From social media to artificial intelligence: improving research on digital harms in youth

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In this Personal View, we critically evaluate the limitations and underlying challenges of existing research into the negative mental health consequences of internet-mediated technologies on young people. We argue that identifying and proactively addressing consistent shortcomings is the most effective method for building an accurate evidence base for the forthcoming influx of research on the effects of artificial intelligence (AI) on children and adolescents. Basic research, advice for caregivers, and evidence for policy makers should tackle the challenges that led to the misunderstanding of social media harms. The Personal View has four sections: first, we conducted a critical appraisal of recent reviews regarding effects of technology on children and adolescents' mental health, aimed at identifying limitations in the evidence base; second, we discuss what we think are the most pressing methodological challenges underlying those limitations; third, we propose effective ways to address these limitations, building on robust methodology, with reference to emerging applications in the study of AI and children and adolescents' wellbeing; and lastly, we articulate steps for conceptualising and rigorously studying the ever-shifting sociotechnological landscape of digital childhood and adolescence. We outline how the most effective approach to understanding how young people shape, and are shaped by, emerging technologies, is by identifying and directly addressing specific challenges. We present an approach grounded in interpreting findings through a coherent and collaborative evidence-based framework in a measured, incremental, and informative way.

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Introduction

A consensus report published by the American National Academies of Science, Engineering, and Medicine (NASEM) concluded that the "committee's review of the literature did not support the conclusion that social media causes changes in adolescent health at the population level".[1] Yet, numerous governments have issued guidelines and passed laws that limit adolescents' social media use to protect their mental health.[2–4] This discrepancy highlights the difference between what researchers know about the influence of technology on adolescent mental health and how technology is discussed in media and policy. Following a long history of media panics,[5] there have been repeated cycles of concern surrounding screen-based technologies, from television (1960–90), home video games (1990–2005), online games (2000–present), and social media (2004–present), to smartphones (2007–present). Throughout these cycles, many studies have problematised innovation, reinforcing concerns instead of informing useful guidance or well targeted health policy.[6] If we do not identify and learn from past mistakes, we could miss a rapidly narrowing opportunity to understand and shape how artificial intelligence (AI) affects children and adolescents in the next decade.

A 2023 report by UK regulator Ofcom found that two of five children (age 7–12 years) and four of five adolescents (age 13–17 years) are now using generative AI tools and services.[7] This rapid adoption has surpassed the pace set by social media—a popular topic of debate and study at present. Nevertheless, the past two decades of study of social media serve as an example to learn from. The importance of the situation is paramount, as emerging technologies based on advances in both hardware and software are utilising decades of research into AI. The ways in which young people interact with AI is constantly changing, with many experts predicting human-like AI this decade.[8] Reflecting on the past challenges to understanding social media's effects on young people's mental health can help to ensure validity and robustness in future studies of how young people are influenced by AI.

In this Personal View, we identify the overarching limitations present in research on social media and adolescents' mental health, supported by appraisal of impactful published reviews of research in this field. We break down these limitations into what we think are the

Key messages

- Technological innovations continuously reframe childhood, triggering concerns of psychological harm to children and adolescents
- Health policy decisions have been implemented based on inconsistent, non-causal, or ungeneralisable evidence of online harms
- Research on social media is often reduced to monocausal technological determinism, neglecting contextual factors that influence technology use and mental health
- With children increasingly exposed to artificial intelligence (AI), understanding the effects of AI requires balancing globally representative data with robust causal inference methodology
- Proactive technology regulation depends on collaboration between researchers, the technology industry, policy makers, practitioners, adolescents, and parents
- Overcoming challenges involves collating online resources for consideration around exposures, contextual factors, generalisability, causal methodology, and policy recommendations

