Research Article

Multidimensional Adolescent Health in The Digital Era: A Review of Mental Well-Being, Health Behaviours, AI-Based Diagnosis, Remote Care, and Biomedical Technologies

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Abstract

Objective: To examine adolescent digital health across mental well-being, health behaviours, risk prediction, remote care and biomedical monitoring, and to distinguish the strength of evidence supporting each application.

Data source: PubMed, Scopus and Web of Science Core Collection were searched on 28 October 2026 for English-language publications from 2020–2026. The recorded searches returned 808 references before deduplication, and the selection flow identified 20 studies for synthesis.

Data synthesis: The included studies comprised observational cohorts, randomised trials, machine-learning investigations, feasibility studies and wearable-device validation. Social-media associations differed by activity and follow-up period; clinical digital interventions reported mixed comparative effects. Prediction discrimination decreased in external populations, while wearable adherence did not establish measurement validity. Results were mapped by domain and compared using study design, outcome validity, clinical comparators and implementation evidence.

Conclusion: Digital exposure, treatment delivery, risk prediction and physiological measurement require distinct standards of interpretation. Stronger adolescent-specific validation and comparative clinical evaluation are needed before routine implementation.

Keywords: Adolescent Health; Mental Health; Digital Health; Artificial Intelligence; Telemedicine; Wearable Electronic Devices.

1. Introduction

Adolescent health is the result of a complex interplay of psychological, behavioural and social factors during a time of significant change.[1] Digital technologies all interact with these aspects in the context of social networking, entertainment, online treatment, predictive algorithms and wearable measurements, all of which affect the health of adolescents.[2] However, exposure in the real world is quite different from exposure by a clinician or exposure in a physiological lab. It is important to remember that lumping together these functions into one measure of screen time hides variation in the purpose, control, risk and potential benefit. It is therefore important to differentiate the kind of technology, the outcome that is being assessed and the evidence that is needed to support the use of the technology in practice, in a developmentally informed assessment.

There have been conflicting findings regarding the psychological harm and benefits of adolescents' online engagement.[3] The reason for these limitations is that time online doesn't necessarily mean that an adolescent is exposed to distressing content, or that they are getting peer support, or that they are sacrificing sleep.[4] Furthermore, the interpretation of associations observed is complicated by the contexts of families and pre-existing psychological vulnerability. Longitudinal evidence can help to explain temporal ordering, but will not necessarily eliminate confounding. Randomised intervention studies, however, answer another question and examine the therapeutic use of structure. These differences are able to underlie a mix of associations that are typical of people's everyday digital involvement and impacts which are due to specifically targeted care.

Digital health care raises further issues of clinical effectiveness and validity as well as equitable access for young people. Digital technologies can also be used to detect trends and patterns of risk in the case of predictive algorithms, or provide access to virtual consultations and measure data outside of the clinic through wearable devices, according to the World Health Organization.[5] Its guidance for artificial intelligence applications also highlights accountability, transparency and proper human oversight in clinical use cases.[6] Algorithms discrimination, however, is not synonymous with reliable diagnosis and prolonged device use is not indicative of physiological accuracy. Likewise, participant satisfaction does not prove that remotely provided treatment is more effective than other effective treatments. A useful synthesis should therefore assess technologies within the context of their specific intended purpose, and differentiate between what is feasible, what can be measured, what is effective and what is practical.

Previous reviews have typically focused on adolescents' exposure to digital material, or on social-media relationships, not on the clinical and technical range.[3] For instance, neither of these frameworks were intended to assess those exposures alongside algorithm validation, remote clinical treatment and performance of wearable devices. This scoping review aimed to bridge this gap across domains by mapping 20 studies focused on adolescents onto five interrelated domains. It aimed to describe the evidence, to compare the results based on design appropriate criteria

and to identify limitations that impact on clinical interpretation. Special focus was placed on the difference between the use of AI to predict risk and validated diagnosis and the difference between wearables and the wider field of biomedical technologies. The contribution is the use of consistent evaluative questions to technologies that produce outcomes that are not comparable.

