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From Social Media to Artificial Intelligence: Improving Research on Digital Harms in Youth

Karen L. Mansfield, PhD[1]
Sakshi Ghai, PhD[1,2]
Thomas Hakman, MSc[1]
Nick Ballou, PhD[1]
Matti Vuorre, PhD[1,3]
Professor Andrew K. Przybylski, PhD[1]

[1]Oxford Internet Institute, University of Oxford, Oxford, OX1 3JS, United Kingdom
[2] Department of Psychological and Behavioural Science, London School of Economics and Political Science, United Kingdom
[3]Department of Social Psychology, Tilburg University, 5037 AB, Tilburg, Netherlands

Corresponding author: Andrew K. Przybylski
andy.przybylski@oii.ox.ac.uk
Oxford Internet Institute, University of Oxford, Oxford, OX1 3JS, United Kingdom

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Summary.

In this Personal View, we critically evaluate the limitations and underlying challenges in 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 best path forward for building an accurate evidence base for the soon-to-be forthcoming flood of research on the impacts of Artificial Intelligence (AI) on children and adolescents. Basic research, advice for caregivers, and evidence for policymakers must tackle the challenges that led our understanding of social media harms astray. The paper has four sections: For the first section we conducted a critical narrative review of recent impactful reviews of technology effects on children and adolescents' mental health, aimed at identifying limitations in the evidence base. In the second section we decompose what we think are the most pressing methodological challenges underlying those limitations. In the third section we propose effective ways to address these limitations, building on robust methodology, with an eye to emerging applications in the study of AI and children's well-being. In the final section we articulate concrete steps for conceptualising and rigorously studying the ever-shifting socio-technological landscape of digital childhood. Our conclusions 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.

Key Messages (5-6 bullets)

- 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 easily falls into the trap of monocausal technological determinism – neglecting contextual factors that influence technology use and mental health
- With children increasingly exposed to artificial intelligence, understanding impacts requires balancing globally representative data with robust causal inference methodology
- Proactive technology regulation depends on collaboration between researchers, the technology industry, policymakers, practitioners, adolescents, and parents
- Overcoming challenges involves collating online resources for considerations around exposures, contextual factors, generalisability, causal methodology, and policy recommendations

Search strategy and selection criteria

References for this paper and integrated narrative review of reviews were guided by structured brainstorming on challenges to researching technology and its impacts on children and adolescents' mental health, considering especially the quality, heterogeneity, generalisability and policy implications of existing evidence. Recent evidence syntheses on this topic were identified using the Dimensions free web application (https://www.dimensions.ai/products/all-products/dimensions-free-version/), searching the titles and abstracts of review papers published in English since January 2020, 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"). The 3,403 results were sorted on Altmetric score and screened by two reviewers, starting with the highest Altmetric score, until 25 publications had been identified that were reviews of research on the relationship between children or adolescents' social media or technology use and their mental health. Discrepancies between reviewers were discussed and resolved. 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 Altmetric score. Additional references were identified from the authors' own files and specific searches to support arguments regarding challenges and recommendations.

Introduction

A consensus report published by the American National Academies of Science, Engineering, and Medicine (NASEM) concluded that the "published literature [does] not support the conclusion that social media causes changes in adolescent health at the population level".[1] Yet, numerous states have issued guidelines and passed laws that limit adolescents' social media use in order to protect their mental health.[2–4] This highlights a mismatch between what researchers know about how technologies influence adolescent mental health, and how these technologies are 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 (1960-1990), home video games (1990-2005), online games (2000-present), 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 closing window to understand and shape how Artificial Intelligence (AI) impacts children in the next decade.

A recent study by UK regulator Ofcom found that two in five children (7 to 12 years) and four in five teenagers (13 to 17 years) in the UK are now using generative AI tools and services.[7] This rapid adoption has eclipsed the pace set by social media, the most popular topic of debate and study today. Nevertheless, the past two decades of study of social media serve as an example to learn from. The stakes could not be higher as emergent technologies built on advances in both hardware and software are leveraging decades of research into AI. The ways young people interact with AI is a moving target with plausibly human-like AI characteristics this decade.[8] Taking a step back, and reflecting on challenges experienced in evaluating social media's impact on young people's mental health, provides an invaluable lens through which to ensure validity and robustness in studies of how young people are influenced by AI.

