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& Technology

UNIVERSITY OF
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Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

May 2025

List of Abbreviations

AI	Artificial Intelligence (see Appendix 6 for definition)
ALSPAC	Avon Longitudinal Study of Parents and Children
AMSTAR-2	A Measurement Tool to Assess Systematic Reviews
API	Application Programming Interface (see Appendix 6 for definition)
ARCHE	Alberta Research Centre for Health Evidence (see Appendix 6 for definition)
BDI	Beck's Depression Inventory
BSI	Brief Symptom Investory
CCA	Corrected Covered Area
CDI	Children's Depression inventory
CDSR	Cochrane Database of Systematic Reviews
CES-D/CESD	Centre for Epidemiologic Studies Depression Scale
CI	Confidence Interval (see Appendix 6 for definition)
CMO	Chief Medical Officer(s)
DAFI	Digital Activities and Feelings Inventory
DAG	Directed Acrylic Graph (see Appendix 6 for definition)
DfE	Department for Education
DIORA	Dynamic Interplay of Online Risk and Resilience in Adolescence
DSIT	Department for Science, Innovation and Technology
DSMV	Diagnostic and Statistical Manual 5
EARS	Effortless Assessment Research System
EMA	Ecological Momentary Assessment (see Appendix 6 for definition)
EPSRC	Engineering and Physical Sciences Research Council
EOP-S	Education and Outcomes Panel Study
ESRC	Economic and Social Research Council
GDPR	General Data Protection Regulation
GRADE	Grading of Recommendations Assessment, Development, and Evaluation
GRIPP2	Guidance for Reporting Involvement of Patients and the Public 2
HADS	Hospital Anxiety and Depression Scale
ICMJE	International Committee of Medical Journal Editors
IPA	Interpretative Phenomenological Analysis
K-6 scale	Kessler 6 Scale
MCS	Millennium Cohort Study
MEDLINE	Medical Literature Analysis and Retrieval System Online
MeSH	Medical Subject Heading(s)
MHRA	Medicines and Healthcare Products Regulatory Authority
MOOSE	Meta-analysis of Observational Studies in Epidemiology
MRC	Medical Research Council
NCCPE	National Co-ordinating Centre for Public Engagement
NGO	Non-governmental Organisation

NIH	National Institute of Health
NIHR	National Institute for Health and Care Research
NIMH	National Institute of Mental Health
NOS	Newcastle-Ottawa scale (see Appendix 6 for definition)
NPD	National Pupil Database
NRSI	Non-randomised Studies of Interventions
NSF	National Science Foundation
OR	Odds ratio
OSA	Online Safety Act
OSCD	Original Symptom Checklist-Depression
PHQ-9/PHQ9	Patient Health Questionnaire
PICO	Population, Intervention/Exposure, Comparison, Outcome framework
PISA	Programme for International Student Assessment
PPI/PPIE	Patient and Public Involvement/Public and Patient Involvement and Engagement
PRIOR	Preferred Reporting Items for Overview of Reviews (see Appendix 6 for definition)
PRISMA	Preferred Reporting Items for Meta-analyses and Systematic Reviews (see Appendix 6 for definition)
PROSPERO	International Prospective Register of Systematic Reviews
PSP	Priority Setting Partnership
RCT	Randomised Control Trial (see Appendix 6 for definition)
RoB	Risk of bias
ROB-2	Risk of Bias tool 2
ROBINS-E	Risk Of Bias In Non-randomized Studies — of Exposures
ROBINS-I	Risk Of Bias In Non-randomised Studies — of Interventions
RRI	Responsible Research and Innovation
SMFQ	Short Mood and Feelings Questionnaire
SNS	Social networking sites
STROBE	Strengthening the Reporting of Observational Studies in Epidemiology
SWiM	Synthesis without meta-analysis
SWOT	Strengths, Weaknesses, Opportunities and Threats
UKRI	UK Research & Innovation
UX	User experience
TYDE	Thriving in a Digital Environment
WEMWBS	Warwick-Edinburgh Mental Well-Being Scale
YRA	Young Researcher Advisor

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The project was coordinated by Amy Orben (Director), Amrit Kaur Purba (Deputy Director) and Zhuo Yao Yap (Project Manager).