2. Methods

2.1. Review Design and Reporting Framework

A scoping review design was adopted because the evidence was of a variety of types that were heterogeneous and did not pool incompatible outcomes. Reporting was based on Joanna Briggs Institute guidance on the formulation of broad review questions and charting evidence and identifying gaps for future research and implementation in clinical practice.[7] Joanna Briggs Institute item-level checklist for scoping reviews was used as a guide for reporting (Supplementary Appendix A2).[8]. The review distinguished measured empirical findings from recommendations for future clinical implementation. A methodological assessment that was design sensitive, and did not make an artificial numerical assessment of study quality, facilitated interpretation.

2.2. Research Question and Population–Concept–Context Framework

The guiding question was: What evidence is there to describe the psychological, behavioural and clinical implications of digital technologies in the adolescent population (10-19 years)? The population–concept–context framework detailed adolescent population, concepts (digital mental well-being, screen associated behaviours, AI prediction and screening, remote care and wearable monitoring), and context (community, school, and clinical context). Studies with general paediatric labels were selected if it was clear that the age range defined as adolescent was included in the reported results. This method has been in line with the guidance for conducting scoping reviews of heterogeneous evidence and multiple study designs.[7]

2.3. Information Sources and Search Strategy

A literature search of PubMed, Scopus and the Web of Science Core Collection was conducted on 28 October 2026 for articles that were written in English and published between 2020 and 2026. The numbers of records identified by the original title-based search expressions were: 282, 307 and 219, respectively; 808 prior to deduplication. The predefined filter for the Adolescent: 13–18 years age group was used in PubMed, along with English and MEDLINE restrictions and the free-full-text query condition. Scopus applied its 2020–2026 publication years, journal-article, English-language and open-access restrictions, while Web of Science applied its year, article-type and language filters. Supplementary Table S1 and Appendix A3 contain the searches and their exact field tags and recorded restrictions. Search coverage differences were taken into account when interpreting the results of the search, in line with transparent reporting of searches.[9]

2.4. Eligibility Criteria

Articles included original empirical research on at least one digital-health domain and adolescents aged 10–19 years, with distinct adolescent-strata in studies with mixed age groups. Studies involving observational investigations, randomised interventions, clinical feasibility studies, prediction-model research and device-validation studies were included. Reviews, protocols, editorials and studies without an adolescent outcome were not included. The fact that the content was available in full-text was not considered to be a characteristic of scientific eligibility but a retrieval issue. Study question and outcome determined the five domains, which were not based on fixed quotas, and the eligibility dimensions are summarised in Table 1 and Supplementary Table S2.[8]

2.5. Study Selection and Screening Process

Study identification and screening were done in accordance with the numerical stages in PRISMA flow diagram (Figure 1 and Supplementary Figure S1). Out of 808 records in the database, 108 were excluded due to being duplicates and 700 were added to the title and abstract screening, of which 400 were excluded. Full text was sought for 300 reports, 20 were not retrieved and 280 were assessed. There were 20 included studies; full-text exclusions comprised population mismatch (70), topic mismatch (120), and ineligible study type or insufficient extractable information (70). Counts have been kept constant from the main to the supplementary figures, according to the PRISMA 2020 reporting categories.[9]

2.6. Data Charting and Extraction

The data from the 20 articles was entered into pre-defined standardised fields: location, population, sample, design, digital exposure or intervention, comparator, outcome, effect estimate, and interpretive limitation. The evidence matrix at the study level is available in Supplementary Tables S3–S5. Selection, measurement, confounding/comparative design, completeness and validation/application were evaluated using the custom appraisal and interpreted in the context of study purpose. The results were not aggregated and presented as a pooled quality score, the appraisal is presented in Supplementary Appendix A1. The methodological principles discussed by Hong et al.[10] were used in the design-sensitive assessment.