We start by identifying the overarching limitations present in research on social media and adolescents' mental health, supported by a review of recent, impactful published reviews of research in this area. We then break down these limitations into what we think are the underlying methodological challenges, and present them in relation to the necessary components when translating research assessing technological harms to policy and practice (Figure 1). These components are: (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 using robust, modern methodologies. We then detail what researchers and policymakers can learn from past pitfalls to benefit future investigations into the impact of other emergent technologies such as AI. Finally, we outline a collaborative framework, with concrete recommendations building on effective approaches, to facilitate application of learnings about emergent technologies in the research, technology, policy, care, and education sectors.

Review of reviews

Our targeted search for the most impactful recent reviews on social media and mental health in children and adolescents identified twelve systematic reviews, five scoping reviews, and eight narrative reviews. These are presented in the Appendix Table S1, with a brief summary and evaluation of each. The focus of our review 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. Except for one, all systematic reviews assessed the quality or risk of bias of synthesised studies (92%), and four systematic reviews also integrated quality evaluations with the main findings (33%). Many scoping and narrative reviews also discussed study quality to varying degrees. The findings from multiple systematic and critical narrative reviews support the conclusion that associations between children and adolescents' social media use and their mental health are highly heterogeneous,[11–15] mostly based on cross-sectional studies,[12,16–18] and more high-quality causal investigations are urgently needed.[11,13,17,19–21] In the next section, 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.

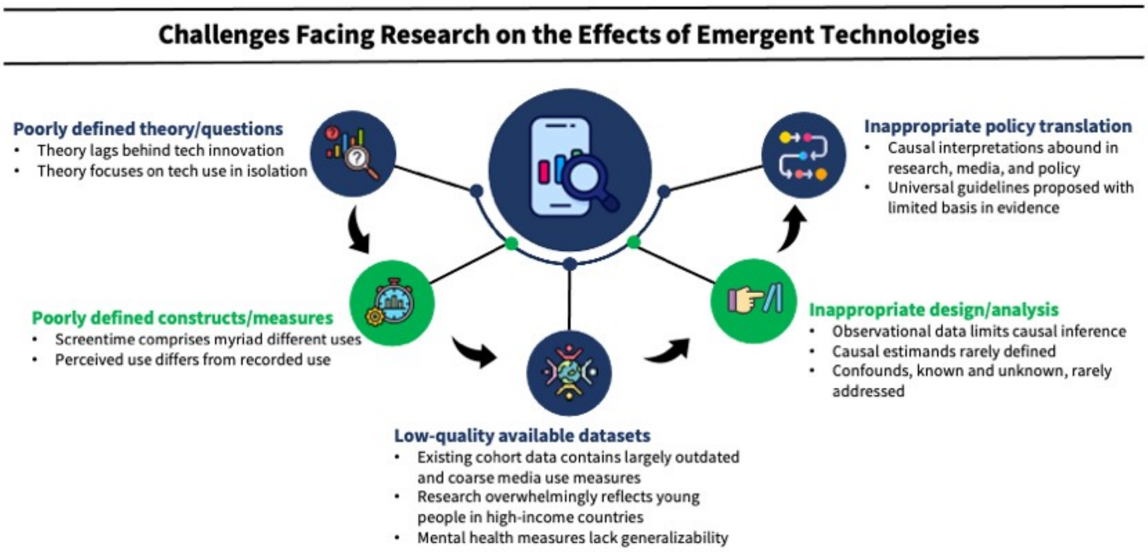

Figure 1. Key limitations and associated methodological challenges, which compromise the validity and robustness of research on the impacts of emergent technologies, set out in relation to steps in the research process from theory to policy translation.

