary assessment. All of these methods can provide information regarding physical activity, sleep, physiological measures, and daily behavior patterns. Walsh et al. (2024) reviewed the existing literature on remote measures for assessing depression in youth highlighting the potential of these measures to detect changes in natural behavior and to offer complimentary data to psychological assessments. Surveying their contextual, methodological, and implementation obstacles found that they pose challenges to the effectiveness of the remote monitoring experience, however (Benaziza et al., 2025; Galal et al., 2025).

Wearable technologies are an emerging topic in research within mental health for adolescents. Bergwerff et al. (2026) reviewed wearable technologies that have been investigated or applied for mental health assessment and support in children and adolescents, pointing to a need for ongoing physiological measurement to help assess mental health and some gaps in evidence. Laiti et al. (2026) also explored the acceptability of - WEARABLES for supporting youth mental health, noting the importance of device comfort, reliability, and the suitability of the device context. The findings indicate the availability of technologies by itself is insufficient to ensure effective monitoring, as it must also be accepted by the adolescents, reliable, and integrated into clinical processes effectively (Aoudia et al., 2025; Abbas et al., 2025).

Predictive healthcare is a newer research area in adolescent health that uses statistical modelling, machine learning, and AI to analyse and identify patterns that may point to future psychological or physical health risks. Predictive approaches seek to identify early signs that can lead to clinical deterioration, as opposed to traditional screening which mainly later detects symptoms. These approaches can encompass a variety of standardized assessments from the psychological perspective, as well as sleep parameters, medical history, activity logging, and behavior data collected electronically for a more complete evaluation of risk (Sawarkar et al., 2025; Raju et al., 2025; Tanveer et al., 2025).

In a nonclinical adolescent population, the possibility of using combined active and passive smartphones to predict multiple mental health risks has been illustrated by Kadirvelu et al. (2026). Likewise, a systematic review and meta-analysis by Di Pierdomenico et al. (2026) illuminated the universal application of digital mental health interventions with children and young people, further insights into the increasing use of digital technologies in preventive mental health care. However, predictive healthcare needs more external validation, explainability of the algorithms, safeguarding against biases in the data, and competent supervision. Therefore, AI can be an adjunctive decision support tool in the care of trained health providers and not a standalone provider of care (Singla, Gupta, et al., 2025; Mbasso et al., 2025).

The literature analyzed provides a foundation for the interdisciplinary nature of adolescent health, in which psychological development and prevention of chronic diseases, lifestyle behaviours, online assessment, an analysis of remote measurement, and predictive technologies play a role. Previous studies have made significant inputs in individual dimensions such as digital mental health interventions, noncommunicable disease prevention, behavioural monitoring, and artificial intelligence applications. The present review, however, takes a more holistic approach and looks at how these dimensions relate to one another and the implications for adolescent care. It does not focus on single diseases or technological applications of it but rather on adolescent health in a holistic system of new determinants, early detection, constant surveillance, and anticipatory intervention. The placement offers a foundation in how traditional clinical evaluations and new digital technologies get along to offer more preventive and individualised healthcare techniques (Abualigah et al., 2025).

Although much research has been performed on the health of adolescents in the last few years, there are significant gaps. Second, psychological risk, chronic disease susceptibility and lifestyle behaviours are often studied separately and the complex impact of interaction on adolescent health remains unknown. Second, while digital screening and wearable technologies are hold promise for application, there are limited data on the long-term reliability, clinical validity, acceptability, and the integration of these into routine healthcare practice. Thirdly, more needs to be done to validate predictive artificial intelligence research with external

evidence, provide transparency regarding algorithms and evaluate the outcomes across various groups of humans with substantially different demographic and socioeconomic features or characteristics. Fourth, there is variability in the effectiveness, engagement of current digital interventions, as well as implementation strategies suggesting a need for more consistent evaluation frameworks (Khodadadi et al., 2025).

Further, the inequalities of access to healthcare and of adolescent representation are also significant issues, as are privacy concerns and the digital divide. The value of integrating information from psychological screening, lifestyle assessments, wearable sensors, and predictive modelling into a coherent framework for adolescent health care has yet to be well documented. To address these limitations, integrated research is needed that brings together data from the clinical, behavioural, and technological aspects so they can inform early risk identification, ongoing risk assessment, and customized prevention strategies (Hysa et al., 2025).

3. Materials and Methods

A multi-domain systematic review with structured narrative synthesis for investigating determinants of adolescent health and digital technologies in screening, monitoring and predicting adolescent health. The review included psychological risks/mental health, chronic disease/physical health, lifestyle and behavioural determinants, digital screening, remote monitoring and wearables, and predictive healthcare/mechanisms based on machine learning and artificial intelligence. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement [1] and extension (PRISMA-S) [2] for Systematic reviews and Meta-analyses were used to inform the review process. Given the differences in design, population, outcomes and analysis of the studies included, no meaningful pooling was possible across the domains, and the evidence was synthesized narratively**.**

3.1. Research Question Formulation

The Population–Intervention/Exposure–Comparator–Outcome–Study design (PICOS) framework guided the formulation of the review questions. The population included adolescents aged 10 to 19 years in school, community and clinical settings. Exposures and interventions covered included psychological and social risk factors, chronic disease determinants, lifestyle and screen-related behaviours, digital screening tools, wearable sensors, remote monitoring and predictive models. Outcomes encompassed mental/physical health indicators, behaviour indicators, intervention outcomes, feasibility, retention, and predictive performance. The framework was employed to help synchronize the research questions and the study-selection criteria with the variables extracted into the extraction database.

The research problem shown above was explored by the general research question shown below: how can psychological, physical and behavioural determinants of adolescent health be evaluated, and what role do digital technologies play in screening, monitoring and prediction? Four supporting questions focused on distribution of health determinants, lifestyle and chronic disease indicators, using digital and remote-monitoring tools, and the methodological needs for predictive models in adolescent health services.

Table 1. Research questions and corresponding objectives

Research question	Research focus	Review objective
RQ1	Psychological and social determinants	Identify psychological risks, mental-health indicators, and social determinants reported in adolescent populations.
RQ2	Chronic disease and lifestyle factors	Examine physical-health, metabolic, lifestyle, sleep, activity, and screen-related indicators.
RQ3	Digital screening and remote monitoring	Describe digital assessment tools, wearable technologies, and remote-monitoring approaches.
RQ4	Predictive healthcare and implementation	Assess predictive-model performance, validation requirements, and implications for technology-supported adolescent care.

3.2. Literature Search Approach

The review included publications dated from 1 January 2022 to October 2026. Searches were conducted across PubMed/MEDLINE and PubMed Central, the JMIR Publications suite, PsycINFO, Embase, Scopus, IEEE Xplore, and the ACM Digital Library. Supplementary searching covered publications and surveillance material from the CDC National Center for Health Statistics and the American Academy of Pediatrics, together with backward and forward citation tracking. These sources were selected to cover clinical, epidemiological, psychological, behavioural, pediatric, and technology-oriented research.

The search strategy combined three concept groups: adolescent populations, health-related determinants and outcomes, and digital or analytical technologies. Population terms included adolescent*, youth, teen*, schoolchildren, student*, and pediatric. Health terms included mental health, depression, anxiety, suicide, self-harm, obesity, eating disorders, and lifestyle. Technology terms included screen time, digital health, mobile applications, wearable sensors, digital phenotyping, machine learning, natural language processing, and artificial intelligence. Boolean operators were used to combine synonyms within each concept group, while database-specific syntax was adapted to the relevant search interface.

A representative search structure was: ("adolescent*" OR "youth" OR "teen*" OR "pediatric") AND ("mental health" OR "depression" OR "anxiety" OR "suicide" OR "self-harm" OR "obesity" OR "eating disorder") AND ("screen time" OR "digital health" OR "wearable*" OR "digital phenotyping" OR "machine learning").

The five source groups returned 138 records before deduplication. The largest contribution came from PubMed/MEDLINE and PMC (n = 46), followed by the JMIR Publications suite (n = 38). The remaining records were identified through PsycINFO/Embase/Scopus, IEEE Xplore/ACM, and supplementary surveillance and citation searching. The distribution of retrieved records is presented in Table 2.

Table 2. Information sources and initial records retrieved

Database or source group	Main coverage	Records (n)
PubMed/MEDLINE and PMC	Clinical, epidemiological, pediatric and psychiatric literature	46
JMIR Publications suite	Digital mental health, mobile applications, sensing and AI	38
PsycINFO, Embase and Scopus	Psychological, behavioural and longitudinal research	26
IEEE Xplore and ACM Digital Library	Wearables, biosensors, machine learning and NLP	16
CDC NCHS, AAP and citation searching	Surveillance, clinical guidance and supplementary references	12
Total	All source groups combined	138

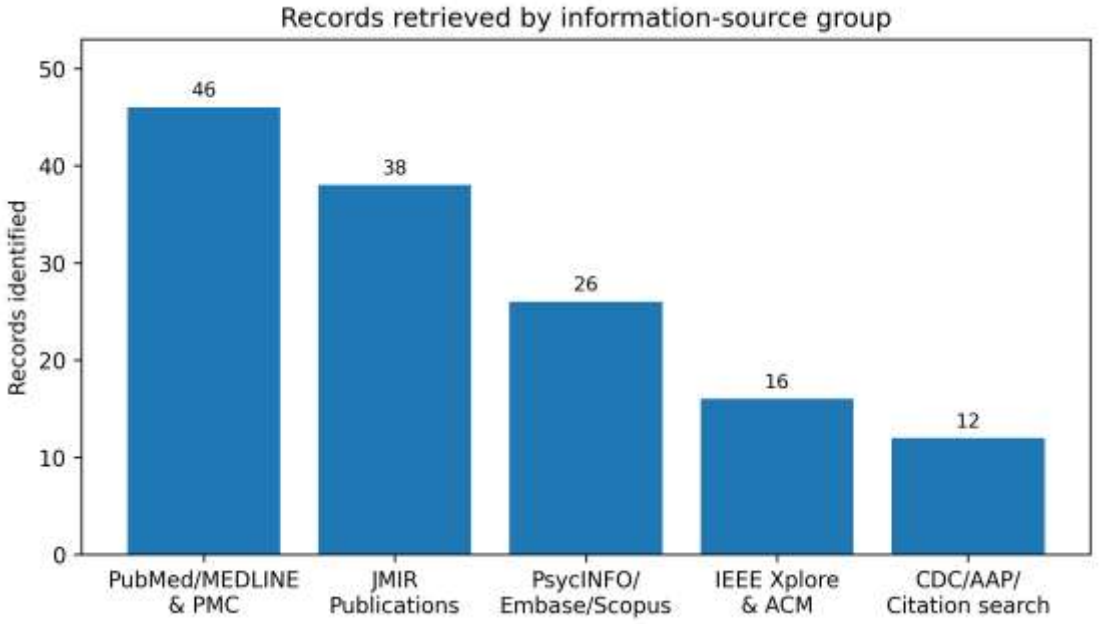


Figure 1. Distribution of the 138 records identified across the five information-source groups.