2.7. Evidence Mapping and Thematic Synthesis

Studies were categorized by their main question and into five domains, and where studies covered more than one technology, the technologies are listed in the extraction tables. Within domain synthesis included outcomes, time horizons, adjustment, comparison groups and uncertainty, whilst cross domain analysis included exposure associations and treatment effects, prediction discrimination and device agreement. Meta-analysis was not done since these measurements refer to different estimands. Four interrelated questions were used in the conceptual integration: Is the technology feasible? Does technology measure or predict the construct of interest? Does the technology improve health outcomes when compared to alternative technologies? Can the technology be implemented responsibly? This type of descriptive evidence mapping is consistent with the guidelines for conducting scoping reviews.[7]

3. Results and Evidence Synthesis

3.1. Study Selection and Characteristics of Included Studies

The search flow identified 20 studies from 808 records (Figure 1) and the studies were organised descriptively in 4 studies per thematic domain. This balanced grouping describes the final included studies and does not represent the distribution of research in the wider literature. These designs encompassed longitudinal and cross-sectional studies, randomised trials, predictive modelling, feasibility studies and the criterion-validation studies. Sample sizes ranged from a videotherapy feasibility study (n = 20) to a Korean prediction cohort (n = 566,875 adolescent records). The main contrasts are summarised in Table 2 and age groups, study populations and outcomes are listed in Supplementary Table S3. These types of evidence were valued based on the clinical question and not as equivalent measures of effectiveness.

Table 1. Eligibility criteria applied in the adolescent digital-health scoping review

Dimension	Included	Excluded
Population	10–19 years; clearly identifiable adolescent results in mixed-age research	Adult-only or no separable adolescent outcomes
Publication	Original peer-reviewed study, English, 2020–2026	Reviews, editorials, protocols, conference-only reports
Topic	Mental well-being; health behaviours; AI screening; remote care; biomedical monitoring	No adolescent digital-health outcome
Data	Extractable empirical population, method and results	No relevant quantitative or qualitative findings
Retrieval	Full reports assessed where accessible through reasonable retrieval routes	Unavailable reports recorded at retrieval stage, not excluded by paywall status