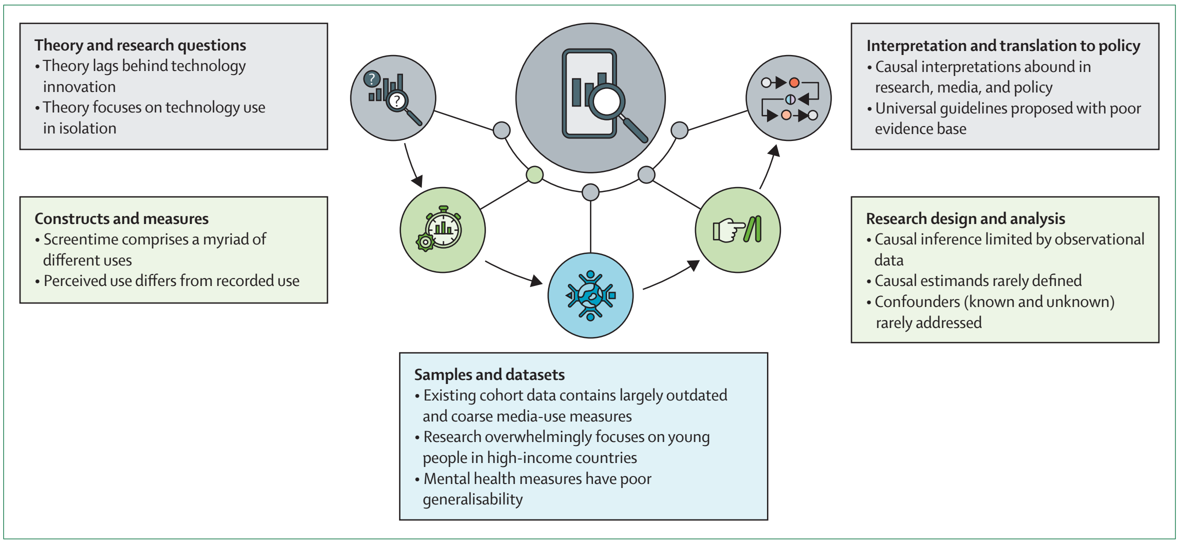

Figure 1: **Limitations and challenges to key steps in the design and interpretation of research on emergent technologies**

underlying methodological challenges and present them in relation to the key steps in the design and interpretation of research on technological harms (figure 1): (1) theory and research questions, (2) constructs and measures, (3) samples and datasets, (4) research designs and analyses, and (5) interpretations and translations to policy. We argue that each of these challenges, which are grounded in key aspects of scientific validity,[9,10] can be addressed with robust modern methodologies. We detail what researchers and policy makers can learn from past issues to benefit future investigations of other emergent technologies, such as AI. Finally, we outline a collaborative framework with recommendations building on effective approaches, to facilitate application of learnings about emergent technologies in research, technology, policy making, care, and education sectors.

Critical appraisal of published reviews on social media or technology use and adolescent mental health

See Online for appendix

Our targeted search identified 12 systematic reviews, five scoping reviews, and eight narrative reviews (appendix pp 1–7). The focus of our appraisal of these reviews was on the extent to which review papers considered the quality or robustness of individual studies, such as using risk of bias tools to score the studies, describing common types of bias in conclusions, and discussing risk of bias in relation to effect heterogeneity. 11 (92%) of 12 systematic reviews assessed the quality or risk of bias of synthesised studies, and four (33%) integrated quality evaluations into the main findings. Six scoping and narrative reviews also discussed study quality to varying degrees. The findings from multiple systematic and narrative reviews support the conclusion that association between children and adolescents' social media use and their mental health is highly heterogeneous.[11–15] These reported associations are mostly based on cross-sectional studies,[12,16–18] with more high-quality causal investigations urgently needed.[11,13,17,19–21] Based on our appraisal of reviews, we address several methodological challenges, some of which are common to other areas of child and adolescent mental health research, which we think account for the heterogeneous effects.

Methodological challenges to investigations into technological harms

Poorly defined theory and research questions

One reason for recent reviews calling for more causal studies relates to monocausal technological determinism, which describes a tendency to blame a range of negative trends on technological advances, neglecting other causal factors.[6] Plotting a timeline of the prevalence of mental health problems reported by adolescents and searching for any visible trends that coincide with a technological advance,[22] such as social media or smartphones, can be tempting, but such an approach is not robust for several reasons. First, the association between mental health and social media use is complex and bidirectional,[23] whereby low mood likely triggers increased social media use. Second, the mental health and wellbeing outcomes assessed in studies of social media effects are highly heterogeneous, and to what extent the effects depend on the choice of outcome is not clear.[24] Third, there are many time-varying contextual factors evolving together, potentially with greater effects on mental health than technology use.[25,26] By neglecting contextual factors, we fail to recognise that mental health and technology use have parallel trajectories with shared underlying causes such as pandemics, social inequalities, and environmental crises. Research controlling for relevant contextual measures suggests that what remains attributable to technology is not strong enough to warrant broad policy changes.[27] For example, among adolescents using social media and smartphones from 2005 to 2017, associations between technology engagement and wellbeing did not increase.[28] Researchers interpreting inconsistent associations as having profound societal implications have missed an invaluable opportunity to properly define causal research questions.