3.3. Study Eligibility and Selection Procedure

The eligibility criteria were developed using the PICOS framework. The main population consisted of adolescents between the ages of 10 and 19. Other studies with wider samples of youth or students (samples including adolescents up to age 21-24) that were not defined within that age range were included only if a robust adolescent sub-sample or adolescent-specific findings could be discerned; otherwise, the findings were considered as contextual evidence rather than adolescent-specific evidence. Eligible exposures/ interventions comprised psychological and social risks, lifestyle and screen related behaviours, digital screening, internet

delivered interventions, wearable sensors, remote monitoring, and predictive machine learning or artificial intelligence models. For descriptive designs, psychometric designs, qualitative designs and non-comparative designs a comparator was not required; for other study designs, a control or wait-list group, lower-exposure group, validated clinical measures or baseline prediction models were included.

Psychological symptoms, self-harm and suicidality, obesity and metabolic risks, behavioural indicators, intervention outcome, feasibility, retention, and model performance were eligible outcomes. The study designs eligible for review were systematic, scoping, and umbrella reviews; meta-analysis; and cross-sectional studies, cohort studies, randomized trials, cluster randomized trials, mixed methods, and model development and validation studies. Editorials, opinion pieces, case reports (no analytical contribution), protocols (no results), non-peer-reviewed blogs and studies (no relevant measurable outcomes) were excluded.

Table 3. Inclusion and exclusion criteria

PICOS element	Inclusion criteria	Exclusion criteria
Population	Adolescents aged 10–19 years; selected youth/student cohorts up to 21–24 years where adolescent-specific findings were identifiable.	Studies with no identifiable adolescent findings or no relevant population information.
Intervention / Exposure	Psychological and social risks; lifestyle and screen exposure; digital screening; internet-delivered interventions; wearables; remote monitoring; predictive models.	Studies unrelated to the six review domains.
Comparator	Control or wait-list condition; lower-exposure group; validated clinical measure; baseline model, where applicable.	No meaningful comparator where one was required by the study design.
Outcomes	Mental and physical health, behaviour, intervention effects, feasibility, retention, and predictive-performance measures.	No relevant measurable or extractable outcome.
Study design	Systematic/scoping/umbrella reviews, meta-analyses, cross-sectional and cohort studies, randomized trials, mixed methods, and model development/validation.	Editorials, opinion pieces, non-analytical case reports, protocols without results, and non-peer-reviewed blogs.
Publication period	English-language publications from January 2022 to October 2026, including relevant official surveillance material.	Publications outside the specified period or language restriction.

The study-selection process followed the screening and eligibility stages of the PRISMA 2020 framework. Of the 138 records initially identified across the information-source groups, 48 were removed before formal screening, leaving 90 records for title-and-abstract screening. Thirty records were excluded at this stage, and 60 reports were sought and successfully retrieved for full-text assessment (reports not retrieved, n = 0). Following full-text assessment, 30 reports were excluded because they did not meet the predefined eligibility criteria. The final review therefore included 30 studies (SR-01 to SR-30), grouped across the six thematic domains. The complete selection sequence is presented in Figure 2.

Title and abstract screening were performed by two reviewers independently, as was full text assessment. Disagreements were resolved via discussion, and if not, the case was sent to a third reviewer. Cohen's k for title and abstract screening and the full-text assessment was 0.88 and 0.92, respectively, in reviews within the database, which is viewed as evidence of high-level inter-reviewer agreement at both phases. The values reported represent those per the study database**.**

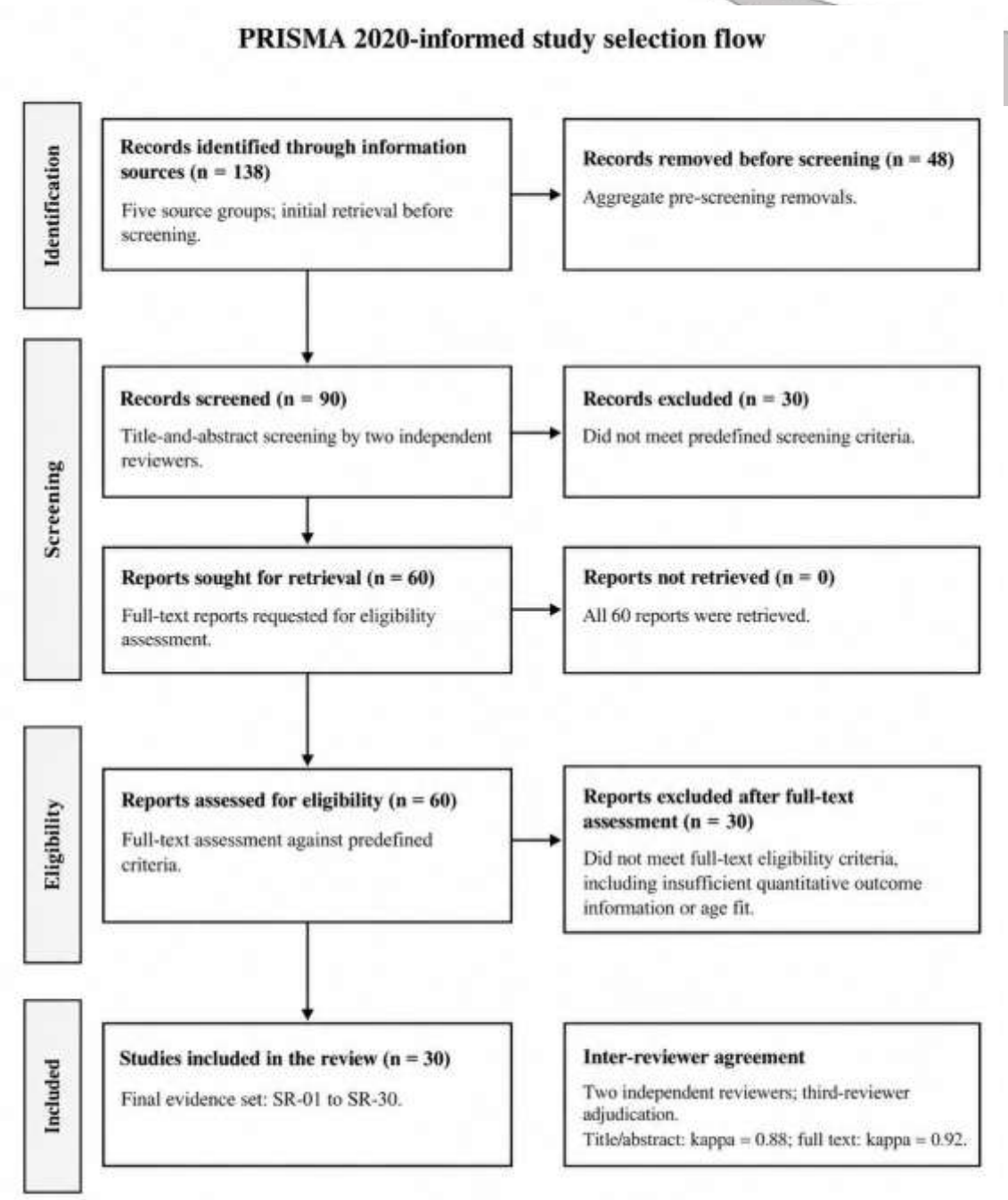


Figure 2. PRISMA 2020-informed flow diagram showing initial identification (n = 138), pre-screening removals (n = 48), title-and-abstract screening (n = 90), full-text assessment (n = 60), and final inclusion (n = 30).

3.4. Methodological Quality Evaluation

Study methodological quality and risk of bias assessment were scored through an instrument appropriate to the study design. The systematic reviews were conducted using AMSTAR 2, while observational and mixed-methods studies used Joanna Briggs Institute (JBI) tools and the 2018 Mixed Methods Appraisal Tool (MMAT); risk of bias was assessed in prediction-model studies with PROBAST. The reporting completeness of predictive studies was also examined in the context of TRIPOD-AI and considerations of large-language-models.

The four descriptive domains for the database appraisal were as follows: Selection and sampling bias, Measurement and outcome validity, Confounding control or model-validation rigor, Attrition and handling of missing data. Where available, the appraisal frameworks used were matched to that of the study design, as follows: AMSTAR 2 for systematic reviews, JBI and MMAT for relevant observational and mixed methods studies, and PROBAST for prediction-model studies. A custom descriptive summary score is also included in the workbook, which is a 5 minus the total number of domain entries scored with "Moderate". According to this

rule, by the study, 4.63/5 (19 studies) were High and 11 studies were Moderate-High, with a mean score of 4.63/5. They are not design-specific instrument critical domain judgements nor validated equivalent risk-of-bias grades, but represent internal descriptive labels. Study level ratings and recorded limitations are given on Supplementary Table S1.

Table 4. Methodological quality and risk-of-bias appraisal domains

Appraisal domain	Assessment focus
Selection and sampling bias	Representativeness of the sampling frame, recruitment strategy, selection procedures, and potential selection bias.
Measurement and outcome validity	Use of validated instruments, reliability of measurements, outcome definitions, and validity of data collection.
Confounding / validation rigor	Adjustment for relevant confounders, appropriateness of analytical methods, model validation, and robustness checks.
Attrition and missing-data handling	Completeness of follow-up, handling of missing observations, attrition patterns, and sensitivity procedures.