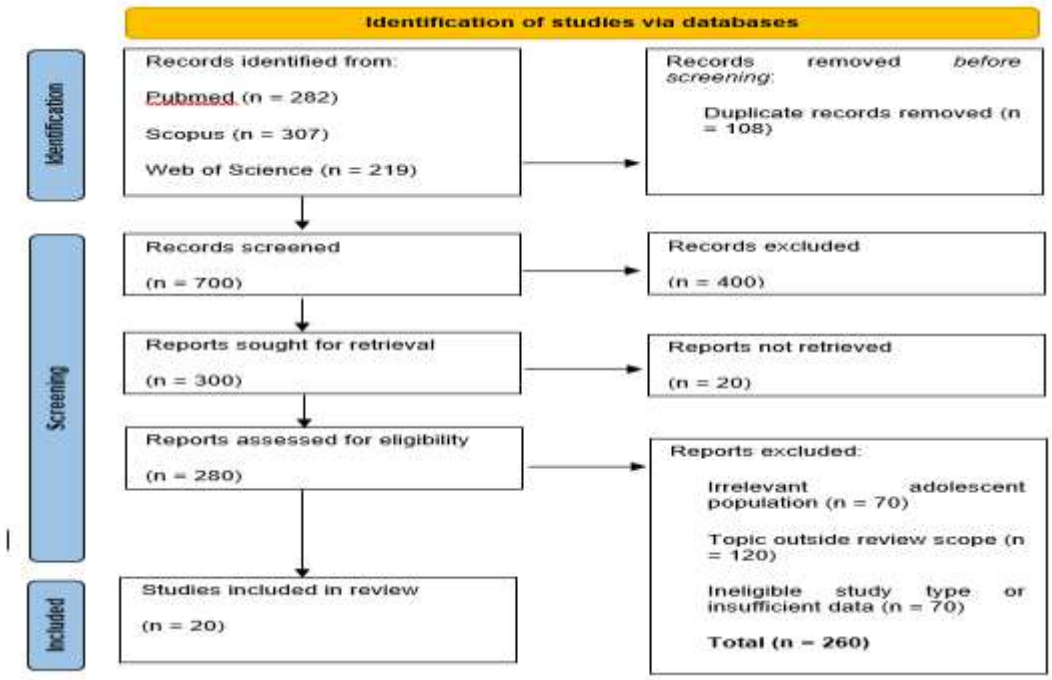


Figure 1. PRISMA 2020 flow diagram for database identification, screening and inclusion.
The study-selection sequence is also reproduced in Supplementary Figure S1 with the same counts.

Table 2. Cross-domain comparison of evidence level and remaining clinical validation gaps

Domain (refs)	Evidence established	Interpretive constraint
Mental well-being (11–14)	Repeated associations; one waitlist-controlled digital intervention	Exposure correlations differ from treatment effects
Health behaviours (15–18)	Screen, activity, sleep and adiposity associations	No direct causal test of screen reduction
AI screening (19–22)	Internal prediction and limited external validation	No evidence of diagnosis or clinical benefit
Remote care (23–26)	Feasibility and mixed comparative treatment outcomes	Small samples, treatment-dose differences
Biomedical monitoring (27–30)	Step-count validity; monitoring adherence; sensing feasibility	Incomplete intensity validity and clinical usefulness

3.2. Mental Well-Being and Psychological Health in the Digital Era

Evidence separated initial emotional reactions from subsequent symptom categorisations, both by using a longitudinal design. In a study by Colasante, et al.,[11] 6,240 momentary reports were obtained from 154 adolescents aged 12-15 years and revealed a small increase in negative emotion following browsing, but not following posting. In a study by Shen, et al.,[12] analytic samples comprised 2,316 adolescents for depression and 2,350 for anxiety, and revealed that more than 3 hours of social networking per day was associated with depression (adjusted odds ratio 1.70; 95% confidence interval 1.19-2.42) and anxiety (1.60; 95% confidence interval 1.11-2.31). There are different observation periods and outcome definitions which preclude direct comparison of effects. Both associations fail to prove that there was any psychological damage that was solely attributed to online activity.

The study by Aziz et al. included 407 Qatari adolescents and found statistical associations between problematic Internet use, distress and family or school environments but the mediation analysis was cross-sectional and therefore did not indicate the direction of the associations.[13] By contrast, Boucher et al. allocated 303 adolescents aged 13 to 17 years with high levels of stress to either a self-guided digital intervention or a waitlist control group, with better outcomes for stress, brooding and loneliness at 12 weeks.[14] However, comparison with a waitlist did not establish superiority over existing psychological treatments. These studies combined demonstrate the reasons for not considering unstructured digital contact and therapeutic digital interventions as equivalent exposures. Their results also confirm that, in addition to the amount of time they use it, content and context and adolescent vulnerability should be assessed.

3.3. Digital Influences on Adolescent Health Behaviours

Behavioural outcome measures were different for the different types of activity. The relationship between social networking and sleep or movement behaviours was not consistent across the weeks.[15] The latter study reported an association between sufficient sleep, physical activity, screen time and nutrition literacy and was a self-reported survey of 18,660 adolescents in China between the ages of 10 and 18 years.[16] Caution must be used in interpreting these findings as cause and effect because several of the exposures and outcomes were reported by the subjects in the study. Neither investigation established that reducing screen time alone would improve physical activity or nutrition.