Methodological challenges that have faced investigations into technological harms

Poorly defined theory and research questions: One reason that recent reviews are calling for more causal studies is that many investigations into the potential harms of a technology such as social media fall into a trap called *mono-causal technological determinism.*[6] It might be tempting to plot a timeline of the prevalence of mental health problems reported by adolescents and try to pin-point a technological advance such as social media or smartphones, interpreting any visible trends as evidence,[22] but such an approach lacks robustness for several reasons. Firstly, the association between mental health and social media use is complex and bi-directional,[23] whereby low mood likely triggers increased social media use. Secondly, the mental health and well-being outcomes used in studies of social media effects are highly heterogeneous, and it is not clear to what extent effects depend on choice of outcome.[24] Thirdly, there are many time-varying contextual factors evolving in parallel, potentially with greater impacts on mental health.[25,26] Neglecting contextual factors also fails 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 between 2005 and 2017, associations linking engagement to well-being did not increase in strength.[28] Researchers interpreting small, 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 well-being relies on self-reported estimates of engagement in terms of amount of 'screentime' over the course of a day or week. A decade of research has revealed 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 well-being.[29–31] Using self-reported screen-time to investigate technology engagement is problematic both as a measure and as a construct. As a measure, self-reported technology engagement is imprecise and prone to bias.[32–34] As a construct, screentime is unidimensional, homogenous and has little validity.[35] Screentime might reflect time not spent on other activities (displacement),[36] it could be a proxy for exposure to a different phenomenon such as social comparison, or might reflect a combination of multiple affordances.[37–39] It fails to differentiate between the many different functions of technology use, including social, educational, entertainment, work, and informational uses, as well different content and purposes, possibly with different effects.[35,40–42] It is possible that social media screen-time might help to identify extreme cases of over- and under-usage, 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 limits the quality and validity of many investigations, and this is especially clear in secondary data analyses of existing data.

Limited datasets and samples: Due to the impracticality of controlled experiments that randomly assign children to different patterns of social media use, studies of social media effects on adolescents' health and well-being are largely observational and frequently studied using secondary data analyses.[11] Open research data, such as longitudinal cohort data, has many strengths, such as improving the reproducibility of research and collaboration between researchers.[43] However, open datasets can also come with limitations regarding the relevance of 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 geographic distribution of young people across the world, yet key groups of technology users are often missing. Minority groups in High-Income Countries (HICs) and adolescents from low-and-middle-income countries (LMICs) are rarely included in these data.[44,45] The lack of representation of adolescents in LMICs is partly explained by the fact that most peer-reviewed health policy research is conducted by researchers in HICs, related to funding streams, geography, industry and publication incentives.[46–48] These sample limitations are further complicated because socio-ecological and demographic determinants are not collected in sufficient detail, meaning it is not possible to test effect heterogeneity and sub-group analysis cannot identify potentially vulnerable groups.[44,45,49] Smaller-scale studies suggest technology can have very different roles between regions and communities; for example, social media use has been shown to promote well-being in minority groups such as LGBTQIA+ communities,[21,50] and helps ethnically diverse adolescents such as black teens navigate positive identity development.[51] Despite this, research investigating how those in diverse cultures and communities may benefit from social media is stalled, in both HICs and LMICs,[52] because large-scale social data is not collected in a way that allows researchers to investigate these dynamics.

Inappropriate designs and analyses: Despite quantitative scientists being trained to recognise that correlation does not imply causation, this essential detail can easily get lost between aims, study design, interpretation, and recommendations. 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 of the meta-analyses reviewed reported that effect sizes or heterogeneity decreased as study quality increased.[12,53] Often neglected is the bi-directional nature of the association between online behaviour and mental health,[23] 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 impact both exposure and outcome.[25] While more 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 the observational, non-randomised studies that are widely used in academic research on technology use.[56] Potential issues include undefined causal estimands (e.g. vaguely defined effects of 'screen-time' on 'mental health'), and inconsistent experimental manipulation of social media "abstinence". These questionable causal inferences can be further aggravated by other Questionable Research Practices (QRPs) 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 (p-hacking) or hypothesising after the results are known (HARK-ing).[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 tech development. Taken together, the collective failure to address multiple sources of bias and error in social media research designs easily produces inconsistent findings, ungrounded causal interpretations, and recommendations which might lead policymakers and practitioners astray.