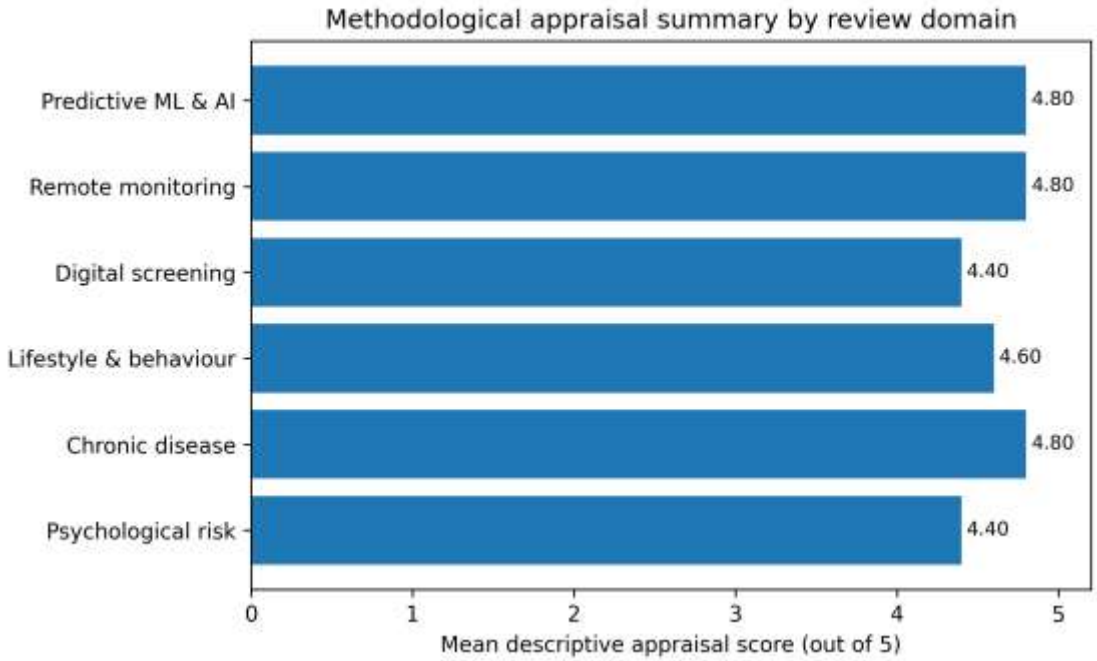


Figure 3. Mean descriptive appraisal score by primary review domain.

The study-level database classified 19 studies as High and 11 as Moderate-High under its custom descriptive scoring rule (mean score = 4.63/5). These labels summarize the workbook coding only and should not be interpreted as directly comparable validated quality grades across study designs. Interpretation therefore prioritizes the design-specific appraisal framework, domain-level judgements, and each study's stated methodological limitations.

3.5. Data Extraction

A structured 26-field data-extraction matrix was used to record bibliographic, population, methodological, analytical, and reporting information. Bibliographic variables comprised author, publication year, journal, as well as source and/or DOI details. Study variables were variables such as country/region, type of study, target population, age range, sample size, inclusion site, sampling frame and eligibility criteria. Exposure and outcome variables comprised the determinant or technology assessed, comparator/referential group if applicable, measurement instruments, and outcomes reported.

Effect estimates and indices of model performance, where reported, and key empirical findings, methodological limitations, risk of bias notes, reviewer or annotator procedures, reporting guidelines, and ethics were reported in analytical fields. An initial concordance of 96.7% was reported by the workbook in the process of which two reviewers extracted responses independently as noted in the workbook; however, an item-level paired extraction records were not provided to allow for an independent determination of the same value. Discrepancies were documented as reconciled through discussion in the protocol. As a result, a folder of

30 study records (SR-01 through SR-30) is created. All studies consist of a main thematic assignment and secondary assignments are documented individually in the domain synthesis matrix.

Table 5. Data-extraction domains and recorded variables

Extraction domain	Variables recorded
Bibliographic details	Study ID, author and year, publication year, journal/source, DOI or direct link.
Study characteristics	Study design, country/region, population and age range, sample size, recruitment setting, sampling frame.
PICOS information	Eligibility criteria, exposure or intervention, comparator/reference group, outcomes and measurement instruments.
Analytical evidence	Effect sizes, statistical estimates, model-performance metrics, key empirical findings.
Quality and reporting	Reviewer/annotator protocol, methodological limitations, risk-of-bias notes, reporting guideline and ethics/IRB information.

3.6. Thematic Analysis and Evidence Synthesis

Structured thematic synthesis was employed in the review to synthesize evidence across the six review domains. This method was chosen because the studies included varied in their approaches regarding design, population, outcome measures, and methods. A matrix of the studies according to the six different domains of evidence was developed, with each study categorized by the main domain research question, exposure or technology investigated, and main outcome highlighted in the study. Secondary domains were recorded if a study containing substantive evidence for another review domain existed but were not entered as separate studies. The primary assignment in the case of a study covering multiple domains followed the dominant objective and outcome; ambiguous assignments were verified by reference to the study title, aims, methods and extracted findings, and were clarified during reviewers' discussion. The complete primary/secondary mapping is included as a Supplementary Table (S2).

The thematic process consisted of familiarisation with the extracted documents, coding of study characteristics and result elements, categorisation of the related codes into organisational themes and structuring of the themes over the review domains. Odds ratios standardized mean differences or Hedges' g, area under the receiver operating characteristic curve (AUROC), F1 scores, feasibility or retention measures were extracted where available. These measures were not combined due to their different definitions, populations and analytic contexts. No attempt was made to harmonize conflicting findings, but they were rather discussed about issues of study design, population, measurement, and risk of bias. Thus, the synthesis has been targeted towards patterns of similarity and difference, limitations of the methodology, applicability for adolescents, and implications for integrated prevention and tech-enabled healthcare.

Table 6. Thematic organization of the six review domains

Grand thematic domain	Main evidence categories
Psychological risk and mental health	Psychological symptoms, self-harm and suicidality, psychosocial exposures, screening and protective factors.
Chronic disease and physical health	Obesity, metabolic risk, physical-health indicators, and associated determinants.
Lifestyle and behavioural determinants	Screen exposure, sleep, physical activity, diet, and behavioural patterns.
Digital screening and technology-supported healthcare	Digital assessment tools, mobile applications, internet-delivered interventions, and screening feasibility.
Remote monitoring and wearables	Wearable sensors, digital biomarkers, passive sensing, adherence, and monitoring performance.
Predictive healthcare, ML and AI	Model development, validation, discrimination, performance metrics, and reporting considerations.

The final synthesis connected health determinants with the technologies used to identify, monitor, and predict adolescent health outcomes. Findings were interpreted with attention to the boundaries of the available evidence, particularly differences in age composition, sampling, measurement validity, model validation, and the transferability of results across settings.

4. Results

The analysis synthesizes all 30 studies recorded in the evidence database. The studies are presented across six thematic domains: psychological risk and mental health; chronic disease and physical health; lifestyle and behavioural determinants; digital screening and technology-supported healthcare; remote monitoring and wearables; and predictive healthcare using machine learning and artificial intelligence. The database currently assigns five studies to each domain; this is a feature of the assembled evidence set and its thematic organization, not a prospective eligibility quota or a criterion used to determine study inclusion. The synthesis compares findings, quantitative indicators, study designs, and methodological limitations. Because the evidence includes primary empirical studies and secondary reviews, their findings are distinguished and potential overlap in underlying evidence is acknowledged. The results are presented as a structured narrative synthesis rather than as a single pooled estimate.

Table 7. Study coverage and allocation across the six analytical themes

Study ID	Author(s), year	Analytical theme	Study design
SR-01	Qasrawi et al. (2022)	Psychological Risk & Mental Health	Cross-Sectional/ Population Survey
SR-02	Gómez-Restrepo et al. (2023)	Psychological Risk & Mental Health	Longitudinal/ Cohort & RCT
SR-03	Fonseca-Pedrero et al. (2023)	Psychological Risk & Mental Health	Cross-Sectional/ Population Survey
SR-04	Town et al. (2024)	Psychological Risk & Mental Health	Scoping/ Umbrella Review & Synthesis
SR-05	Mukherjee et al. (2024)	Psychological Risk & Mental Health	Cross-Sectional/ Population Survey
SR-06	Haghjoo et al. (2022)	Chronic Disease & Physical Health	Systematic Review & Meta-Analysis
SR-07	Bakour et al. (2022)	Chronic Disease & Physical Health	Cross-Sectional/ Population Survey
SR-08	Motahari-Nezhad et al. (2022)	Chronic Disease & Physical Health	Scoping/ Umbrella Review & Synthesis
SR-09	Chu et al. (2024)	Chronic Disease & Physical Health	Longitudinal/ Cohort & RCT
SR-10	Muth et al. (2024)	Chronic Disease & Physical Health	Scoping/ Umbrella Review & Synthesis
SR-11	Hedderson et al. (2023)	Lifestyle & Behavioural Determinants	Longitudinal/ Cohort & RCT
SR-12	Zhu et al. (2023)	Lifestyle & Behavioural Determinants	Longitudinal/ Cohort & RCT
SR-13	Khalaf et al. (2023)	Lifestyle & Behavioural Determinants	Systematic Review & Meta-Analysis
SR-14	Zablotsky et al. (2024)	Lifestyle & Behavioural Determinants	Cross-Sectional/ Population Survey
SR-15	Tremblay et al. (2024)	Lifestyle & Behavioural Determinants	Scoping/ Umbrella Review & Synthesis
SR-16	Eilert et al. (2022)	Digital Screening & Tech Healthcare	Systematic Review & Meta-Analysis
SR-17	Kadirvelu et al. (2023)	Digital Screening & Tech Healthcare	Cross-Sectional/ Population Survey
SR-18	Pozuelo et al. (2023)	Digital Screening & Tech Healthcare	Cross-Sectional/ Population Survey
SR-19	Fleming et al. (2025)	Digital Screening & Tech	Scoping/

		Healthcare	Umbrella Review & Synthesis
SR-20	Edgcomb et al. (2026)	Digital Screening & Tech Healthcare	Predictive ML/ Digital Phenotyping
SR-21	Welch et al. (2022)	Remote Monitoring & Wearables	Scoping/ Umbrella Review & Synthesis
SR-22	Huhn et al. (2022)	Remote Monitoring & Wearables	Scoping/ Umbrella Review & Synthesis
SR-23	de Angel et al. (2023)	Remote Monitoring & Wearables	Longitudinal/ Cohort & RCT
SR-24	Choi et al. (2024)	Remote Monitoring & Wearables	Systematic Review & Meta-Analysis
SR-25	Lipschitz et al. (2025)	Remote Monitoring & Wearables	Predictive ML/ Digital Phenotyping
SR-26	Mullick et al. (2022)	Predictive Healthcare, ML & AI	Predictive ML/ Digital Phenotyping
SR-27	Abd-Alrazaq et al. (2023)	Predictive Healthcare, ML & AI	Scoping/ Umbrella Review & Synthesis
SR-28	Abd-Alrazaq et al. (2024)	Predictive Healthcare, ML & AI	Systematic Review & Meta-Analysis
SR-29	Zhong et al. (2024)	Predictive Healthcare, ML & AI	Predictive ML/ Digital Phenotyping
SR-30	Qadir et al. (2026)	Predictive Healthcare, ML & AI	Predictive ML/ Digital Phenotyping