Poorly defined measures and constructs

Another potential contributor to the heterogeneity of effects is that most published research investigating the influence of social media on child and adolescent wellbeing relies on self-reported estimates of engagement (ie, the amount of screentime over the course of a day or week). The majority of research in the past decade has shown mixed effects of screentime on adolescent mental health,[11] while other studies have suggested that, for some forms of technology engagement, there might instead be an optimal level for mental wellbeing.[29–31] Self-reported screentime to investigate technology engagement is problematic both as a measure and as a construct. As a measure, self-reported screentime is imprecise and prone to bias.[32–34] As a construct, self-reported screentime is unidimensional, homogenous, and has poor validity.[35] Screentime might reflect time not spent on other activities (displacement),[36] be a proxy for exposure to different technology-related phenomena (such as social comparison), or reflect a combination of multiple affordances.[37–39] The use of screentime as an exposure fails to differentiate between the many different functions of technology use, including social, educational, entertainment, work, and informational uses, as well as different content and purposes, possibly with different effects.[35,40–42] Social media screentime might help to identify extreme cases of overusage and underusage, but it provides no information into which types of adolescent experiences or behaviours are exacerbating negative outcomes. Social media research grounded in poorly defined and outdated measures of technology use undermines the quality and validity of many investigations, especially in secondary analyses of existing data.

Limited datasets and samples

Due to the impracticality of controlled experiments that randomly assign children and adolescents to different patterns of social media use, studies of social media effects on adolescents' health and wellbeing are largely observational and frequently studied via secondary data analyses.[11] Open research data, particularly longitudinal cohort data, has many strengths, such as improving the reproducibility of research and collaboration between researchers.[43] However, open datasets can be limited by rapidly outdated social media use measures and the representativeness or generalisability of research samples and mental health measures. External validity is especially important given the global reach of social media and geographical distribution of young people across the world; however, key groups of technology users are often missing. Minority groups in high-income countries (HICs) and adolescents from low-income and middle-income countries (LMICs) are rarely included in these data.[44,45] The absence of representation of adolescents in LMICs is partly due to most peer-reviewed health policy research being conducted by researchers in HICs, and related to funding streams, geography, industry, and publication incentives.[46–48] These sample limitations are further exacerbated by socioecological and demographic determinants not being collected in sufficient detail, meaning that testing effect heterogeneity is not possible, and subgroup analysis cannot identify potentially vulnerable groups.[44,45,49] Small-scale studies suggest technology can have different roles between regions and communities; for example, social media use has been shown to promote wellbeing in minority groups, such as LGBTQIA+ communities,[21,50] and help Black adolescent females navigate positive identity development.[51] Despite these advantages, research into how diverse cultures and communities can benefit from social media is stagnant in both HICs and LMICs.[52] This stagnation of investigating heterogeneity is because large-scale social data do not currently include enough relevant detail to investigate these dynamics effectively.

Inappropriate designs and analyses

Most studies assessing the relationship between adolescents' technology use and their health or wellbeing are correlational, of low quality, and highlight that more causal investigations are needed.[11–13,16–20] Notably, two meta-analyses reported that effect sizes and heterogeneity decreased as study quality increased.[12,53] The bidirectional nature of the association between online behaviour and mental health is often neglected,[23] which is in line with findings from our review that associations in observational studies are weaker when controlling for baseline mental health,[12,53] as well as the many confounding factors that affect both exposure and outcome.[25] Although appropriate methods and models have been proposed to account for both baseline effects and time-invariant confounders,[54] causal misinterpretations can still happen when additional sources of bias are neglected. Inferring causality depends on complex assumptions,[55] which is especially true with observational, non-randomised studies that are widely used in academic research on technology use.[56] Potential issues include undefined causal estimands (eg, vaguely defined effects of screentime on mental health), and inconsistent experimental manipulation of social media abstinence. These inappropriate causal inferences can be further aggravated by other questionable research practices that undermine the validity of statistical conclusions.[43] Few studies are computationally reproducible,[57] nor are they protected against practices such as running multiple models until a significant result is reached (ie, p-hacking) or hypothesising after the results are known (ie, HARKing).[58] The pattern is likely similar or worse for studies investigating associations between adolescents' social media use and their mental health, due to the rapidly changing landscape of technology development. Considering these factors, the collective failure to address multiple sources of bias and error in social media research designs produces inconsistent findings, ungrounded causal interpretations, and recommendations that might lead policy makers and practitioners astray.