Inappropriate interpretation and translation to policy: Policy relating to adolescents' use of technology has historically been at odds with the best scientific evidence about how technology influences adolescents.[59–61] Numerous recent reviews, plus a consensus report by NASEM, are clear that the evidence on social media does not support drastic policy action,[1,11–14,19,20,62] yet several jurisdictions have legislated social media bans for adolescents. This contradiction arises for social media partly due to lack of robust evidence, and partly because of exaggerated interpretations of study findings by scientists or journalists, such as interpreting correlational results as causal evidence.[63] Concerns driven by anecdotes in media reports can motivate reactive policies,[64] while limitations to validity and ungrounded causal inferences can produce ill-conceived recommendations. For example, the "2x2 Rule" proposed by the American Academy of Pediatrics – no screens for the under twos and no more than two hours a day for the over twos – was entirely revised in 2016 after a review concluded that there was insufficient evidence to support specific screentime limitation guidelines.[65] Despite this, a similar rule was later adopted in 2019 by the World Health Organisation.[66] From 2011 to 2021 the South Korean government prohibited those under the age of 16 from accessing online games platforms between 00:00 and 06:00, levelling civil and criminal penalties for platforms that did not comply, even though research suggested this law had no effect.[67] The Chinese government now limits those under the age of 18 to three hours of video game play a week, [68] and one study already suggested these limits are ineffective in reducing the prevalence of heavy play.[69] In November 2024, the Australian government banned social media accounts for the under sixteens,[2] potentially misinterpreting research reporting bidirectional associations between adolescents' social media use and their life satisfaction,[70] and despite prior research suggesting screen-use limitations were impossible to implement.[71] While there are clear reasons why technology should not be seen as a replacement for human interaction in young children's development,[72] calls for social media bans for older children are frequently reactive and based on flawed interpretations of evidence. Time limits and age cut-offs in particular shift responsibility away from the need to regulate harmful content, putting responsibility instead on parents, or risking mass-integration of unproven age estimation technologies,[73] which have been judged to present "privacy, security, implementation and enforcement risks".[74] 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 re-thinking our approach to social media.

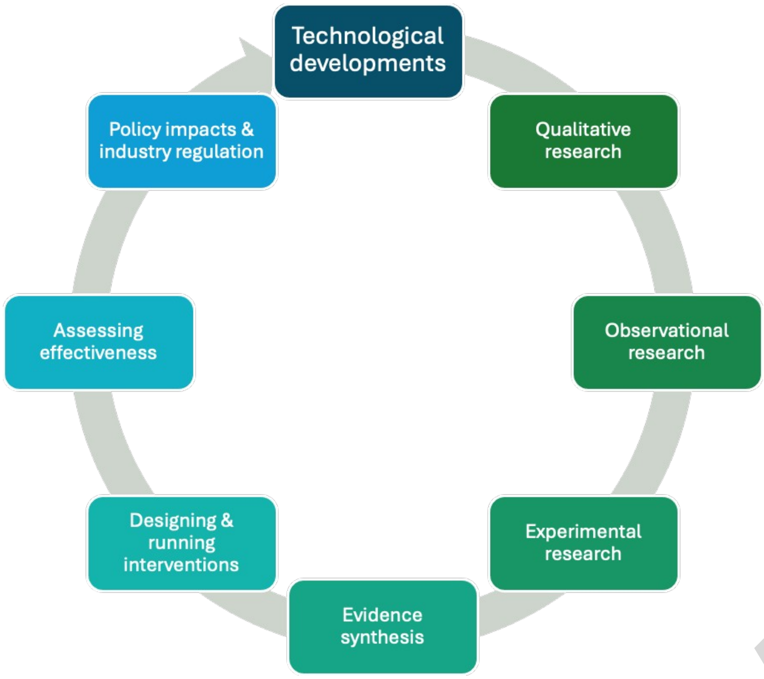

Figure 2. Representation of a proposed order of research activities for an effective cycle of technological innovation, research, policy, and industry regulation.