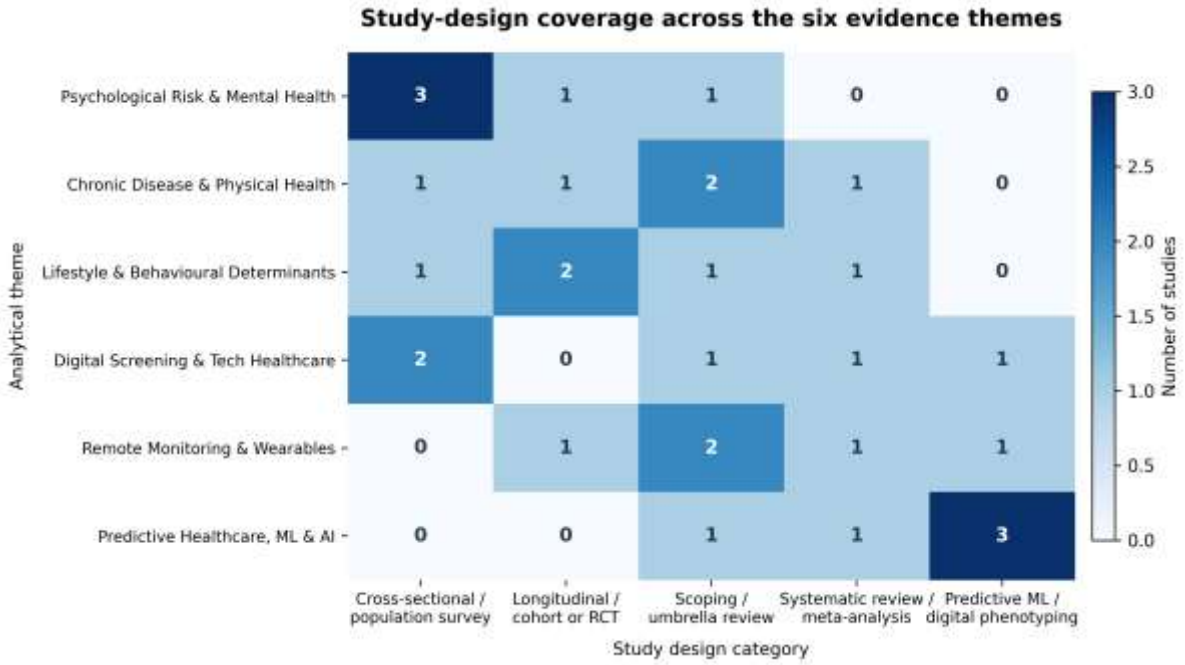


Figure 4. Distribution of study-design categories across the six analytical themes (n = 30).

4.1 Psychological Risk and Mental Health

The five studies presented here demonstrate that individual, interpersonal, and structural factors interact in influencing adolescent psychological risk, and screening and support should be developmentally and culturally responsive. Qasrawi et al. (2022) found significant rates of depressive and anxiety symptomology in school children, as well as significant correlates related to trauma, bullying, domestic violence, school and academic

challenges, and the lack of family and school support. In their ("machine learning") services, they indicate that psychosocial factors can help in risk categorisation but caution that one should not infer causation from model performance. Data from Gómez-Restrepo et al. (2023) brings this evidence to a post-conflict school context, showing that teacher delivered DIALOG+S was related to increases in quality of life and resilience and in the reported reduction of depression, anxiety, PTSD and general difficulties after 6 months. Fonseca-Pedrero et al. (2023) examined measurement quality; the findings replicated ITM for PHQ-9 in adolescents, with high fit and reliability for adolescents of comparable cohorts (for adolescents, reporting problems only warrants comparable screening; for clinical follow-ups, suicidal ideation remains the criterion since ITM was the lowest in this group). Town et al. (2024) reported that the self-management and self-help strategies are used by young people but need to be age-appropriate and co-designed with them to keep them engaged. Mukherjee et al. (2024) indicated that the academic pressure, gender discrimination, violence, and financial insecurity are factors that should be considered, and screening in low-resource urban communities requires a focus on anti-stigma activities and community-based support. Taken together these studies suggest a stepped model with validated screening, attention to social adversity, and interventions readily available in the school and community setting, and human eyes and minds to monitor. The evidence is still mixed, and screening scores or algorithmic predictions should not supplant or replace professional assessment.

Table 8. Evidence summary of psychological risk and adolescent mental health

Study ID	Author(s), year	Study approach	Principal contribution
SR-01	Qasrawi et al. (2022)	Cross-Sectional / Population Survey	Over one-quarter of early adolescents exhibited clinical depressive and anxiety symptoms. Trauma exposure (PTSD), peer bullying, domestic violence, poor academic achievement, and low family/school support were the strongest determinants of internalizing
SR-02	Gómez-Restrepo et al. (2023)	Longitudinal / Cohort & RCT	Task-sharing a structured tablet-assisted psychosocial intervention (DIALOG+S) to secondary school teachers was feasible, culturally acceptable, and improved adolescent resilience, quality of life, and internalizing distress in a resource-constrained setting.
SR-03	Fonseca-Pedrero et al. (2023)	Cross-Sectional / Population Survey	Confirmed that the PHQ-9 is a psychometrically sound, brief, and invariant screening instrument for identifying depressive severity and suicidal ideation in community and school-based adolescent populations, with significantly higher depressive scores among
SR-04	Town et al. (2024)	Scoping / Umbrella Review & Synthesis	Demonstrated that adolescents facing

			emotional distress actively rely on self-management and digital self-care strategies, particularly when formal services are inaccessible or stigmatized, but require developmentally tailored, co-designed scaffolding to
SR-05	Mukherjee et al. (2024)	Cross-Sectional / Population Survey	Revealed that addressing adolescent depression and self-harm in low-resource urban slums requires pairing mobile clinical decision-support screening (EDSS) with community-embedded, youth-co-designed anti-stigma campaigns to overcome cultural and structural

4.2 Chronic Disease and Physical Health

There are five studies in this theme that link adolescent physical health to sedentary behaviours when using screens, eating-related symptoms, use of digital feedback, and the clinical setting that supports healthy behaviours. Haghjoo et al. (2022) found a positive dose-response relationship between the highest screen-time category and overweight and obesity (OR = 1.27, 95% CI 1.16–1.39). After adjusting for various behaviour and demographic factors, Bakour et al. (2022) reported increased odds of obesity with 4+ hours of screen time per day among adolescents in the U.S. (adjusted OR = 1.69, 95% CI 1.44–1.99). These findings are in the same direction but observational counterparts are not indicative of screen cues causing weight gain. Motahari-Nezhad et al. (2022) conducted a review of digital-biomarker interventions and reported gains in activity and anthropometric outcomes in the evidence reviewed; however, the review also noted significant deficit in quality and confidence of much of that evidence. While the amount of screen time matters, the type of screen use can, at times, make a difference too. Chu et al. (2024) expanded the physical-health debate by connecting total screen time and "problematic" screen time to eating-disorder symptoms during early adolescence. Muth et al. (2024) highlighted the importance of a healthy eating, active living, sleep, and media use, or non-stigmatizing socioecological model in pediatric prevention that is embedded in a family-centered primary-care framework. In the five studies, chronic-disease prevention has been understood best as a combination of behavioural and clinical work rather than this being a weight-loss intervention solely. Results of the study agree with current recommendations on the value of systematic assessment of movement, sleep, diet and digital habits, and point to the need for better longitudinal and intervention evidence to inform causal pathways and evidence-based equitable prevention approaches.

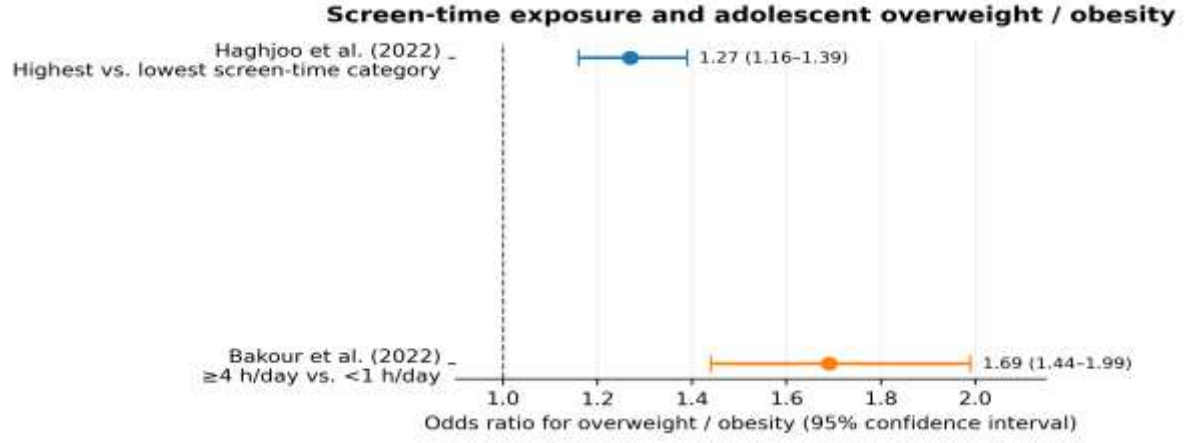


Figure 5. Reported associations between screen-time exposure and overweight/obesity. Estimates are shown as odds ratios with 95% confidence intervals; the two study contrasts differ and should not be interpreted as a direct head-to-head comparison.

4.3 Lifestyle and Behavioural Determinants

The five studies in this theme indicate that adolescent lifestyle is influenced not simply by the amount of time spent using digital media, but also by developmental trajectories, timing, purpose, and the broader allocation of time across sleep and movement. Hedderson et al. (2023) documented sustained increases in recreational screen exposure during and after the COVID-19 period, with larger changes reported among adolescents and some socioeconomically disadvantaged groups. Zhu et al. (2023) showed that longitudinal patterns of screen use across adolescence were associated with later mental-health and behavioural outcomes, suggesting that persistent or escalating exposure may be more informative than a single measurement. Khalaf et al. (2023) further distinguished passive, comparison-oriented and nighttime social-media use from active peer connection, describing both potential risks and protective social functions. National surveillance reported by Zablotsky et al. (2024) found that 50.4% of US teenagers aged 12–17 had at least four hours of daily recreational screen time; this group also had higher reported prevalence of anxiety and depressive symptoms than those below the threshold. Tremblay et al. (2024) provided a broader conceptual framework by treating sleep, sedentary behaviour, light activity, and moderate-to-vigorous physical activity as interdependent components of a fixed 24-hour day. This compositional perspective cautions against interpreting any one behaviour in isolation: reallocating time from sedentary screen use to sleep or physical activity may have different implications depending on age, sex, chronotype, and socioeconomic circumstances. Collectively, the studies support assessment of duration, context, and developmental pattern, alongside sleep, activity, and social connection. However, much of the evidence is observational or conceptual, and screen-time thresholds should not be treated as universal causal cut-offs.