The analyses conducted by Nagata et al. included 5,797 adolescents from the United States, and showed risk ratios of 1.24 and 1.29 for the medium and high screen-time groups, respectively, compared to the lowest screen-time group.[17] Objective steps also gave information beyond self-reports of screen time. Alosaimi et al., however, followed 3,065 adolescents over 3 years, and observed that different groups of diet, activity, sleep and screen behaviour were different with respect to adiposity, but these groups are not necessarily biologically distinct.[18] Each of the above findings adds up to an investigation of interacting routines with residual confounding and difference in measurement. Behavioural intervention trials would be needed to establish if there is any benefit to changing specific screen activities to enhance clinically relevant outcomes.

3.4. Artificial Intelligence in Adolescent Health Screening and Diagnosis

Prediction studies were done on risk identification and not the real clinical diagnosis. Kim et al. created a machine-learning algorithm based on data from 566,875 Korean adolescents and tested it in two independent cohorts of adolescents from the United States and Norway, respectively, in which the area under the receiver operating characteristic curve dropped from 0.901 in the development cohort to 0.831 and 0.813 in the United States and Norwegian cohorts, respectively.[19] This attenuation demonstrates a transportability issue but the result was self-reported suicidal thinking instead of a diagnosis made by a clinician. Discrimination is a measure of a model's ability to order the cases while calibration is a measure of the model's ability to agree with the observed probabilities.

Discrimination and calibration do not, by themselves, demonstrate treatment benefit, clinical safety or readiness for deployment.

Yoo et al. predicted adolescent depression from early-life ALSPAC data and reported accuracy of 0.64, recall of 0.59 and specificity of 0.61.[20] Liu et al. obtained internal test-set AUC values of 0.835–0.879 using childhood and adolescent features.[21] Wang et al. examined 103 adolescents prospectively and found that conventional regression could outperform complex machine-learning models.[22] Differences in outcomes, samples and follow-up preclude ranking these models by AUC alone. No study showed that using an algorithm to make a diagnosis had a beneficial impact on the health outcomes of adolescents.

3.5. Remote Healthcare and Digital Care Delivery for Adolescents

Remote care trials provided information on feasibility and treatment response, with mixed effect comparisons. In the uncontrolled feasibility design, Klein et al. provided remote videoconferencing OCD-CBT[23] to 20 adolescents (12-18 years) and found an effect of symptom reduction within groups (d=1.87), but the uncontrolled design could not isolate effects attributable to remote delivery. Friedman et al. randomly assigned 100 youth (10-18 years) to either a telehealth or in-person obesity intervention and conducted a follow-up assessment six months after, with 65 youth completing the assessment.[24] At 6 months, the mean decrease in BMI z-score was smaller for telehealth than for in-person treatment (−0.05 vs. −0.16; P=.002). Mode of delivery could not be attributed to this contrast alone as a result of the various treatment doses and the incompleteness of follow-up.

A pilot study of a transdiagnostic emotion regulation intervention compared to an active intervention conducted by Sjöblom et al. with 30 adolescents with mental-health issues, showed encouraging symptom changes but was limited by a sex imbalance and small sample size.[25] In a multisite web-based intervention feasibility study, Edwards et al. randomised 40 adolescent girls with elevated anxiety, with the results of retention and acceptability supporting delivery of the intervention, though outcomes for exploratory cardiometabolic outcomes were underpowered to establish comparative efficacy.[26] Practical delivery, preliminary symptom response and direct comparative treatment were therefore the various levels tested in these studies. Remote access cannot be equated with clinical effectiveness across conditions without adequately powered and balanced-dose studies.

3.6. Biomedical Technologies and Adolescent Health Monitoring

In the wearable studies the feasibility of data collection was distinct from criterion validity. One accurate output does not validate the whole device: Casado-Robles et al. compared four generations of Xiaomi Mi Band to ActiGraph to assess their ability to estimate physical-activity intensity in 62 adolescents (ages 12-18) and found that the daily step count was better.[27] These high rates of adherence (95% in orthopaedic injury recovery and 93% following concussion) among 34 adolescent athletes suggested feasible monitoring under study conditions, but did not establish that wearable measurements could diagnose injury recovery.[28] These findings need to be measured individually on the device performability, adherence to the use of the device and the clinical decision making.