Doing Better Research in the Era of AI

Replacing mono-causal technological determinism. We are at a point in history where the temptation to default, once again, to framing the impact of a new technology on children and adolescents as one force will be immense. AI will be integrated into the apps that children use at home and school, and embedded into the systems and platforms they work with as young adults. Encounters with AI will be ubiquitous, including interaction with large language models (LLMs), as both co-creators and conversation partners. For example, LLMs may take on human roles, such as AI therapists,[75] or produce images and video content convincing enough as to be indistinguishable from authentic content,[76] having the potential to influence children's emotions and behaviour. Other applications will include content recommendation systems and online diagnostics tools for depression, anxiety or eating disorders, increasingly used for self-diagnosis.[77] 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 games alone have been. Psychologists, mental health researchers, and practitioners have little control over the development of AI applications, but do have the power to start our inquiry with constructive research questions that don't implicitly problematise all AI, such as: How can we best ensure that children and adolescents adapt optimally to technological innovation, making them aware of its capabilities and risks? Understanding both capabilities and risks to children requires a structured approach to researching emergent technologies (figure 2), avoiding the pitfalls of social media research. Scientists will first need to embrace qualitative, ethnographic, and other observational data, to identify children's diverse exposures to integrated AI, along with exploratory insight into potential effects on their well-being.

Prioritising causal designs. Eventually, robust causal investigations will require experimental and interventional designs, using randomised allocation where it is ethical and practical to do so, with comprehensive measures of adherence to the manipulated exposures. This might involve manipulation of content filters or digital literacy training. But scientists will first need to rely on exploratory and observational data, potentially including natural experiments, to inform the development of large-scale interventions. To build informative models with observational data, researchers must directly engage with causal inference methods.[56,78,79] For example, the Structural Causal Model Framework makes use of 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.[78] Structural Equation Model (SEM) diagrams have been used to conceptualise statistical models and to visualise results, including confounders, moderators and mediators, but cannot always be interpreted causally.[80] Controlling for baseline measures of outcomes and time-invariant confounders in analyses can reduce the risk of biased results,[54] but many potential confounders are not measured or even considered (see 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 critical to reducing bias.

Identifying significant exposures and measures: The thought of using the self-reported frequency or duration that adolescents use integrated AI throughout the day or week as the exposure measure of interest is perhaps even more concerning than counting the total time young people spend on social media. Only behavioural data on exposure to a range of AI applications would provide the level of detail needed. However, understanding the range of exposures to integrated AI and their potential impacts on children and adolescents will first require qualitative work with adolescent users, such as the involvement of youth advisory groups,[81] as well as with the architects of these systems in the technology sector. Research addressing AI exposures needs to better account for other evolving social and contextual determinants, like political and environmental changes, but at this stage it is hard to predict which forms of AI are likely to be most helpful or harmful, and the situations where we might expect to observe these dynamics. Deepfakes are already raising concerns, together with other effects of disinformation,[82,83] and have many potential implications for children and adolescents. A combination of behavioural and self-reported measures must be developed, and it will be critical to explicitly test the generalisability of these measures between populations and communities as they find their way into the datasets and samples we investigate.