Inappropriate interpretation and translation to policy

Policy relating to adolescents' use of technology has historically misaligned with scientific evidence regarding how technology influences adolescents.[59–61] Numerous reviews, as well as a consensus report by NASEM, state that evidence on social media use by adolescents does not support drastic policy action,[1,11–14,19,20] yet several jurisdictions have legislated social media bans for adolescents. This contradiction arises due to low-quality evidence and because of exaggerated interpretations of study findings by scientists or journalists, such as interpreting correlational results as causal evidence.[62] Concerns caused by anecdotes in media reports can motivate reactive policies,[63] while limitations to validity and ungrounded causal inferences can produce ill-conceived recommendations. For example, the 2×2 rule proposed by the American Academy of Pediatrics (ie, no screens for children younger than 2 years and no more than 2 hours per day for children older than 2 years) was entirely revised in 2016 after a review concluded that there was insufficient evidence to support specific screentime limitation guidelines.[64] Despite this revision, a similar rule was later adopted in 2019 by WHO.[65] From 2011 to 2021, the South Korean government prohibited those younger than 16 years from accessing online gaming platforms between 0000 h and 0600 h, levelling civil and criminal penalties for platforms that did not comply, even though research suggested this law had no effect.[66] The Chinese government now restricts those younger than 18 years to 3 h of video game play a week,[67] and one study has already suggested these restrictions are ineffective in reducing the prevalence of heavy play.[68] On Nov 29, 2024, the Australian government banned social media accounts for those younger than 16 years,[2] potentially misinterpreting research reporting bidirectional associations between adolescents' social media use and their life satisfaction,[69] and despite previous research suggesting screen-use limitations were impossible to implement.[70] Although there are clear reasons why technology should not be seen as a replacement for human interaction in young children's development,[71] calls for social media bans for older children and adolescents are frequently reactive and based on flawed interpretations of evidence. Time limits and age cutoffs shift responsibility away from the need to regulate harmful content, putting responsibility instead on parents and guardians, or risking mass integration of unproven age estimation technologies,[72] which have been judged to present "privacy, security, implementation and enforcement risks".[73] Technological regulations based on insufficient evidence, inconsistent effects, or misinterpreted findings are potentially harmful. Effective policy for adolescents' engagement with emerging technologies will require fundamentally rethinking our approach to social media.

Improving research in the era of AI

Replacing monocausal technological determinism

We are at the stage where there is temptation to view the effects of all new technologies on children and adolescents as a unitary phenomenon. AI will be integrated into the apps that children use at home and school, embedded into the systems and platforms they work with as young adults. Encounters with AI will be ubiquitous, including interaction with large language models, as both co-creators and conversation partners. For example, large language models might have human roles (such as AI therapists),[74] or produce images and video content convincing enough to be indistinguishable from authentic content,[75] potentially influencing children's emotions and behaviour. Other apps will include content recommendation systems and online diagnostics tools for depression, anxiety, or eating disorders, which are increasingly being used for self-diagnosis.[76] With human-like AI enhancing or moderating online interactions, the range of potential benefits and harms to children and adolescents are simultaneously more diverse and contextually dependent than social media and online games alone have ever been. Psychologists, mental health researchers, and practitioners have little control over the development of AI apps, but do have the power to ask constructive research questions that do not implicitly problematise all AI; for example, how can we ensure that children and adolescents adapt to technological innovation, making them aware of its capabilities and risks? Understanding both capabilities and risks requires a structured approach to researching emergent technologies (figure 2), while circumventing the challenges of social media research. Researchers will first need to embrace qualitative, ethnographic, and other observational data to identify children's and adolescencts' diverse exposures to integrated AI and the potential effects on their wellbeing.