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Peer Review

Peer review was provided by Michael Rich (Harvard Medical School), Jacqueline Nesi (Brown University), Adrian Meier (University of Erlangen-Nürnberg), Ravi Iyer (University of Southern California) and Zach Rausch (New York University). Appendix 1 was additionally reviewed by Jessica Packer (University College London). Peer review reports are available on reasonable request and pending approval from the reviewers.

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Team Contributions

We applied the Contributor Roles Taxonomy (CRediT), which defines specific roles in research contributions, individually to each standalone section of the report.

Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People (Main Report)

Amy Orben: Conceptualisation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Supervision, Funding Acquisition; Amrit Kaur Purba: Conceptualisation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Supervision, Funding Acquisition; Ioanna Fokas: Writing — Original Draft Preparation, Writing — Reviewing and Editing; Lukas J. Gunschera: Writing — Reviewing and Editing; Zhuo Yao Yap: Project Administration, Writing — Reviewing and Editing; Brandon Davidson: Visualisation; Writing — Reviewing and Editing; Oliver S. P. Davis: Writing — Reviewing and Editing; David A. Ellis: Writing — Reviewing and Editing; Victoria Goodyear: Writing — Reviewing and Editing; Claire M. A. Haworth: Writing — Reviewing and Editing; Chris Hollis: Writing — Reviewing and Editing; Adam Joinson: Writing — Reviewing and Editing; Srinivasa Vittal Katikireddi: Writing — Reviewing and Editing; Sonia Livingstone: Writing — Reviewing and Editing; Margarita Panayiotou: Writing — Original Draft Preparation, Writing — Reviewing and Editing; Andrew K. Przybylski: Writing — Reviewing and

Editing; Ellen Townsend: Writing — Original Draft Preparation, Writing — Reviewing and Editing; David Zendle: Writing — Reviewing and Editing

Evidence Review Summary (Appendix 1)

Ioanna Fokas: Conceptualisation, Investigation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Visualisation, Data Curation; Lukas J. Gunschera: Conceptualisation, Investigation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Supervision, Validation; Brandon Davidson: Writing — Original Draft Preparation, Validation; Matthew Richards: Validation; Zhuo Yao Yap: Project Administration; Amrit Kaur Purba: Conceptualisation, Methodology, Writing — Reviewing and Editing, Supervision, Funding Acquisition; Amy Orben: Conceptualisation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Supervision, Funding Acquisition

Research Activity Overview (Appendix 2)

Ioanna Fokas: Conceptualisation, Investigation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Data Curation; Zhuo Yao Yap: Conceptualisation, Investigation, Project Administration, Writing — Reviewing and Editing, Data Curation; Lukas J. Gunschera: Writing - Reviewing and Editing; Amrit Kaur Purba: Writing — Reviewing and Editing, Supervision, Funding Acquisition; Amy Orben: Conceptualisation, Investigation, Writing — Reviewing and Editing, Supervision, Funding Acquisition

Social Media Research: Limitations and Opportunities Report (Appendix 3)

Lukas J. Gunschera: Conceptualisation, Investigation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Project Administration; Oliver S. P. Davis: Writing — Reviewing and Editing; David A. Ellis: Writing - Reviewing and Editing; Victoria Goodyear: Writing — Reviewing and Editing; Claire M. A. Haworth: Writing — Reviewing and Editing; Chris Hollis: Writing — Reviewing and Editing; Adam Joinson: Writing — Reviewing and Editing; Srinivasa Vittal Katikireddi: Writing — Reviewing and Editing; Sonia Livingstone: Writing — Reviewing and Editing; Margarita Panayiotou: Writing — Reviewing and Editing; Andrew K. Przybylski: Writing — Reviewing and Editing; Ellen Townsend: Writing — Reviewing and Editing; David Zendle: Writing — Reviewing and Editing; Zhuo Yao Yap: Project Administration; Amrit Kaur Purba: Writing — Reviewing and Editing, Supervision, Funding Acquisition; Amy Orben: Writing — Reviewing and Editing, Supervision, Funding Acquisition

Expert Roundtable Discussion Report (Appendix 4)