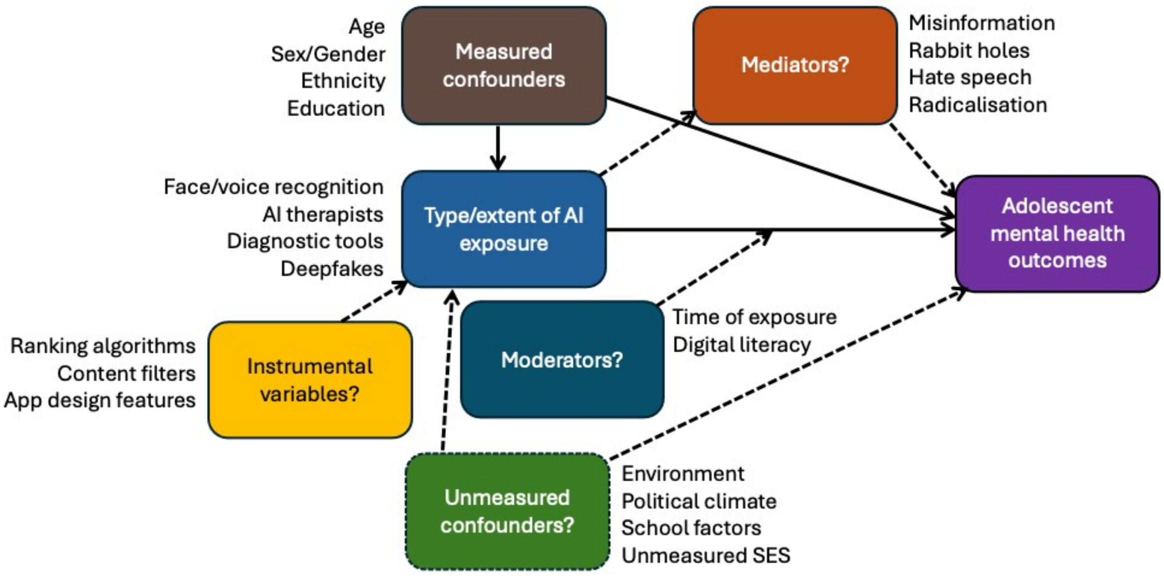

Figure 3 – Conceptual map of relationships and factors relevant to investigating causal effects of technology exposure on adolescent mental health. Example exposures, with instrumental variables, plus potential confounders, mediators and moderators of their effects on mental health are listed. SES = Socio-economic status.

Enhancing research datasets: There are several untapped opportunities for harnessing better data to understand technology effects on children and adolescents globally, drawing on cohort data from academic research, accessing data from the tech 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, such as primary school students in the UK, to maximise local representativeness, collect key socio-demographics, and include validated or consistently repeated measures of mental health and well-being. The use of such active cohorts could be maximised by augmenting future waves of data collection with triangulated data from compatible sources (e.g., objective behavioural telemetry or technology use recorded in participants' schools), and by adding informative measures of relevant exposures and contextual factors, co-designed with adolescents and other stakeholders. This would increase the value of active cohorts like the Understanding Society's Innovation Panel in the UK and the ABCD Study in the United States.[84,85] However, addressing the sampling limitations in technology research to date will require building the ability to collect data on AI sociotechnical systems directly as a foundational part of new cohort data projects.

Widening sample generalisability and heterogeneity: Debates about AI's impact on childhood and adolescents will repeat the well-worn paths of Northern and Western societies if we do not start our inquiry knowing that the benefits and deleterious influences of these emerging technologies will be used by young people all around the world.[86] This makes it crucial that we study the interests of historically marginalised children who have been overlooked by mainstream research,[87] which should involve co-development of a research agenda with partners in LMICs.[88] New data collections involving both existing and forthcoming cohorts might make it possible to directly compare the effects of emergent technologies on diverse demographics in LMICs representing those living in urban and rural settings, across ethnicities, incomes, identities, and sexual orientations. Gaining insight into technology effects in LMICs will require greatly expanding on examples like Gallup polls, World Values Survey, and Disrupting Harm,[89–91] so that well-documented reliable, representative data can be made available to the global scholarly community. Moving past a simple Western versus non-Western dichotomy will enable those studying AI's embedding in childhood and adolescence to capture the nuances across LMIC regions (e.g. Asia versus Africa) and across HICs and LMICs (e.g., USA versus China). Encouraging scholars to analyse culturally adapted mental health data, such as UNICEF MICS,[92] will be a step towards improving and diversifying measures, as the ways young people use these technologies continue to evolve.

Pipelines for technology sector data: Social media and other online platforms regularly collect rich, longitudinal behavioural data from their global audience, which can help alleviate limitations of both narrow sampling and self-reported measures. However, only in vanishingly rare cases has this data been made available to independent scientists. The limited cases of academic-industry collaboration demonstrate the exceptional insights that such cooperation can produce. For example, an experimental collaboration with Meta demonstrated that echo chambers are common on Facebook but have minimal effects on polarization.[93] Another collaboration with games companies including Nintendo of America and Electronic Arts found that the amount of time spent playing games did not meaningfully relate to well-being over time.[94] Such collaborations must become more common over time, supported by transparent communication between platforms, media and policymakers. With recent concerns around online privacy and other online dangers, expectations for the tech industry are increasing.[95] Changing norms and stricter regulations may soon create easier access to industry data by independent scientists such as a forthcoming collaboration between the Center for Open Science's and Meta Platforms.[96] Clear rules for the disclosure of actual or perceived conflicts of interest are needed to protect the integrity of this work. Without a context to evaluate claims interests, both for and against, profitable industries threaten to undermine the credibility of science.[97] For now, the slow, privileged, and unstable nature of direct collaborations—which also tend to exclude underage users due to privacy concerns — mean that alternative approaches to behavioural data access are necessary.[98] 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: Finally, due to the complexity of this ever-changing field, science journalists, policymakers, and practitioners need a structured picture of the evidence base as it develops. Clear guidelines for judging the validity of and accurately reporting newly published findings are long overdue for technology research. This can best be achieved by a combination of outstanding evidence synthesis and balanced recommendations by independent researchers. This includes care with causal interpretation,[63] avoiding strong headlines such as "have smartphones destroyed a generation?".[99] To achieve this ultimate goal, structured collaboration is urgently needed between academics, the technology sector, policymakers, and practitioners, outlined in the next section and in Figure 4.