Table 9. Evidence summary of lifestyle and behavioural determinants

Study ID	Author(s), year	Study approach	Principal contribution
SR-11	Hedderson et al. (2023)	Longitudinal / Cohort & RCT	Demonstrated that lifestyle shifts toward heavy daily recreational screen exposure established during the COVID-19 pandemic persisted as a new behavioral baseline among adolescents, widening socioeconomic and racial lifestyle disparities.
SR-12	Zhu et al. (2023)	Longitudinal / Cohort & RCT	suggested that long-term developmental trajectories of escalating screen exposure across ages 11–17—rather than isolated single-timepoint use—predict subsequent mental health and behavioral morbidity in transition to adulthood.
SR-13	Khalaf et al. (2023)	Systematic Review & Meta-Analysis	Demonstrated that the behavioral quality and timing of social media engagement (passive comparison and nighttime sleep displacement vs. active peer support) are critical

			lifestyle determinants governing whether digital media harms or supports adolescent
SR-14	Zablotsky et al. (2024)	Cross-Sectional / Population Survey	Provided official US CDC national surveillance estimates proving that over half of US teenagers spend >=4 hours/day on recreational screens, and that this lifestyle threshold is associated with a >2-fold higher prevalence of recent anxiety (27.1%) and
SR-15	Tremblay et al. (2024)	Scoping / Umbrella Review & Synthesis	Establishes the paradigm of precision 24-hour movement behavior recommendations, showing how continuous wearable sensing and compositional modeling can transition adolescent lifestyle guidance from rigid universal cutoffs to tailored, equitable behavioral

4.4 Digital Screening and Technology-Supported Healthcare

The five studies in this theme examine digital tools as routes to screening, intervention, monitoring, and clinical decision support, while showing that usability, privacy, context, and human involvement determine whether these tools can be implemented successfully. Eilert et al. (2022), synthesizing 16 randomized trials involving 1,985 young people, reported a small but statistically significant reduction in anxiety symptoms (Hedges' g = −0.25) and an improvement in global functioning (g = 0.52); the pooled depression effect did not reach conventional statistical significance. Kadirvelu et al. (2023) found high completion of active ecological momentary assessment items in a two-week adolescent pilot, but sensor opt-in varied, with lower acceptance of GPS and microphone collection than step-count or device-status data. This highlights the importance of granular consent and privacy controls. Pozuelo et al. (2023) demonstrated the feasibility of an offline-first, culturally adapted and gamified intervention supported by peer mentors in a low-resource setting, although the pilot sample was small. Fleming et al. (2025) emphasized that digital mental-health systems can fail when alerts overwhelm clinicians, outputs are difficult to explain, or design excludes users; their human-centred framework prioritizes co-design, workflow fit, explainability, and equity. Edgcomb et al. (2026) showed how combining structured electronic health-record data with language-model analysis of clinical notes improved detection of pediatric suicide- and self-harm-related emergency encounters in a large retrospective dataset, with the hybrid model reporting AUROC 0.977. The latter is a promising clinical informatics result, but its single-system retrospective design limits generalizability. Overall, digital tools appear most useful when embedded in accessible care pathways, supported by clear privacy governance, and interpreted by trained professionals rather than deployed as stand-alone diagnostic substitutes.

Table 10. Evidence summary of digital screening and technology-supported healthcare

Study ID	Author(s), year	Study approach	Principal contribution
SR-16	Eilert et al. (2022)	Systematic Review & Meta-Analysis	Confirmed across 16 RCTs (N = 1,985 youth) that internet-delivered psychological interventions

			significantly reduce adolescent anxiety and substantially improve real-world psychosocial functioning, while indicating that youth depression requires more
SR-17	Kadirvelu et al. (2023)	Cross-Sectional / Population Survey	Demonstrated that a co-designed, modular mobile mental health monitoring platform (Mindcraft) achieves >90% daily EMA completion on active days among 14–18-year-olds when transparent, granular privacy controls allow teens to toggle individual passive sensors.
SR-18	Pozuelo et al. (2023)	Cross-Sectional / Population Survey	suggested that culturally adapted, offline-first gamified behavioral activation apps paired with brief peer-mentor phone support can achieve 75% module completion among depressed rural adolescents in Sub-Saharan Africa.
SR-19	Fleming et al. (2025)	Scoping / Umbrella Review & Synthesis	Establishes that digital screening and AI mental health tools fail in routine clinical care unless human-centered design (HCD) aligns technical outputs with youth lived experience, clinician workflow capacity, and user-centric explainability.
SR-20	Edgcomb et al. (2026)	Predictive ML / Digital Phenotyping	suggested in 3,828 pediatric ED encounters that standard ICD-10 diagnostic codes miss substantial youth suicidality—especially in boys, preadolescents, and neurodivergent youth—whereas hybrid structured EHR + LLM clinical note phenotyping achieves

		AUROC = 0.977

4.5 Remote Monitoring and Wearable Technologies

The five studies in this theme describe the potential of wearables and passive sensing to capture physiological and behavioural changes between clinical encounters, while identifying persistent challenges in data completeness, validation, and adolescent-specific applicability. Welch et al. (2022) mapped pediatric and adolescent studies using wearable biosensors and machine learning, reporting classification performance ranging from 70% to 96% across selected applications involving neurodevelopmental and emotional outcomes. The review also noted that many primary studies used small samples and short monitoring periods. Huhn et al. (2022) examined a much broader health-research evidence base and found that wrist-worn devices, accelerometers, step counts, heart rate, and sleep measures dominated wearable research; however, the review covered multiple age groups and its findings should not be interpreted as adolescent-specific validation. de Angel et al. (2023), in a seven-month depression-monitoring cohort, reported that passive wearable data remained more available than active questionnaire data by the end of follow-up, although overall retention and sensor completeness declined. This demonstrates both the relative advantage of passive monitoring and the practical burden of long-term device use. Choi et al. (2024) synthesized digital phenotyping studies and identified recurring signals such as reduced mobility, irregular sleep-wake patterns, fewer social-proximity events, and late-night phone activity in relation to stress, anxiety, and depressive symptoms. Lipschitz et al. (2025) added that personalized models based on an individual's own Fitbit activity, heart-rate, and sleep patterns may outperform population-level models when predicting mood fluctuations, but require a calibration period and rely partly on proprietary device algorithms. Together, the studies support the feasibility of continuous, low-burden monitoring but do not establish that sensor signals independently diagnose mental-health conditions. Adolescent deployment requires transparent consent, data minimization, attention to missingness, external validation, and integration with clinical assessment.

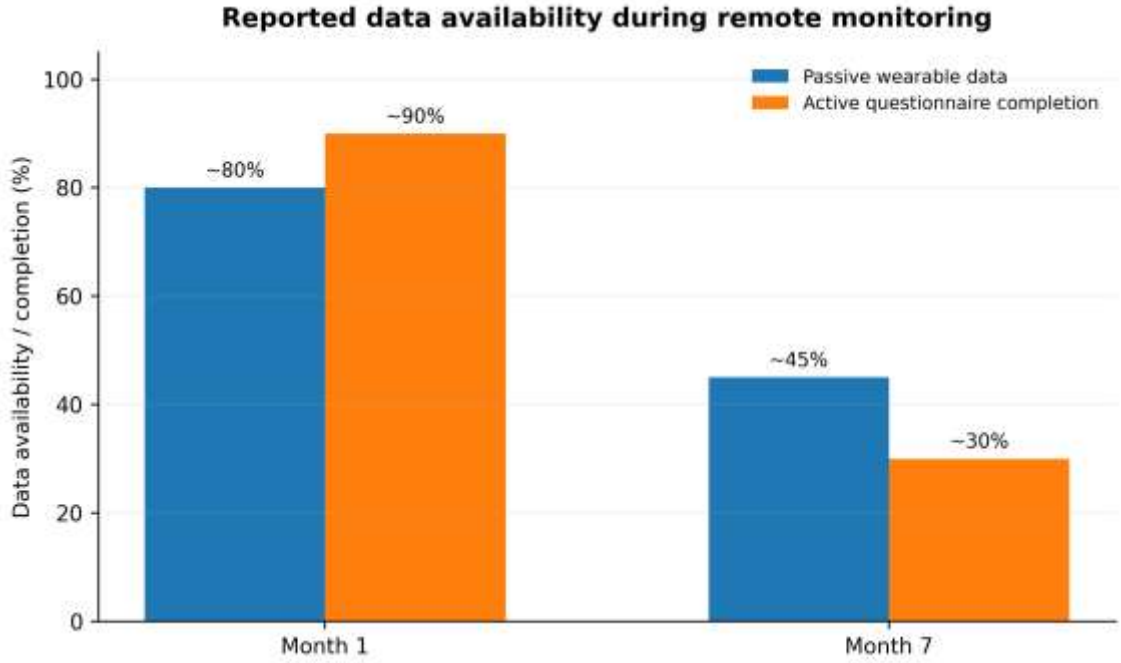


Figure 6. Reported wearable and active-questionnaire data availability at months 1 and 7 in the remote-monitoring cohort (de Angel et al., 2023). Values are approximate as reported in the evidence database; intermediate values are not interpolated.

4.6 Predictive Healthcare, Machine Learning and Artificial Intelligence

The five studies in this theme illustrate how predictive models can combine behavioural, physiological, clinical, and language-based data to support earlier identification of adolescent health risks. Mullick et al. (2022) reported that combining Fitbit-derived sleep and activity measures with smartphone mobility and screen-use features improved adolescent depression prediction compared with single-sensor models, with reported accuracy reaching 84%–89%. Abd-Alrazaq et al. (2023) mapped wearable-AI research on anxiety and depression, identifying physical activity, sleep, and heart-rate signals as common inputs and Random Forest and support-vector machines as frequently used algorithms; however, fewer than 15% of primary studies reportedly used external validation. Abd-Alrazaq et al. (2024) pooled wearable-AI evaluations for student stress

and reported mean accuracy of 85.6%, sensitivity of 75.5%, specificity of 74.4%, and F1 of 75.9%, while also identifying substantial heterogeneity across stress protocols. Zhong et al. (2024) developed models for non-suicidal self-injury risk among adolescents, reporting AUROC values above 0.85 for ensemble methods and identifying depression, trauma, sleep disturbance, bullying, and problematic internet use as important predictors. Qadir et al. (2026) demonstrated high performance for transformer-based detection of self-harm and suicide-related language in donated youth social-media conversations, while showing that conversational context improved differentiation between genuine disclosure, third-party discussion, and hyperbole. These findings indicate that multimodal and context-aware models may support risk stratification, but high internal performance does not by itself establish clinical utility. Cross-sectional designs limited external validation, population and platform specificity, synthetic data augmentation, and potential demographic bias remain important concerns. Predictive systems should therefore be evaluated for calibration, fairness, prospective performance, interpretability, and impact on clinical decisions before routine deployment.