Zhuo Yao Yap: Conceptualisation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Project Administration; Ioanna Fokas: Writing — Reviewing and Editing, Project Administration; Lukas J. Gunschera: Writing — Reviewing and Editing, Project Administration; Brandon Davidson: Project Administration; Matthew Richards: Project Administration; Myriam Hadnes: Conceptualisation; Amrit Kaur Purba: Conceptualisation, Writing — Reviewing and Editing, Supervision, Project Administration, Funding Acquisition; Amy Orben: Conceptualisation, Writing — Reviewing and Editing, Supervision, Funding Acquisition

Funder Involvement

The DSIT policy team was consulted to understand the context of the report and set its scope; the team provided feedback on a draft of the outputs. They did not inform the results or conclusions of the work produced.

Conflicts of Interest

All authors contributing to this report have completed the International Committee of Medical Journal Editors (ICMJE) Disclosure of Interest Form at http://www.icmje.org/disclosure-of-interest/. In the interest of full transparency, the completed forms are provided in full in Appendix 8.

Executive Summary

There is growing concern about the risks digital technologies, particularly social media, smartphones and Artificial Intelligence (AI), may pose to individual children and adolescents, including severe outcomes such as sexual exploitation, bullying-related distress and premature death. These individual-level harms require urgent attention from research, industry and policy.

Beyond these individual-level impacts, it is also important to understand the average impact of such technologies across the entire population of children and young people, in order to help inform policy choices that will impact them collectively. While our public and policy discourse often conflates individual- and population-level impacts, it is important to treat them as distinct when evaluating current research. DSIT therefore commissioned this report to specifically explore how research of the causal relationship between digital technology use and population-level child and adolescent developmental outcomes can be improved.

This report is the product of a Scientific Consortium comprising 14 leading UK scholars, who collaborated to synthesise existing evidence on population-level impacts of social media, smartphones and AI, review current research funding in this area, and recommend strategic research projects for strengthening the causal evidence base over the next two to three years.

Strategic investment in research has the potential to help position the UK as a global leader in online safety. This research must target the most urgent and policy-relevant questions, co-developed by policymakers, researchers and affected communities. If causal evidence of technologies' population-level impacts is a priority to be created in the next 2–3 years, supporting experimental research and natural experiment evaluations should be prioritised. Further, investments in improving measures of digital technology use in large-scale UK cohort and household panel assets would generate world-class data assets that could support longer-term research provision.

Evidence Review: A systematic and pre-specified synthesis of existing systematic reviews found that adolescents who spent more time on social media reported poorer mental health. This small but consistent correlation located in cross-sectional research could be due to social media negatively influencing mental health, mental health issues influencing social media use, or other factors — such as socioeconomic circumstance, parenting or genetic factors — that impact both social media use and mental health. Longitudinal data also revealed some evidence of a positive association between increased time spent on social media and poorer adolescent mental health outcomes, with evidence suggesting that increased social media use may precede declines in mental health, though the strength and presence of this association varied across studies. However, while longitudinal studies can demonstrate the sequence of events, they cannot confirm causality without the use of more robust causal methods.

Only one review, out of seven, was found to be of high quality. Further, the quality of the majority of primary studies included in the reviews was also of low quality. This could, in part, explain why there was substantial variation in what primary studies found within each of the reviews. Further, our evidence synthesis did not find any reviews on the impact of time spent using AI chat applications or smartphones on adolescents' mental health and wellbeing.

In our supplementary narrative review, we found no experimental studies on healthy adolescents that sought to reduce time spent on social media to see if it affected adolescent mental health or wellbeing. Due to this substantial gap, our ability to determine whether there is a causal impact of time spent on social media on population-level mental health and wellbeing remains poor. High quality experimental studies that test whether reducing adolescent social media use improves mental health would improve our understanding of whether there is a negative causal relationship.

Further, it is widely recognised by academics that research on time spent using social media routinely fails to investigate how its impact on individuals — both positive or negative — might be determined not by time spent engaging with platforms, but by the specific activities engaged in, types of content consumed, context of use, or what other activities are being displaced. In our narrative review, we therefore also examine the impact of content exposure, finding evidence that its effects can be either positive or negative depending on the type of content engaged with.