Prioritising causal designs

Robust causal investigations will eventually require experimental and interventional designs with use of randomised allocation when ethical and practical to do so, and with comprehensive measures of adherence to the manipulated exposures. These investigations might involve manipulation of content filters or digital literacy training. Before any experimental work can be informative, researchers will first need to rely on exploratory and observational data, potentially including natural experiments, to inform the development of large-scale

***Figure 2:* Proposed order and divison of research activities for an effective cycle of technological innovation, research, policy making, and industry regulation outlining key responsibilities for stakeholders**

interventions. To build informative models with observational data, researchers should directly engage with causal inference methods.[56,77,78] For example, the Structural Causal Model framework uses Directed Acyclic Graphs (DAGs) to clearly define causal estimands, differentiate measured and unmeasured confounders, and consider potential moderators and mediators of the effects of interest.[77] Structural equation model diagrams have been used to conceptualise statistical models and to visualise results, including confounders, moderators and mediators, but cannot always be interpreted causally.[79] Controlling for baseline measures of outcomes and time-invariant confounders in analyses can reduce the risk of biased results;[54] however, many potential confounders are not measured or even considered (figure 3), risking inappropriate causal interpretations. Therefore, attention to formal causal methods, clearly defined causal estimands, and the use of tools such as DAGs to define measured and unmeasured confounders is crucial to reducing bias.

Identifying exposures and measures

Relying on adolescents' self-reported use of integrated AI as an exposure measure is even more concerning than simply counting their total time spent on social media. Only behavioural data on exposure to a range of AI apps would provide the amount of detail needed. However,

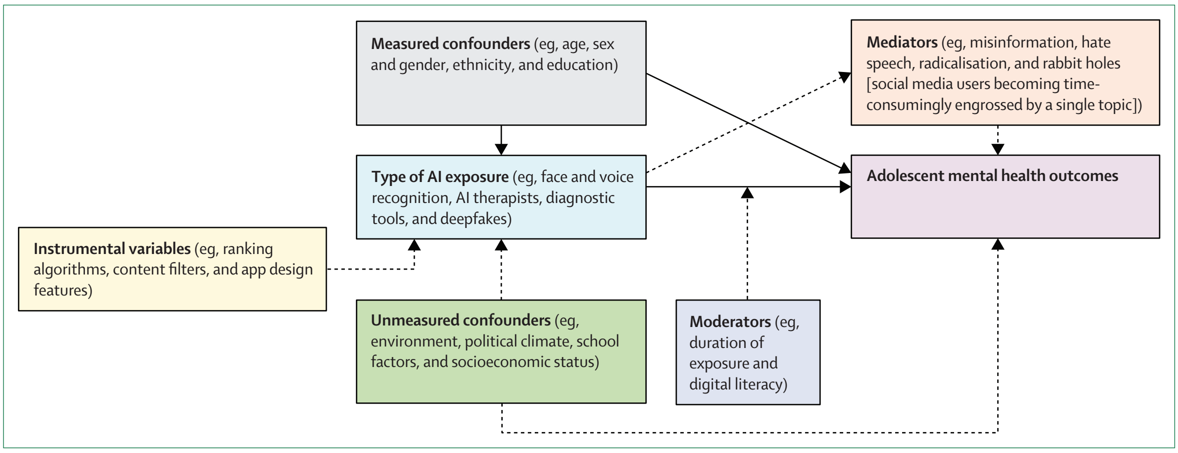

Figure 3: **Relationships and factors relevant to investigating causal effects of AI exposure on adolescent mental health**
AI=artificial intelligence. Solid arrows=common approach to testing the effects of an exposure on an outcome, adjusting for available (measured) confounders. Dashed arrows=other potential influences on exposures and outcomes or on the relationship between exposures and outcomes.

understanding the range of exposures to integrated AI and their potential effects on children and adolescents will first require qualitative work with adolescent users, including the involvement of youth advisory groups,[80] as well as with the designers of these systems in the technology sector. Research addressing AI exposures needs to better account for other evolving social and contextual determinants, such as political and environmental changes; however, predicting which forms of AI are likely to be helpful or harmful and the situations where we might expect to observe these dynamics is difficult. Deepfakes—whereby AI is used to create realistic yet false images, videos, or audio speech—are already raising concerns, together with other effects of disinformation,[81,82] and have many potential implications for children and adolescents. A combination of behavioural and self-reported measures should be developed, and explicitly testing the generalisability of these measures between populations and communities will be crucial as they start to be included in the datasets and samples we analyse.