4.7 Cross-theme comparison of selected quantitative findings

Table 11 brings together selected numerical findings that illustrate the range of outcomes reported across the six themes. The measures are retained in their original metric types; odds ratios, standardized mean differences, data-completion percentages, classification accuracy, and AUROC are not directly comparable and should not be ranked against one another.

Table 11. Selected quantitative findings reported across the six themes

Theme	Illustrative studies	Selected result (reported metric)
Psychological risk	Qasrawi et al. (2022)	Depression prevalence 26.3%; anxiety prevalence 27.6%; SVM depression accuracy 92.5% (AUC 0.968).
Chronic disease	Haghjoo et al. (2022); Bakour et al. (2022)	Highest vs. lowest screen-time category: OR 1.27 (95% CI 1.16–1.39); ≥4 h/day vs. <1 h/day: adjusted OR 1.69 (95% CI 1.44–1.99) for obesity.
Lifestyle	Zablotsky et al. (2024)	50.4% of US teenagers aged 12–17 reported ≥4 hours/day of recreational screen time; anxiety symptoms 27.1% vs. 12.3%, depression symptoms 25.9% vs. 9.5%.
Digital screening	Eilert et al. (2022)	Internet-delivered interventions: anxiety Hedges' g = −0.25 (95% CI −0.38 to −0.12); global functioning g = 0.52 (95% CI 0.24–0.80).
Remote monitoring	de Angel et al. (2023)	At month 7, wearable data availability was approximately 45%, compared with approximately 30% for active questionnaire completion.
Predictive healthcare	Abd-Alrazaq et al. (2024); Zhong et al. (2024)	Wearable stress detection: pooled accuracy 85.6%; sensitivity 75.5%; specificity 74.4%; F1 75.9%. NSSI prediction models reported AUROC > 0.85.

4.8 Cross-theme integration

Taken together, the six themes suggest a connected evidence-to-care pathway. Psychological and social risk, physical-health indicators, and lifestyle behaviours provide the context for adolescent assessment. Information may be obtained through validated questionnaires, wearable and smartphone sensors, clinical records, and digital text. Screening tools, longitudinal analysis, and machine-learning or natural-language-processing

methods can help identify patterns that warrant attention. The final step remains human assessment and an appropriate response, which may include prevention, psychosocial support, referral, or follow-up. Figure 6 is a conceptual synthesis of the included studies, not a causal pathway tested by a single investigation. Privacy, youth participation, data minimization, equity, external validation, explainability, and clinical oversight are cross-cutting requirements at every stage.

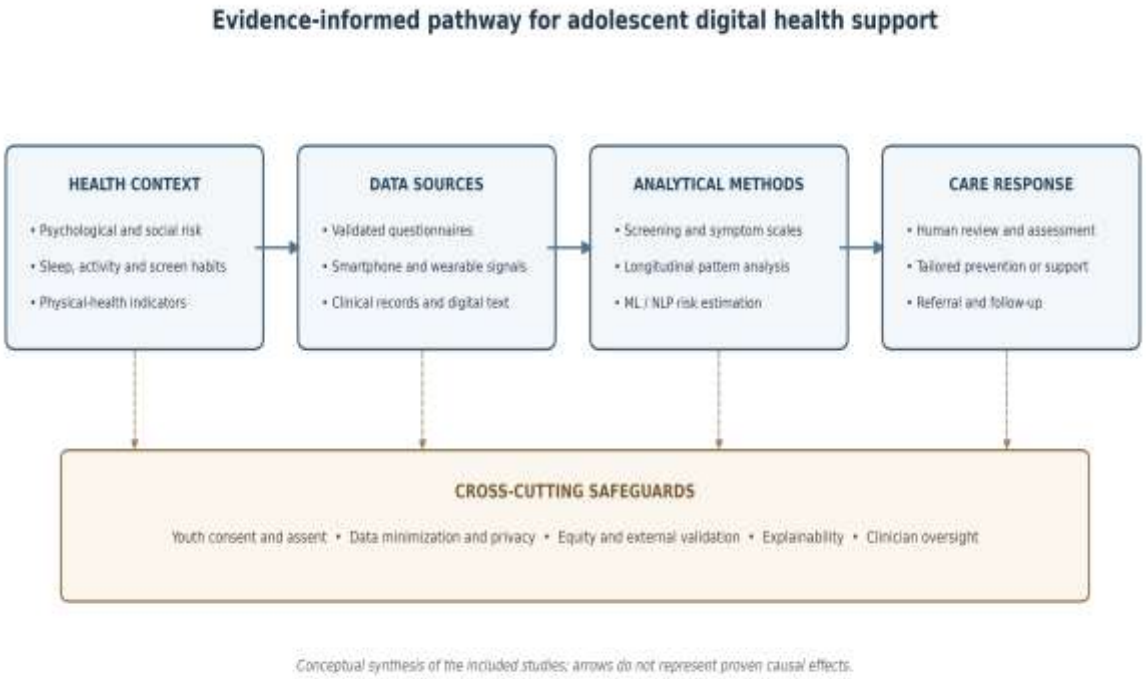


Figure 7. Evidence-informed pathway linking adolescent health context, digital data sources, analytical methods, and care responses, with cross-cutting safeguards.

4.9 Methodological limitations of the evidence

The studies included are aged, population, context, design, outcome definition, and technology platform. The evidence available for this review is the most direct for adolescents between 10 and 19 years. If a study incorporated a larger number of young people (university students, clinical youth and/or adults), results are considered indirect or contextual unless the relevant information has been extracted from the clinical record seen only in adolescents. Secondary studies can overlap with primary studies; therefore, the findings of the secondary studies are based on review-level evidence and do not contribute to the primary-study count of participants and events. These numerical estimates do not directly compare because they are based on different accomplishments, performance and quality measures, samples, and validation processes. Classification accuracy and AUROC are statistics that measure model discrimination within the validation set and do not necessarily reflect clinical efficacy/benefits or health outcomes. Multiple prediction studies are based on cross-sectional data, internal validation or single site samples; wearable and smartphone studies have incomplete data, lost data, privacy issues, and different algorithms. Limits Interpretation and justification for conducting any prospective, externally validated, equitable comparisons prior to routine use.

5. Discussion

The results showed that psychological, physical, behavioural and social factors interact to some extent and should be seen as one construct rather than one risk factor separately affecting adolescent health. Emotional distress is positively predicted by trauma, bullying, domestic violence, academic setbacks, family and school support (Qasrawi et al., 2022). Meanwhile, Intervention studies indicate that when screening is validated at the same time that developmentally appropriate and accessible care is available, there are suggestions that such screening can support identification. In parallel, Measurement studies suggest that when screening is validated at the same time that developmentally appropriate and accessible care is provided, screening can support identification (Fonseca-Pedrero et al., 2023; Gómez-Restrepo et al., 2023). Self-management and digital self-

care can be other pathways that support, but co-design and scaffolding for successful sustained engagement is also a key consideration (Town et al., 2024). These results indicate that a screening program should not be considered as an isolated intervention but as an important component of strong school, family, and community services and systems (Karki et al., 2025).

The physical-health and lifestyle findings reinforce the importance to consider digital behaviour in addition to sleep, diet and physical activity. The associations, reported by Haghjoo et al. (2022) and Bakour et al. (2022) between higher screen exposure and overweight/obesity, as well as the potential association between engagement as problematic and eating-related symptoms reported by Chu et al. (2024) are included. But much of this evidence is of an observation type which restricts causal interpretation. The lifestyle studies also highlight how featuring only the duration of media use is insufficient: both the timing and the intent of media use shape a supportive versus potentially harmful pattern, as do the context and social setting in which media use occurs (Khalaf et al., 2023). The 24-hour movement perspective, then, provides a more comprehensive approach to understanding screen, sleep and sedentary time and physical activity. (Tremblay et al., 2024; Singh et al., 2025; Bilal et al., 2025; Kaur et al., 2025).

The opportunities presented by digital screening, remote monitoring and predictive analytics allow for assessment to go beyond the occasional clinical interactions. Internet delivered interventions have been found beneficial for anxiety and functioning, but there is variability in effect size across outcomes and the effect may need to be supported with human resources (Eilert et al., 2022). However, a mobile monitoring study shows that adolescents will engage in digital assessment when privacy options are clearly and specifically proffered (Kadirvelu et al., 2023). Longitudinal information of activity, sleep and mobility and mood may also be provided by wearable and smartphone data, however, the data are incomplete over time, and signals derived from the device are not diagnostic per se (de Angel et al., 2023; Choi et al., 2024). Personalized models might better capture within-person variability than population-level models, but remain challenges are calibration and device-specific algorithms (Lipschitz et al., 2025; Singla, Muhammed Ali, et al., 2025; Aljaidi et al., 2025; Prabu et al., 2025).

Machine-learning or language-based methods might help with risk stratification, especially including multiple sources of data. The built-in studies include products that have been shown to perform well for depression, stress, non-suicidal self-injury, and self-harm-related language (Mullick et al., 2022; Abd-Alrazaq et al., 2024; Zhong et al., 2024; Qadir et al., 2026). It is not, however, a guarantee of clinical benefit to predict performance of a product. Transferability is limited by limited external validation, population specificity, missing data and potential demographic and linguistic bias. This therefore indicates that a human-in-the-loop system may be more appropriate wherein the digital systems detect patterns for review, and trained professionals are responsible for interpretation, assessment, and intervention. In every theme, implementing should focus on considerations for youth participation, privacy, equity, explainability, and prospective evaluation (Fleming et al., 2025; Edgcomb et al., 2026; Zga et al., 2025; Lin et al., 2025; Imran et al., 2025).

6. Conclusions

The study of 30 studies uncovered six interrelated areas relevant to adolescent health: psychological risk, chronic disease, lifestyle behaviors, distance monitoring, remote monitoring, and predictive health. Psychosocial stressors and screen-related behaviors were persistent issues, with the promise of digital tools and wearable technologies for earlier assessment and monitoring. Several machine-learning models were reported to deliver good predictive performance, especially when using multiple datasets. However these tools should complement judgement and clear care pathways, rather than supplant, in a range of adolescent care settings.

The studies included in the evidence base varied widely in design, age of the study population, population characteristics, study context, outcome measures, and technology platform. There are several reviews and technology studies on broader youth, university, pediatric or adult populations that cannot be directly interpreted for adolescents. There was significant overlap in many associations, and in many predictive models there was either not enough validation or validation was conducted internally or at a single location. There were no comparable quantitative measures. Missing data, attrition, privacy issues, and algorithms specific to the technology and the device hindered wearable and smartphone research, necessitating thoughtful interpretation of study results.