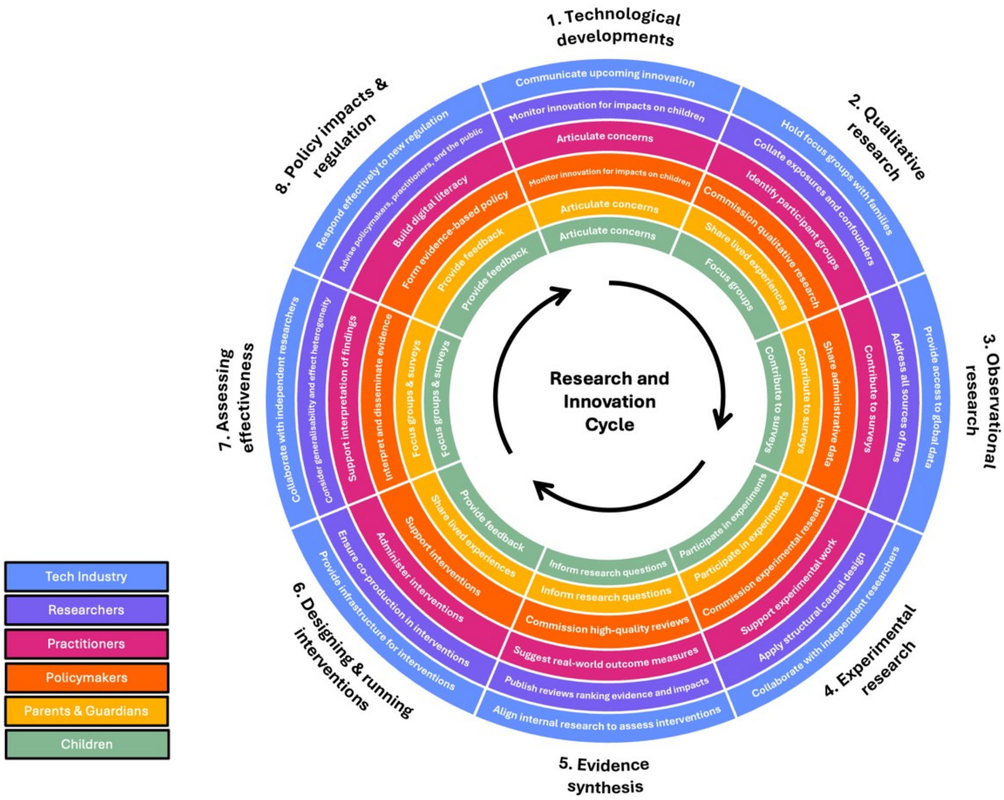

Figure 4. A framework depicting suggested collaboration in a cycle of research and policy in response to technological innovation, broken down into key responsibilities for independent researchers (academics), the technology industry, policymakers, practitioners, parents or guardians, and adolescents.

A framework for structured collaboration

It is important to set a well-calibrated agenda for ensuring that policy to safeguard children and adolescents from the potential harmful effects of emerging technology such as AI is effective. 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 scholars, the technology sector, policymakers, and other stakeholders, each bringing their own expertise to each step in the research process (Figure 4). Academics and other independent researchers have the greatest role to play 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 pitfalls 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, policymakers, and all those involved in the safeguarding of children and adolescents.