For more on the **ABCD Study** see https://abcdstudy.org

Enhancing research datasets

There are several underutilised opportunities for collecting and analysing more informative data to understand technology effects on children and adolescents globally, which could involve maximising the use of cohort data from academic research, accessing data from the technology sector, and collecting new data from representative samples. Active cohort data could already provide insight into the effects of technology on specific adolescent populations. Cohort studies often use targeted sampling of a specific population (eg, primary school students in the UK) to maximise local representativeness, collect data on key sociodemographic factors, and include validated or consistently repeated measures of mental health and wellbeing. The use of such active cohorts could be maximised by augmenting future data collection with triangulated data from compatible sources (eg, objective behavioural telemetry or technology use recorded in participants' schools) and by adding informative measures of relevant exposures and contextual factors, codesigned with adolescents and other stakeholders. This approach would increase the value of active cohorts, such as the Understanding Society's Innovation Panel in the UK and the ABCD Study in the USA.[83] However, addressing the sampling limitations in technology research will require building the ability to collect data on AI sociotechnical systems directly as a foundational part of new cohort data projects.

For more on the **World Values Survey** see https://www.worldvaluessurvey.org

Increasing sample generalisability and heterogeneity

Debate about AI's effect on childhood and adolescence will encounter the same limitations (focusing on high-income, non-diverse populations) if we do not start our inquiry knowing that the benefits and deleterious influences of these emerging technologies will be experienced by young people all around the world.[84] Studying the interests of historically marginalised children who have been overlooked by mainstream research is crucial,[85] and should involve codevelopment of a research agenda with partners in LMICs.[86] New data collections, featuring both existing and forthcoming cohorts, might make it possible to differentiate effects of emergent technologies on diverse demographics in LMICs, representing those living in urban and rural settings, and across ethnicities, incomes, identities, and sexual orientations. Gaining insight into technology effects in LMICs will require greatly expanding on examples such as Gallup polls,[87] World Values Survey, and Disrupting Harm,[88] so that well documented, reliable, and representative data can be made available to the global scholar community. Overcoming a simple HIC versus LMIC dichotomy will enable those studying AI's effect on childhood and adolescence to investigate differences within and between LMICs, as well as between LMICs and HICs. Encouraging researchers to

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analyse culturally adapted mental health data, such as UNICEF–MICS,[89] will help improve and diversify measures as young people's use of these technologies continue to evolve.

Developments for technology sector data

Social media and other online platforms regularly collect detailed longitudinal behavioural data from global audiences, which can help alleviate the limitations of narrow sampling and self-reported measures; however, only in rare cases have these data been made available to independent researchers. Despite this scarcity, academic–industry collaboration shows the exceptional insights that such cooperation can produce. For example, an experimental collaboration with Meta showed that people encountering only beliefs or opinions that coincide with their own (ie, echo chamber) is common on Facebook, but has minimal effects on political polarisation.[90] Another collaboration with video game companies, including Nintendo of America and Electronic Arts, found little to no evidence for a causal connection between game play and wellbeing.[91] Such collaborations should become more common over time, supported by transparent communication between platforms, media, and policy makers. With recent concerns around online privacy and other online dangers, expectations for the technology industry are increasing.[92] Changing norms and stricter regulations might soon create easier access to industry data by independent researchers, such as the forthcoming collaboration between the Center for Open Science and Meta platforms.[93] Clear rules for the disclosure of actual or perceived conflicts of interest are needed to protect the integrity of work by independent researchers. Academic publishers must enforce the full disclosure of all conflicts of interest to prevent many profitable incentives from undermining the credibility of science.[94] For now, the slow, privileged, and unstable nature of direct collaborations—which also exclude underage users due to privacy concerns—means that alternative approaches to behavioural data access are necessary.[95] New ways of conducting research, such as embedding independent researchers in technology companies and firms engaging in large-scale team-based collaboration, will be required to understand how these emerging platforms might be tailored to prevent rather than cause harm.