This narrative review additionally examined evidence regarding the effectiveness of school-level smartphone restrictions to improve children and young people's mental health and wellbeing. Evidence was more consistent for restrictive school phone policies positively influencing in-school behaviours (e.g. reducing screen time in school and bullying, or increasing physical activity), yet it was less robust and more context-dependent for mental health and wellbeing outcomes that are likely determined by both in- and out-of-school factors.

Our evidence synthesis did not find any reviews on the impact of time spent using AI chat applications or smartphones on adolescents' mental health and wellbeing.

Funding Landscape Review: Our review of past, current and planned research activities investigating child and adolescent developmental outcomes and social media, smartphone and AI chat application use in the UK and other countries, found that despite the need for more experimental or quasi-experimental studies to improve the ability to make causal claims at population-level, funding remains concentrated on other methods.

More funding currently supports research on adolescents rather than children. Similarly, more funding supports research on wellbeing and non-clinical mental health outcomes rather than other developmental outcomes, such as physical health (including exercise and sleep), behaviours and academic performance. While this might align with current policy and societal priorities, it is a funding gap.

The UK is furthermore not yet supporting extensive research on how AI impacts children and adolescents. It also lacks large-scale and strategic research investments present in other countries, such as research centres, that would allow for a more proactive and effective research approach.

Recommendations for Potential Research Investments:

1. Any DSIT-funded research must target the most urgent and policy-relevant questions. Prioritisation is best co-developed by policymakers, researchers and affected communities and consideration should be given to whether generating high-quality causal evidence of population-level impacts is a priority.

2. If generating causal evidence is confirmed as a research aim, the most effective approaches will be natural experiment evaluations (e.g. of policy changes or real-world events) and Randomised Controlled Trials (RCTs). These methods offer rigorous insight, and RCTs can scale to small or large interventions — even though larger efforts might be difficult to deliver in time. Given that technology companies already conduct frequent experimental evaluations of their products, it would be worth exploring regulatory mechanisms for mandating collecting and sharing of societally relevant aggregate outcome data during such tests (e.g. mood or well-being), particularly concerning children and adolescents.
3. Beyond the short-term two- to three-year time scale for producing research outputs, investment should prioritise enhancing existing large-scale UK cohort and household panel study investments with improved measures of digital technology use. This would generate world-class data assets and support long-term research. A national research strategy on online harms could further coordinate long-term investment and ensure alignment across government, funders and research communities.
4. If research moves beyond strict causal research questions, diverse disciplines and methods will also be essential to capture the complexity and dynamism of digital experiences and impacts, including ensuring young people's online wellbeing and safety through improved social media platform design. For example, developing and testing interventions that help individuals, families, schools and communities navigate a rapidly evolving digital environment should also be seen as a priority. This includes promoting strategies that mitigate harm and build digital resilience. Investments in a) allowing children and adolescents, as well as other affected communities, to be engaged in research as co-creators, and b) research collaborations to create better theory, should be seen as foundational investments that would also increase research quality across the landscape.

Strategic, sustained investment in research and infrastructure has the potential to position the UK as a global leader in online safety, allowing good quality scientific evidence to drive — not delay — effective responses to the many growing challenges children and adolescents face in a digital world.

Introduction

There is widespread concern that the digitalisation of our society, and in turn the digitalisation of childhood and adolescence, is leading to a variety of negative outcomes for children and young people (Haidt, 2024; Odgers & Jensen, 2020; Orben & Blakemore, 2023; Twenge, 2018). Across many high-income English-speaking countries, the mental health of children and adolescents has been declining over the last two decades (McGorry et al., 2024). Mental ill health is linked to 45% of the burden of disease for the 10–24-year-old age group (Patton et al., 2016), with mental health problems now the leading cause of disability among this demographic (Castelpietra et al., 2022).

Growing evidence highlights that young people with severe mental illness increasingly die prematurely due to both suicidality and co-morbid physical health conditions associated with mental health and distress, with suicidality acting as the third leading cause of death in older adolescents and young adults (O'Connor et al., 2023; World Health Organization, 2025b, 2025c). It is likely that even small changes to children and young people's mental health, as well as other outcomes, will have long-term and cumulative impacts — economically, socially and personally — on the UK for decades to come. Understanding what is driving large-scale changes in the thriving of our children and young people is urgent.