Reflecting the rapidly-evolving field of technology, this would need to be living online resources that can be updated as new data arises.

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, potential moderators and mediators, along the lines of the Structural Causal Model Framework.[78] Figure 3 illustrates how 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. 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 impact adolescents in the populations studied. Depending on the results of exploratory work, the repository might include self-reported measures such as individual experience and attitudes towards different types of AI, administrative data such as population density and green space, and ideally consented or anonymous data from online platforms informing the types of integrated AI exposures and how 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 as well as 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, ranging from the gravest offenses like online sexual child exploitation and trafficking, to other harmful content such as cyber-bullying, racism or homophobia. This would also provide context for a cluster of concerns including privacy issues and body image issues, which may also adversely affect the health and well-being of children and adolescents. It will be challenging to establish clear boundaries between direct harms like trafficking, online child sexual abuse, and self-harm or suicide-related material, and indirect potential harms such as misinformation, algorithmic ranking or dark patterns. Multi-stakeholder, international consensus and robust evidence is needed to advance research on online harms, in order 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, as well as facilitating insight into the effects of various AI implementations. Specifically, we want to highlight data donation models that leverage legal frameworks (e.g. [UK]

General Data Protection Regulation, the California Consumer Privacy Act, and the Act on the Protection of Personal Information in Japan) guaranteeing users the right to obtain a copy of their own data and potentially share it with researchers using open source software.[100] Other options include Application Programming Interfaces (API, although we note concerns about movement towards a "post-API" landscape in which tech companies remove or heavily restrict access),[101] web scraping,[102] third-party tracking tools,[103] and mock social media platforms.[104] These models could support both observational work to identify exposures and potential moderators and mediators, as well as experimental manipulation of AI exposure. Other potential forms of collaboration need to be investigated in discussion with all stakeholders.

Evidence hierarchy: Finally, policymakers, clinicians, teachers and parents need a clear and simplified understanding of the growing body of 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 and social care. An explicit hierarchy of evidence such as evidence readiness levels could be used to inform this framework.[105] Online evidence syntheses and educational resources could be developed by teams of independent researchers, policy advisors, educators, 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",[106] addressing determinants, outcomes, moderators and mediators, each with a critical evaluation of study quality, causal inference and global relevance, both for existing technologies and emergent ones like 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,[107] observational studies,[108] and qualitative studies.[109] Essential to any evidence hierarchy are clear reporting guidelines, building on successful methodologies used to develop existing guidelines,[110] ensuring that interpretations and recommendations reflect the strength of the evidence, and taking particular care with observational studies.[63,111]

Further considerations: One key challenge will be potential conflict between the parallel priorities of improving the representation of adolescents in LMICs at the same time as improving the robustness of causal methodology and evidence readiness. This is because researchers and organisations based in LMICs have critical expertise for understanding nuances between regions and cultures but less access to research funding, time, and other resources, implying a potential trade-off between robustness and global reach. Balancing all priorities effectively will require developing effective collaboration strategies to support research in LMICs both practically and financially.

Conclusions

Our collective popular, research, and legal attention is presently focused on the potential negative effects of social media on adolescent mental health but it is clear that young people are already adopting fundamentally new ways of interacting with AI.[7] If history is any guide, research and evidence-based policy will lag behind. Examining our collective failure to adequately disentangle the heterogeneous effects of young people's social media use provides a concrete guide for keeping pace with the new platforms young people may be influenced by. Overcoming the key challenges in research on the effects of technology means systematically engaging with diverse stakeholders, rejecting narratives that invoke monocausal determinism, and synthesising data continuously for causal interpretability and policy implications. Without building on past lessons, in ten years we could be back to square one, viewing social media in the same way we do radio dramas, comics, and Dungeons and Dragons, caught up in the next media panic, and failing to make AI safe and beneficial for children and adolescents.

Contributors' statement

The first draft was written by KLM, AKP and SG. KLM performed project administration, with supervision by AKP. Visualisations were created by KLM, TH, and NB. KLM and SG performed literature search and screening, KLM performed the review and created Appendix Table S1. 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 substantially reviewed and edited the manuscript and approved the submitted draft.

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