Policy translation

Due to the complexity of this ever-changing field, science journalists, policy makers, and practitioners need a structured understanding of the evidence base as it develops. Clear guidelines for judging the validity and accurate reporting of newly published findings are long overdue for technology research. These guidelines can be achieved by combining unbiased comprehensive evidence synthesis and balancing recommendations by independent researchers. Developing reporting and policy recommendations will include taking care with causal interpretation[62] and avoiding strong headlines such as "Have smartphones destroyed a generation?".[96] To achieve this ultimate goal, structured collaboration is urgently needed between academics, the technology sector, policy makers, and practitioners (figure 2).

A framework for structured collaboration

A well calibrated agenda is needed to guide development of policy that will safeguard children and adolescents from the potentially harmful effects of emerging technologies, such as AI. Our aim is to inform a flexible and targeted technology regulation approach instead of blanket legislation specifying age, feature, or time limits. A successful framework will require collaboration between independent researchers, the technology sector, policy makers, and other stakeholders, each bringing their own expertise to each step in the research process (figure 2). Academics and other independent researchers have the most important role in improving the validity and translational capacity of research, defining clear and realistic causal questions, ensuring globally representative samples, and addressing heterogeneity between and among populations. However, all stakeholders will need to contribute to identifying exposures, outcomes, and confounders, and will need to be aware of the key challenges that have led to ungrounded policy advice on social media and gaming. We therefore propose developing a set of resources that can be used by researchers, the technology sector, policy makers, and all those involved in the safeguarding of children and adolescents. This set of resources would need to be a living online resource that can be updated as new data arises, reflecting the rapidly evolving field of technology.

Measures repository

Exploratory work with all stakeholders could be used to identify prominent types of AI that children and adolescents are exposed to, along with measured and unmeasured confounders, and potential moderators and mediators (similar to the Structural Causal Model framework).[77] Researchers might start to build a DAG for each exposure-outcome mapping, outlining examples of measures that might be important to include in an experimental design or analysis plan (figure 3). However, each study and analysis will be unique, depending on the exposure and outcome of interest, as well as any other contextual factors likely to affect children and adolescents in the populations studied. Depending on the results of exploratory work, the repository might include self-reported measures (eg, individual experience and attitudes towards different types of AI), administrative data (eg, population density and green space), and ideally consented or anonymous data from online platforms informing the types of integrated AI exposures and how

Search strategy and selection criteria

References for this Personal View were guided by structured brainstorming on challenges to researching technology and the effects on children and adolescents' mental health, considering especially the quality, heterogeneity, generalisability, and policy implications of existing evidence. References for the critical appraisal section of this Personal View were identified through Dimensions, a free web application, to search the titles and abstracts of review papers published in English from Jan 1, 2020, to July 29, 2024, using the terms: ("review" OR "meta-analysis") AND ("social media" OR "technology" OR "screens") AND ("mental health" OR "well-being" OR "depression" OR "anxiety" OR "harm*" OR "risk*") AND ("child*" OR "adolescen*" OR "young people" OR "youth"). 3403 results were sorted based on Altmetric Attention Score and screened by two reviewers, KLM and SG, starting with the highest Altmetric Attention Score, until 25 reviews were identified. Discrepancies were resolved by discussion between KLM and SG considering relevance to the scope of this Personal View. Two high-impact but problematic publications were excluded based on research integrity concerns raised during full-text review and replaced by the next two eligible review papers according to their Altmetric Attention Score. Additional references were identified using the authors' own files, as well as specific searches (using Google, Google Scholar, PubMed, and Dimensions) for online publications reporting relevant methodologies, guidelines, and policy recommendations.

they are moderated. Avoiding monocausal technology determinism will depend on identifying a comprehensive set of contextual confounding factors, such as economic circumstances, social inequalities, climate, war, crime, and local public services. Such a repository could ideally be overseen by an international coalition of stakeholders, aiding broad sharing of resources and communication of cultural and geographical differences that might demand a more tailored approach.

Harm severity

Complementing the repository of measures, we propose developing a comprehensive and living taxonomy delineating potential harmful outcomes associated with AI, from the gravest offences (such as online sexual child exploitation and trafficking) to other harmful content such as cyberbullying, racism, or homophobia. This taxonomy would also provide context for various concerns including privacy and body image issues, which may also adversely affect the health and wellbeing of children and adolescents. Establishing clear boundaries between direct harms (eg, trafficking, online child sexual abuse, and self-harm or suicide-related material) and indirect potential harms (eg, misinformation, algorithmic ranking, or dark patterns [harmful strategies designed to influence consumers]) will be challenging. Multistakeholder international consensus and robust evidence is needed to advance research on online harms to identify priorities and build networks of relevant expertise and resources.