The indicators of activity and HR obtained from the Fitbit device in the study by Damme et al., from 5,007 adolescents, were not confirmed as diagnostic biomarkers.[29] In 69 adolescents with depressive symptoms, Guo et al. conducted an ecological momentary assessment along with actigraphy and smartphone data collection for one month, but there was variability in the availability of passive data, depending on the smartphone's operating system, and privacy concerns were reported, with 91% completing the protocol.[30] So, the acceptability of monitoring, the accuracy of instruments and clinical benefit, were still separate outcomes. To allow for general adoption, there needs to be clear missing data protocols, developmentally appropriate consent-making process, and demonstration that measured signals facilitate, and do not just add, to better decision-making.

3.7. Cross-Cutting Findings Across Adolescent Digital Health Domains

Four evidence stages were identified, across domains: feasibility, measurement or predictive validity, comparative effectiveness and implementation (Table 2; Supplementary Table S6). Comparative evidence was more likely to be provided by digital intervention studies, while criterion agreement and adherence were more likely to be assessed by wearable studies. Prediction studies have assessed discrimination, occasionally between countries, and have not tested patient benefit post clinical deployment. The privacy aspect was specifically addressed in smartphone monitoring studies, and subgroup fairness and wider equity impacts were very few. This four stage sequence is an interpretive framework that is based on the study mapping, and is not a validated clinical pathway. It shows priority evidence steps that are not yet complete to support the routine care of adolescents with digital applications.

4. Discussion

The synthesis suggests that clinical function of digital technologies is the appropriate way of assessing technologies, instead of using a single label. Exposures are everyday social networking, interventions are online psychological treatments, risk is estimated using machine learning and particular behaviours or signals are measured through wearables. They provide answers to different questions and can't be added together to provide an overall estimate of benefit.[3] The added value is a common framework for the comparison of therapeutic effectiveness, model validity

and sensor performance, without equating these. It will therefore have conceptual value if these design specific limits are maintained when making empirical to clinical translations.

The mental-health results illustrate the value of temporal ordering and intentions for intervention. There are differences between the time of exposure window and the clinical meaning of short-term browsing associations and later depression or anxiety classifications; neither can make inferences about what the ramifications of any one adolescent's Internet use might be. Association might also change as a function of family and school context, but causal pathways cannot be addressed using cross sectional mediation. These discrepancies indicate that what is displayed, when, in what social context and how vulnerable individuals are should be focused upon more than simply the total amount of screen time spent.[14] This would imply that the content, timing, social context and individual vulnerability should be taken into account more so than the amount of total screen time. The clinical implication is to have a specific assessment, not a blanket assumption of hurt.

A comparable interpretation based on behavioural evidence is appropriate as well. Objective step measurement and self-reported screen time assess different constructs and data-driven lifestyle clusters represent interrelated routines and not single risk factors. However, none of the observational studies experimentally reduced screen exposure, so a causal claim that screen reduction prevents obesity would be premature.[18] A better research design would have measured a change in one kind of screen activity, and measured the substitution by either sleep or exercise, and taken into account family resources and family physical environment. This separation corresponds with more general principles that adolescent health risks are generated by a complex interaction between behavioural and social determinants.[2]

Apparently favourable algorithm discrimination is not enough for clinical prediction. None of the included models measured clinical benefit following deployment[19] and none of the included evidence established clinical benefit in terms of calibration, subgroup fairness or diagnostic substitution.[22] Thus, for clinical research, requirements of transparency, oversight and safeguarding remain suggested based on general principles of governance[6] and not a product of these prediction studies.