There are concerns that digitalisation can lead to declines in mental health, educational attainment and wellbeing, as well as leading to the rise of physical health conditions (Boer et al., 2020; Gordon & Ohannessian, 2023; D. S. Lee et al., 2022). Each of these aspects of childhood is inherently complex and determined by a range of different factors and global changes, including political, social, environmental and economic trends. These factors interact with each other in often non-linear and dynamic ways, forming complex systems that can affect future outcomes (McGorry et al., 2024). One widely discussed societal change is the introduction of smartphones into children and adolescents' lives and the broader digitalisation of society. Notably, the rise in symptoms of poor mental health appears to coincide in time with this technological shift, in particular the emergence of social media platforms and smartphones in the early 2010s (Haidt, 2024; Twenge et al., 2017). The parallels between these trends have fuelled widespread concern and debate over whether technological progress is harming national populations of children and adolescents and, by extension, society and the economy over time.

There are serious concerns about the harms that digital technologies — including social media and smartphones — may pose to individual children and adolescents. Documented harms are wide-ranging, including deaths (North London Coroner's Service, 2022), problematic patterns of application or device use (US Department of Health and Human Services, 2023), sexual risks (Bryce et al., 2023), and instances of bullying that cause substantial distress. Evidence of such individual-level harm from technologies including social media has been documented by both researchers and civil society organisations (Baker et al., 2024; Bryce et al., 2023; Centre for Countering Digital Hate, 2025; Molly Rose Foundation, 2023; Regehr et al., 2024). These concerns warrant urgent attention from decision-makers across both industry and policy.

However, another perspective on understanding the harms or benefits of novel technologies is to examine their effects across the whole population of children and young people, rather than focusing on individual cases. This approach often draws on classical epidemiological methods, which attempt to link individual-level differences in exposure, such as to a specific technology, with population-level changes in outcomes such as mental health or educational attainment.

Although public and policy discussions often conflate this population-level research approach with individual-level investigations of harms or benefits, the two are generally — though not completely — treated as distinct in the scientific literature. Nonetheless, there is good reason to question and challenge this dichotomy. Specific types of research into population-level impacts also aim to uncover the mechanisms through which such effects may occur, and to identify whether certain subgroups are more likely to experience heightened levels of harm or benefit. Here, individual-level evidence of case studies or groups can serve as an important guide to shaping future research priorities.

Given the relatively early stage of work in this area, such integration is rare, and this report focuses primarily on the epidemiological approach to causality: that is, on how smartphones and social media are affecting national populations of children and young people on average. We also concentrate chiefly on harms rather than benefits, due to the urgency of addressing these risks. Our decision not to examine individual-level harms in detail should not be interpreted as a dismissal of their importance but rather reflects the defined scope of this report.

Pinpointing the extent and nature of the influence of digitalisation on population outcomes such as mental health is an increasingly important — yet a dynamic and constantly developing — target for researchers. Digitalisation is progressing at accelerating speeds, with new products and services being released constantly, and novel behaviours (e.g. remote working, online shopping) supported and encouraged across our population. Many of these technologies represent novel infrastructure that supports much of modern life: including communication, work, dating, identity exploration and skills building. However, in contrast to traditional infrastructure, new digital technologies are most often built by private companies whose ultimate aim is to maximise profit (Simons, 2023). For many free-at-point-of-use digital technologies such as social media, that are dependent on advertising and personal data to support profits, there is therefore pressure to maximise the time individuals, including children and young people, spend on platforms. The wide-reaching implications of this for the design and functioning of these platforms has been considered by many researchers across disciplines (for an accessible introduction see Grimmelmann, 2018).

There has been an accelerating decrease in public trust that technology companies are building products and services — and therefore social infrastructure — that prioritise the health of individuals and society (Edelman, 2022). Across the last decade, there have been repeated calls for digital technology companies to make their products and services safe by design for children and young people and wider society (Hawkes, 2019; Livingstone et al., 2023a; US Department of Health and Human Services, 2023). Yet progress has been severely lacking due to a mix of lack of investment or effort, the ever-evolving nature of digital change, and the market pressures to deploy new products rapidly (Horwitz et al., 2021; Wynn-Williams, 2025).