Future studies should focus on studies designed using representative, diverse, and clearly defined age groups of adolescents followed over time. External validation, calibration, and fairness assessment, along with impact evaluation on health decisions and outcomes, are needed for digital screening and predictive models. Research needs to set the parameters for clear consent, privacy protections and youth engagement in technology design.

Wearable research needs standardized measures and reporting of adherence and missingness. Pragmatic trials ought to evaluate the integration of the intervention into schools, primary care, and community-based care services without making things worse or increasing inequities for clinicians.

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Supplementary Materials

Supplementary Table S1. Study-level domain judgements recorded in the Quality & RoB Appraisal worksheet

Study ID	Author/ year	Design	Framework recorded	Selection/sampling	Measurement/ outcome	Confounding/validation	Attrition/missingness
SR-01	Qasrawi et al. (2022)	Cross-Sectional / Population Survey	MMAT (2018) / JBI Cross-Sectional	Low (Stratified 100-school random sample)	Low (Validated Arabic DSRS, GAD-7, CPTS-RI)	Low (10-fold CV + multivariable ANOVA adjustment)	Low (Complete survey capture across sampled classrooms)
SR-02	Gómez-Restrepo et al. (2023)	Longitudinal / Cohort & RCT	MMAT (2018) / Cochrane RoB-2 Cluster	Low (Cluster randomization by teacher strata)	Low (Validated Spanish MANSA, CD-RISC, PHQ-8, GAD-7)	Moderate (Exploratory sample size; baseline imbalances noted)	Low (88.6% retention at 6-month follow-up)
SR-03	Fonseca-Pedrero et al. (2023)	Cross-Sectional / Population Survey	JBI Cross-Sectional / COSMIN Psychometric	Low (Representative stratified school probability sample)	Low (Rigorous CFA, IRT, and invariance testing)	Low (Measurement invariance tested across sex and age)	Low (High completeness with quality-control infrequency scale)
SR-04	Town et al. (2024)	Scoping / Umbrella Review & Synthesis	JBI Scoping Review / PRISMA-ScR	Low (Comprehensive 6-database search with dual screening)	Low (Structured thematic framework and data charting)	Moderate (Heterogeneity of underlying study designs)	Low (Transparent PRISMA-ScR flow reporting)
SR-05	Mukherjee et al. (2024)	Cross-Sectional / Population Survey	MMAT (2018) Mixed-Methods	Low (Purposive multi-stakeholder sampling across 2 states)	Low (WHO mhGAP-IG & PHQ-9 grounded framework)	Moderate (Formative pre-RCT phase without control arm efficacy readout)	Low (Complete formative data capture and iterative co-design)
SR-06	Haghjoo et al. (2022)	Systematic Review & Meta-	AMSTAR-2	Low (Comprehensive multi-database	Low (Standardized BMI percentile/z-	Low (Subgroup and dose-response meta-regression	Low (Formal Egger/Begg publication bias and trim-

		Analysis		PRISMA search)	score definitions)	conducted)	and-fill checks)
SR-07	Bakour et al. (2022)	Cross-Sectional / Population Survey	JBI Cross-Sectional / STROBE	Low (Nationally representative probability sample with survey weights)	Moderate (Parent-reported anthropometrics and screen time)	Low (Adjusted for physical activity, sleep, depression, SES, race)	Low (Complex survey weighting accounts for non-response)
SR-08	Motahari-Nezhad et al. (2022)	Scoping / Umbrella Review & Synthesis	AMSTAR-2 / Umbrella Review	Low (Pre-registered PROSPERO CRD42021283225; dual screening)	Low (Formal AMSTAR-2 and GRADE appraisal of all 91 outcomes)	Low (Stratified by device type, population, and outcome domain)	Low (Complete reporting of excluded reviews and overlap)
SR-09	Chu et al. (2024)	Longitudinal / Cohort & RCT	JBI Cohort / STROBE	Low (National 21-site probability cohort with propensity weights)	Low (Validated KSADS-5 eating disorder modules and screen scales)	Low (Adjusted for baseline BMI, demographics, SES, and prior symptoms)	Low (High longitudinal retention in ABCD cohort)
SR-10	Muth et al. (2024)	Scoping / Umbrella Review & Synthesis	AGREE-II / JBI Expert Evidence Synthesis	Low (Formal AAP multidisciplinary committee consensus and review)	Low (Grounded in validated CDC/WHO/AAP physiological thresholds)	Low (Explicitly incorporates SDOH, equity, and physiological puberty)	Low (Complete policy and clinical action framework)
SR-11	Hedderson et al. (2023)	Longitudinal / Cohort & RCT	JBI Cohort / STROBE	Low (Multi-site national NIH ECHO longitudinal consortium)	Low (Harmonized ECHO longitudinal screen time instruments)	Low (Mixed-effects models adjusted for age, sex, race, maternal education)	Low (Repeated longitudinal measures with missing-data sensitivity checks)
SR-12	Zhu et al. (2023)	Longitudinal / Cohort & RCT	JBI Cohort / STROBE	Low (Stratified random school sample with 5-wave prospective tracking)	Low (Validated multi-wave SBQ and mental health scales)	Low (Controlled for age-11 baseline behavioral problems, sex, SES)	Low (FIML handling of longitudinal attrition across 9 years)
SR-13	Khalaf et al. (2023)	Systematic Review & Meta-Analysis	AMSTAR-2 / PRISMA	Low (Multi-database PRISMA search with explicit inclusion criteria)	Low (Extracted validated depression, anxiety, sleep, and body image scales)	Moderate (Narrative synthesis without quantitative meta-analytic pooling)	Low (Clear PRISMA screening and study table reporting)
SR-	Zablotsk	Cross-	JBI Cross-	Low (Gold-	Low (Teen self-	Low (Stratified	Low (NCHS

14	y et al. (2024)	Sectional / Population Survey	Sectional / NCHS Standards	standard CDC NCHS national probability sampling & weighting)	report via validated PHQ-2, GAD-2, and NCHS items)	by age, sex, race/ethnicity, family income, urbanicity)	survey weights adjust for household/teen non-response)
SR-15	Tremblay et al. (2024)	Scoping / Umbrella Review & Synthesis	JBI Text & Policy Synthesis	Low (Authored by the international founders of 24-Hour Movement Guidelines)	Low (Grounded in compositional data analysis and accelerometry standards)	Moderate (Conceptual policy synthesis without de novo meta-analytic pooling)	Low (Complete framework from population guidelines to AI personalizatio n)
SR-16	Eilert et al. (2022)	Systematic Review & Meta-Analysis	AMSTAR-2	Low (Comprehensive multi-database PRISMA search with dual independent extraction)	Low (Random-effects Hedges g pooling of validated clinical scales)	Low (Cochrane Risk of Bias appraisal and subgroup moderator checks)	Low (Publication bias and sensitivity analyses reported)
SR-17	Kadirvelu et al. (2023)	Cross-Sectional / Population Survey	MMAT (2018) Mixed-Methods	Moderate (Single-school volunteer sample aged 14–18)	Low (Objective app telemetry logs + structured UAT questionnaires)	Low (Granular breakdown by sensor modality and active vs. passive capture)	Low (Exact day-by-day telemetry retention curves reported)
SR-18	Pozuelo et al. (2023)	Cross-Sectional / Population Survey	MMAT (2018) Mixed-Methods	Low (Community-based sampling across two Sub-Saharan African sites)	Low (Objective in-app telemetry + validated SUS and PHQ-A scales)	Moderate (Single-arm prepilot design for clinical outcomes)	Low (94% retention in prepilot; 75% full module completion)
SR-19	Fleming et al. (2025)	Scoping / Umbrella Review & Synthesis	JBI Text & Implementation Synthesis	Low (Grounded in multidisciplinary human-factors and health systems literature)	Low (Clearly distinguishes technical interpretability from user explainability)	Moderate (Narrative implementation synthesis without quantitative meta-analysis)	Low (Complete implementation governance framework)
SR-20	Edgcomb et al. (2026)	Predictive ML / Digital Phenotyping	PROBAST / TRIPOD-AI & TRIPOD-LLM	Low (All 3,828 eligible unique pediatric MH-ED encounters included)	Low (Dual C-CASA expert annotation of 28,861 notes + psychiatrist adjudication)	Low (Systematic fairness audit across 20 demographic and 15 diagnostic subgroups)	Low (<=6% missingness on core fields; gatekeeping C-SSRS structure modeled)
SR-21	Welch et al.	Scoping /	JBI Scoping	Low (Pre-specified 5-	Low (Detailed extraction of	Low (Systematic subgrouping by	Low (Full PRISMA-ScR

	(2022)	Umbrella Review & Synthesis	Review / PRISMA-ScR	database search across medical and engineering indices)	sensor hardware, biosignals, and ML architectures)	pediatric diagnosis, sensor type, and ML validation)	flow and study tables reported)
SR-22	Huhn et al. (2022)	Scoping / Umbrella Review & Synthesis	JBI Scoping Review / PRISMA-ScR	Low (Rigorous PRISMA-ScR screening of 179 studies)	Low (Quantitative classification of 189 wearable devices and parameters)	Low (Stratified by medical specialty, study design, and sensor modality)	Low (Complete open-access data extraction tables provided)
SR-23	de Angel et al. (2023)	Longitudinal / Cohort & RCT	MMAT (2018) Mixed-Methods / STROBE	Low (Real-world NHS treatment-seeking clinical cohort)	Low (Objective RADAR-base server telemetry across 7 months)	Low (Analyzed clinical severity and demographic predictors of dropout)	Low (Attrition and missing data trajectories were the primary measured endpoints)
SR-24	Choi et al. (2024)	Systematic Review & Meta-Analysis	AMSTAR-2 / PRISMA	Low (Comprehensive 5-database PRISMA search across CS and medicine)	Low (Detailed mapping of passive sensor channels to behavioral constructs)	Moderate (Primary studies varied in cross-validation vs. subject-independent splits)	Low (Complete study characteristics and sensor tables reported)
SR-25	Lipschitz et al. (2025)	Predictive ML / Digital Phenotyping	PROBAST / STROBE	Low (Clinically diagnosed longitudinal mood disorder cohort)	Low (Continuous objective Fitbit telemetry + validated clinical mood scales)	Low (Direct head-to-head comparison of idiographic vs. nomothetic ML splits)	Low (Strict wear-time quality filtering and longitudinal completeness checks)
SR-26	Mullick et al. (2022)	Predictive ML / Digital Phenotyping	PROBAST / TRIPOD	Moderate (Exploratory clinical/community adolescent cohort size)	Low (Objective AWARE + Fitbit sensor fusion and weekly PHQ-9)	Low (Evaluated unimodal vs. multimodal feature sets under cross-validation)	Low (Window-level missingness filtering and imputation documented)
SR-27	Abd-Alrazaq et al. (2023)	Scoping / Umbrella Review & Synthesis	JBI Scoping Review / PRISMA-ScR	Low (Comprehensive 7-database search screening 1,203 records)	Low (Granular quantitative coding of sensors, features, and ML models)	Low (Stratified by disorder, device class, and validation split)	Low (Full PRISMA-ScR flow and appendix tables provided)
SR-28	Abd-Alrazaq et al. (2024)	Systematic Review & Meta-	AMSTAR-2 / QUADAS-2	Low (Pre-registered PRISMA-DTA protocol	Low (Formal QUADAS-2 appraisal and random-effects	Low (Extensive subgroup meta-analyses by algorithm,	Low (Complete diagnostic accuracy