A comparison of engagement and comparative effectiveness was demonstrated in remote treatment. An uncontrolled small-scale videotherapy study was conducted to provide feasibility, but to determine causality of treatment was not possible. By contrast, the randomised obesity trial directly compared remote and in-person care, but differences in treatment dose and incomplete follow-up limited interpretation.[24] Smaller online psychological intervention trials also showed acceptability and preliminary symptom improvements, without supporting broad claims of superiority. Therefore, the assumption of equivalence and inferiority of digital delivery does not hold for any two unrelated clinical conditions. Clinical contact should be balanced in future comparative studies and co-interventions described; and outcomes should be clinically meaningful to adolescents. The World Health Organization's digital health strategy also highlights the need to integrate digital solutions into an adequate health service as opposed to technology adoption alone.[5]

Evidence gaps emerged when the biomedical monitoring was done. From the study by Casado-Robles et al., wearable step counts showed stronger agreement with a reference instrument than physical-activity intensity estimates, and high adherence to the injury monitoring indicated the feasibility of participation, but not diagnostic accuracy.[27] In contrast, general statements about the fairness of these algorithms and their ability to be implemented widely and affordably due to population-level access, were not directly assessed for these technologies in Guo et al.'s smartphone-sensing study.[30] Evaluation should therefore differentiate reported barriers of implementation from recommended safeguards, such as involving adolescents, obtaining consent and ensuring access/equality.

This review combined data from the literature specific to the adolescent population in 5 domains and differentiated observational association, intervention effect, predictive performance and technical agreement. The cross-domain evidence matrix distinguished the levels of evidence available for different clinical interpretations. Given that this search strategy only included article titles, and applied filters for access, English-language publications only, and three databases, relevant evidence that was only indexed by abstracts or keywords or outside of these filters may not have been captured. The filter for the age of adolescents (13-18 years) that is already in place in PubMed was not customisable to the review eligibility range of 10 to 19 years, likely to result in fewer studies in the age range 10-12 years or 19 years being retrieved. There is no indication of the relative amount of research in the five fields in the evidence set (20 studies) or even the domain grouping. The follow-up periods and heterogeneous endpoints precluded meaningful quantitative pooling and the custom design-sensitive appraisal did not replace formal risk-of-bias assessment. These limitations limit the completeness, generalisability and uncertainty of the evidence map that is produced.

4.1. Complementary Clinical, AI and Digital-Infrastructure Evidence

The adolescent mental-health evidence in this review requires a clear separation between symptom measurement, vulnerability, behavioural practices and clinical outcomes. Validation of an Arabic parent-report depression questionnaire in children [31] concerns the measurement of symptoms, rather than the causal effects of digital exposure. Research on childhood trauma and maladaptive schemas in the context of intimate partner violence [32] examines psychological vulnerability, but its adult population and outcome cannot establish an effect of social media

on adolescents. Similarly, research on self-care practices in adults with type 1 diabetes [33] considers health behaviour and self-management, not the effectiveness of a digital intervention. A prospective study of preoperative anxiety, depressive symptoms and subsequent delirium following cardiac surgery [34] illustrates the distinct task of relating a psychological risk marker to a later clinical endpoint. These examples highlight why adolescent digital-health studies must specify whether they measure symptoms, predict risks or demonstrate treatment benefits. Findings from the other patient populations cannot be treated as adolescent-specific evidence.

Clinical artificial intelligence offers useful comparisons for validation, while leaving important differences in target populations and outcomes. Automated grading of knee osteoarthritis from clinical imaging [35] and deep-learning assessment of Alzheimer's disease from neuroimaging [36] involve defined diagnostic classification tasks. They therefore differ from predicting future depressive symptoms using adolescent questionnaire responses. A privacy-preserving skin-cancer classification study combining federated deep learning with explainable methods [37] raises additional questions about distributed data governance and model interpretation. These methods suggest technical approaches worth considering, but no result from those studies verifies accuracy, calibration, fairness or clinical benefit in adolescent mental-health screening. The performance and acceptability of a model must be assessed in the population, setting and decision process for which it is intended.