Integrating technology sector data

There are several models for collaboration with the technology sector that could be beneficial, especially to achieving more representative global samples of technology users and facilitating insight into the effects of various AI implementations. Specifically, we want to highlight data donation models that use legal frameworks (eg, the General Data Protection Regulation [UK], the California Consumer Privacy Act [USA], and the Act on the Protection of Personal Information [Japan]), guaranteeing users the right to obtain a copy of their own data and potentially share it with researchers using open source software.[97] Other options include Application Programming Interfaces (although we note concerns about technology companies removing or heavily restricting access),[98] web scraping,[99] third-party tracking tools,[100] and mock social media platforms.[101] These models could support both observational work (to identify potential exposures, moderators, and mediators) and the experimental manipulation of AI exposure. Other potential forms of collaboration need to be investigated in discussion with all stakeholders.

Evidence hierarchy

Policy makers, clinicians, teachers, parents, and young people themselves need a clear and simplified understanding of the growing evidence as it arises. The collating, filtering, and evaluation of all emerging research findings needs to be guided by clear criteria for assessing quality, causal inference, generalisability, and relevance to policy, education, health care, and social care. An explicit hierarchy of evidence, such as evidence readiness, could be used to inform this framework.[102] Online evidence syntheses and educational resources could be developed by teams of independent researchers, policy advisors, educators, youth advisors, and scientific writers to ensure that coherent summaries are available for all those involved in the safeguarding of children and young people. We propose a series of Cochrane-style living systematic reviews[103] that address determinants, outcomes, and moderators and mediators, each with a critical evaluation of study quality, causal inference, and global relevance, both for existing technologies and emergent ones such as AI. Available tools for evaluation of study quality will need to be considered or adapted depending on the type of studies being reviewed, including non-randomised studies,[104] observational studies,[105] and qualitative studies.[106] Essential to any evidence hierarchy are clear reporting guidelines, building on successful methodologies used to develop existing guidelines,[107] ensuring that interpretations and recommendations reflect the strength of the evidence, and taking particular care with observational studies, which can be easily confounded.[62,108]

Further considerations

One additional challenge will be potential tension between the parallel priorities of improving the representation of children and adolescents in LMICs and improving the robustness of causal methodology and evidence readiness. This challenge is due to researchers and organisations based in LMICs having

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crucial expertise for understanding nuances between regions and cultures, but restricted access to research funding, time, and other resources, implying a potential compromise between robustness and global reach. Balancing all priorities effectively will require developing strong collaboration strategies to support research in LMICs both practically and financially.

Conclusions

Our collective popular, research, and legal attention is focused on the potential negative effects of social media on adolescent mental health, but young people are already adopting new ways of interacting with AI.[7] If history is any guide, research and evidence-based policy will lag behind these new interactions. Examining our collective failure to adequately disentangle the heterogeneous effects of young people's social media use provides a guide for staying up-to-date with the new platforms young people might be influenced by. Overcoming the key challenges in research on the effects of technology means systematically engaging with diverse stakeholders, rejecting viewpoints that invoke monocausal determinism, and synthesising data continuously for causal interpretability and policy implications. Without learning from past experiences, we may find ourselves in a similar situation ten years from now, treating social media in the same way we currently view radio dramas, comics, and some types of boardgames, absorbed by another cycle of media panic and failing to make AI safe and beneficial for children and adolescents.

Contributors

The first draft was written by KLM, AKP, and SG. KLM performed project administration, with supervision by AKP. Figures 1–3 were created by KLM, TH, and NB. KLM and SG performed literature search and screening. KLM performed the review and created the appendix. TH and KLM performed data curation to produce the final reference list. All authors performed literature searches for published examples to illustrate challenges, and contributed to conceptualisation, including development of recommendations. All authors reviewed and edited the manuscript and approved the submitted draft. All authors had full access to the manuscript and any data relevant to the review and accept responsibility to submit for publication.

Declaration of interests

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