		Analysis		across 7 databases)	logit meta-analysis)	device, and setting)	forest plots and sensitivity checks)
SR-29	Zhong et al. (2024)	Predictive ML / Digital Phenotyping	PROBAST / TRIPOD	Low (Multicenter school and clinical sampling in Western China)	Low (Validated NSSI, depression, trauma, and sleep instruments)	Low (LASSO regularization + calibration and decision curve analysis)	Low (High survey completion with split-sample validation)
SR-30	Qadir et al. (2026)	Predictive ML / Digital Phenotyping	PROBAST / TRIPOD-AI	Low (Ecologically valid youth-donated private Instagram DM dataset)	Low (Insider youth self-labeling + rigorous multi-annotator coding)	Low (Benchmarked 10 ML/DL/Transformer models + error taxonomy analysis)	Low (Complete confusion matrix and misclassification analysis reported)

Supplementary Table S2. Primary-domain assignments and cross-domain synthesis notes

Study ID	Author/year	Primary domain	Domains recorded as covered	Synthesis note
SR-01	Qasrawi et al. (2022)	1. Psychological Risk & Mental Health	Psychological Risk, Lifestyle & Screen, Digital Screening, Predictive ML & AI	Establishes quantitative hierarchy of adolescent psychological risk factors (trauma, bullying, family support) and demonstrates high-accuracy school screening.
SR-02	Gómez-Restrepo et al. (2023)	1. Psychological Risk & Mental Health	Psychological Risk, Digital Screening	Demonstrates how school-based digital decision-support empowers non-specialist teachers to buffer adolescent trauma, depression, and anxiety.
SR-03	Fonseca-Pedrero et al. (2023)	1. Psychological Risk & Mental Health	Psychological Risk, Digital Screening	Validates the primary clinical screening backbone (PHQ-9) used across both school-based psychological assessments and digital mental health platforms.
SR-04	Town et al. (2024)	1. Psychological Risk & Mental Health	Psychological Risk, Lifestyle & Screen, Digital Screening	Bridges psychological risk determinants with lifestyle self-care and digital self-help interventions in adolescent emotional disorders.
SR-05	Mukherjee et al. (2024)	1. Psychological Risk & Mental Health	Psychological Risk, Digital Screening	Provides vital LMIC equity evidence linking socioeconomic adversity and stigma in

				urban slums with mobile clinical decision support (EDSS).
SR-06	Haghjoo et al. (2022)	2. Chronic Disease & Physical Health	Chronic Disease, Lifestyle & Screen	Establishes the quantitative dose-response link between sedentary screen exposure and adolescent obesity/cardiometabolic risk.
SR-07	Bakour et al. (2022)	2. Chronic Disease & Physical Health	Chronic Disease, Lifestyle & Screen	Quantifies the independent and interactive roles of heavy screen time (>=4h/day) and short sleep in driving US adolescent obesity.
SR-08	Motahari-Nezhad et al. (2022)	2. Chronic Disease & Physical Health	Chronic Disease, Lifestyle & Screen, Remote Wearables	Links chronic disease/obesity prevention with wearable digital biomarkers, providing AMSTAR-2 and GRADE benchmarks across 91 clinical outcomes.
SR-09	Chu et al. (2024)	2. Chronic Disease & Physical Health	Psychological Risk, Chronic Disease, Lifestyle & Screen	Demonstrates how problematic screen and social media exposure drives early-adolescent eating disorder and weight-related chronic pathology in the ABCD cohort.
SR-10	Muth et al. (2024)	2. Chronic Disease & Physical Health	Chronic Disease, Lifestyle & Screen, Digital Screening	Provides the authoritative 2024 AAP clinical framework uniting adolescent chronic disease prevention with lifestyle, sleep, and digital media screening.
SR-11	Hedderson et al. (2023)	3. Lifestyle & Behavioural Determinants	Psychological Risk, Lifestyle & Screen	Documents the persistent upward structural shift in adolescent recreational screen time and its sociodemographic gradients in the NIH ECHO consortium.
SR-12	Zhu et al. (2023)	3. Lifestyle & Behavioural Determinants	Psychological Risk, Lifestyle & Screen	Provides 10-year prospective trajectory evidence showing how escalating adolescent screen habits shape young adult mental

				health.
SR-13	Khalaf et al. (2023)	3. Lifestyle & Behavioural Determinants	Psychological Risk, Lifestyle & Screen	Disentangles passive scrolling, cyberbullying, and nocturnal sleep displacement from positive peer connection in adolescent social media lifestyles.
SR-14	Zablotsky et al. (2024)	3. Lifestyle & Behavioural Determinants	Psychological Risk, Lifestyle & Screen	Provides exact CDC national benchmarks on teen screen time prevalence (50.4% >=4h/day) and the >2x surge in anxiety (27.1%) and depression (25.9%).
SR-15	Tremblay et al. (2024)	3. Lifestyle & Behavioural Determinants	Chronic Disease, Lifestyle & Screen, Remote Wearables, Predictive ML & AI	Unifies the 24-hour movement continuum (physical activity, screen time, sleep) with wearable sensing and AI-driven precision lifestyle medicine.
SR-16	Eilert et al. (2022)	4. Digital Screening & Tech Healthcare	Psychological Risk, Digital Screening	Provides rigorous meta-analytic effect sizes (N = 1,985 youth across 16 RCTs) proving internet interventions improve adolescent anxiety (g = -0.25) and functioning (g = 0.52).
SR-17	Kadirvelu et al. (2023)	4. Digital Screening & Tech Healthcare	Psychological Risk, Lifestyle & Screen, Digital Screening, Remote Wearables	Establishes technical design and privacy-by-design benchmarks for adolescent active/passive smartphone mental health screening.
SR-18	Pozuelo et al. (2023)	4. Digital Screening & Tech Healthcare	Psychological Risk, Digital Screening	Demonstrates how offline gamification and peer-mentor human-in-the-loop coaching solve the digital divide and engagement crisis in rural LMICs.
SR-19	Fleming et al. (2025)	4. Digital Screening & Tech Healthcare	Psychological Risk, Digital Screening, Predictive ML & AI	Provides the 2025 human-factors governance blueprint for translating digital screening and explainable AI into routine mental health care.
SR-20	Edgcomb et al. (2026)	4. Digital Screening & Tech Healthcare	Psychological Risk, Digital Screening, Predictive ML & AI	Landmark 2026 study (N = 3,828 visits) showing hybrid EHR + LLaMA

				NLP screening reaches AUROC = 0.977 and corrects diagnostic bias in neurodivergent and male youth.
SR-21	Welch et al. (2022)	5. Remote Monitoring & Wearables	Psychological Risk, Digital Screening, Remote Wearables, Predictive ML & AI	Maps the specific wearable biosensor hardware (Empatica E4, Fitbit, ActiGraph, ECG) and physiological signals (HRV, EDA) used in child and adolescent psychiatry.
SR-22	Huhn et al. (2022)	5. Remote Monitoring & Wearables	Chronic Disease, Lifestyle & Screen, Remote Wearables	Provides macro-level quantitative benchmarks (k = 179 studies, N = 10.84M) on wearable form factors (73% wrist-worn) and core biosignals (steps 53%, HR 31%, sleep 29%).
SR-23	de Angel et al. (2023)	5. Remote Monitoring & Wearables	Psychological Risk, Lifestyle & Screen, Digital Screening, Remote Wearables	Quantifies the real-world 7-month longitudinal adherence gap between passive wrist wearables (80%->45%) and active self-report apps (90%->30%).
SR-24	Choi et al. (2024)	5. Remote Monitoring & Wearables	Psychological Risk, Lifestyle & Screen, Digital Screening, Remote Wearables, Predictive ML & AI	Maps passive smartphone and wearable sensor streams (GPS homestay, Bluetooth proximity, circadian sleep, screen unlocks) to early anxiety and depression phenotypes.
SR-25	Lipschitz et al. (2025)	5. Remote Monitoring & Wearables	Psychological Risk, Lifestyle & Screen, Remote Wearables, Predictive ML & AI	Demonstrates why 2025 remote wearable monitoring must use personalized within-person ML baselines rather than static population thresholds.
SR-26	Mullick et al. (2022)	6. Predictive Healthcare, ML & AI	Psychological Risk, Lifestyle & Screen, Digital Screening, Remote Wearables, Predictive ML & AI	Directly proves in adolescents (aged 12–18) that multimodal fusion of wearable Fitbit + smartphone sensors outperforms single-modality ML for depression prediction.
SR-27	Abd-Alrazaq et al. (2023)	6. Predictive Healthcare, ML &	Psychological Risk, Lifestyle & Screen,	Provides exact architectural prevalence

		AI	Digital Screening, Remote Wearables, Predictive ML & AI	across 69 wearable AI studies: physical activity (90%), sleep (77%), HR (46%), Random Forest (52%), and SVM (38%).
SR-28	Abd-Alrazaq et al. (2024)	6. Predictive Healthcare, ML & AI	Psychological Risk, Digital Screening, Remote Wearables, Predictive ML & AI	Meta-analyzes 19 studies (N = 11,425 students) to establish pooled benchmark accuracy (85.6%) and F1-score (75.9%) for wearable AI stress detection.
SR-29	Zhong et al. (2024)	6. Predictive Healthcare, ML & AI	Psychological Risk, Lifestyle & Screen, Digital Screening, Predictive ML & AI	Demonstrates high-accuracy multicenter ML prediction (AUROC > 0.85) of adolescent non-suicidal self-injury (NSSI) integrating trauma, sleep, and problematic internet use.
SR-30	Qadir et al. (2026)	6. Predictive Healthcare, ML & AI	Psychological Risk, Lifestyle & Screen, Digital Screening, Predictive ML & AI	Cutting-edge 2026 transformer NLP study showing DistilBERT achieves 99% binary AUC and 91% context-aware 3-class triage of youth suicide/self-harm in private social media DMs.