Biomedical technologies also need outcome-specific standards. Research on terahertz-range dopamine detection using a metasurface biosensor [38] addresses the production of an analytical signal, whereas the adolescent wearable studies in this review mainly concern activity measurement and monitoring feasibility. Zinc-oxide-loaded wound-dressing materials [39] represent the separate problem of material antibacterial activity. Hospital research assessing the appropriateness and outcomes of colistin treatment [40] investigates clinical decisions and patient outcomes rather than sensor performance. These areas demonstrate that analytical detection, material efficacy, therapeutic appropriateness and reliable physiological measurement are different evaluative targets. None of these non-adolescent studies establishes that a wearable or remotely delivered intervention improves adolescent health. The distinction matters because technical feasibility alone should not be promoted as evidence of patient benefit.

For remote care, the quality of digital infrastructure must be evaluated alongside therapeutic effectiveness. A 5G-enabled intelligent patient-monitoring architecture [41] deals with secure transmission and automated handling of medical information. Research reviewing smartphone sensor-based authentication [42] concerns device access, while distributed secure aggregation in mobile ad hoc networks [43] addresses a different part of the data-transfer problem. Deep-learning-based phishing detection [44] targets threats to information access rather than medical diagnosis. Work on predictive maintenance using edge computing and connected devices [45] examines equipment reliability in an industrial setting; its operational concepts are relevant by analogy, but its results are not evidence about health-service reliability. Together, these distinct areas motivate attention to authentication, confidentiality, device maintenance and service continuity. Adolescent telehealth systems still need their own evaluations of consent, accessibility, usability, safety and clinical outcomes.

Digital engagement and trustworthy algorithmic decisions present a further distinction. Research on commercial AI-chatbot experience [46] investigates user satisfaction and expectation confirmation, which cannot substitute for symptom improvement or comparative effectiveness in a mental-health service. A neuro-symbolic reinforcement-learning system designed for autonomous vehicles [47] addresses rule-constrained decisions under safety requirements, while an explainable disaster-classification framework [48] examines predictive interpretation in changing environments. Transfer-learning research on maize disease image classification [49] provides another example of a classification problem with its own training data, targets and validation assumptions. These studies concern different sectors, yet they make the methodological distinction clear: performance within one task cannot be presumed to transfer to an adolescent diagnostic or therapeutic setting. Human oversight, subgroup testing and external validation must be assessed directly in the intended healthcare context.

Finally, a hierarchical mathematical model of human-rodent monkeypox transmission [50] illustrates how population-level disease modelling differs from an individual's clinical risk estimate. Although both can involve computational methods, they require different target definitions, reference standards and decision thresholds. Consequently, contextual literature helps identify methodological and implementation questions but does not extend the primary evidence base. The review's 20 included adolescent studies remain the basis for its numerical summaries, domain comparisons and conclusions. The broader sources identify issues for future research rather than additional findings about adolescent digital-health outcomes.

5. Conclusion

Adolescent digital technologies were related to a range of outcomes, with varying levels of evidence that were dependent on the purpose of the technology. Digital exposure studies revealed context-specific relationships, and structured interventions showed specific positive effects in specific comparison. The results of remote care were not consistent across the treatments and algorithm studies were not used to validate clinical diagnosis. Differentiation of the monitoring feasibility and the measurement accuracy were conducted in the wearable investigations. The findings

do not allow a single causal conclusion to be drawn about the use of technology and it cannot be assumed that digital tools automatically result in the betterment of the health of adolescents.

The review adds a cross domain interpretative framework of feasibility, validity and comparative effectiveness and implementation. Outcome-based evidence, developmentally appropriate safeguards and oversight from professionals are needed to make clinical decisions. Future research priorities are representative samples of adolescents, external model validation, criterion standard wearable testing and adequately powered trials of digital versus established care. This evidence-based approach can help ensure more balanced evaluation of digital health apps, avoiding the mistake of unduly prematurely declaring their 'readiness for use in routine clinical practice'.

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