As digital companies face growing distrust over their willingness to conduct adequate safety testing, the responsibility for assessing the impacts, and potential individual- and population-level harms, of new technologies has shifted to independent research teams, often based at universities or other research organisations (Orben, 2020b; Orben & Matias, 2025). Yet such researchers face significant barriers to rapidly producing high-quality studies that identify potential harms of technologies like social media and smartphones on large scale and diverse populations. These challenges include limited access to high-quality data including data from platforms (Ellis et al., 2019; Vuorre et al., 2022), lack of sustainable funding or strategic oversight, and ever-changing technologies and outcomes that are dynamic and complex (Orben & Matias, 2025). This report will explore these barriers and potential solutions to addressing them, but their overall effect is clear: the generation of scientific evidence in this area remains slow and of lower quality, especially in contrast to the rapid acceleration of digital technology and societal importance of this area of work.

This report provides an evidence map of current research on the causal impact of social media and smartphones on child and adolescent populations, as well as ongoing and planned funding efforts to strengthen the evidence base. Crucially, its purpose is to go beyond summarising existing work to explore strategic methods and approaches that could generate better causal evidence within a short timeframe of two to three years.

Report Development Methodology

This report builds on three standalone research reports that have been produced between December 2024 and March 2025 as part of this research project, delivered through a Scientific Consortium across 10 universities and 14 leading academics in the UK (Table 1). Further researcher biographies and information can be found in Appendix 5.

Table 1. Scientific Consortium

Name	Affiliation	Role
Professor Oliver Davis	MRC Integrative Epidemiology Unit at the University of Bristol	Associate Professor and Mental Health Data Scientist
Professor David A. Ellis	University of Bath	Professor of Behavioural Science
Dr Victoria Goodyear	University of Birmingham	Associate Professor in Pedagogy in Sport, Physical Activity and Health
Professor Claire Haworth	University of Bristol	Professor in Psychological Science and Mental Health
Professor Chris Hollis	University of Nottingham	Professor of Child & Adolescent Psychiatry and Digital Mental Health
Professor Adam Joinson	University of Bath	Professor of Information Systems
Professor S. Vittal Katikireddi	University of Glasgow	Professor of Public Health and Health Inequalities

Professor Sonia Livingstone	London School of Economics and Political Science	Professor of Social Psychology and Director of Digital Futures for Children Centre
Dr Amy Orben	University of Cambridge	Programme Leader of Digital Mental Health Group
Dr Margarita Panayiotou	University of Manchester	Senior Lecturer in Educational Psychology
Professor Andrew Przybylski	University of Oxford	Professor of Human Behaviour and Technology
Dr Amrit Kaur Purba	University of Cambridge	Senior Research Associate of Digital Mental Health Group
Professor Ellen Townsend	University of Nottingham	Professor of Psychology
Dr David Zendle	University of York	Senior Lecturer in Computer Science and Director of the Smart Data Donation Service

The three standalone research reports include:

- *Evidence Review Summary — [Appendix 1]:* A systematic umbrella review of the evidence on the relationship between time spent on social media, smartphones, and AI chat applications and adolescent mental health and wellbeing, with further supplementary pre-specified narrative reviews of social media content, smartphone bans and social media bans, and their impacts on adolescent mental health and wellbeing.
- *Research Activity Overview — [Appendix 2]:* A summary of the current funding landscape in the UK, US and internationally.
- *Social Media Research: Limitations and Opportunities Report — [Appendix 3]:* A report detailing the strengths and limitations of current research, and recommendations for future research, compiled with direct input from the Scientific Consortium.

Scientific Consortium members, representatives from government and regulatory bodies met in Cambridge for a two-day Science and Policy workshop in February 2025 to collaboratively identify research strategies capable of delivering causal evidence within a two-to-three-year timeframe. Appendix 4 provides a summary of the workshop specifically.

This report was drafted in March and April 2025, with one round of peer review in April 2025, and the final report completed in May 2025.

Overview of Report

We start this final report by providing summaries of the status of child and adolescent digital technology use in the UK and a review of the current research and policy landscape. We then provide summaries of the standalone Reports 1–3 (Appendices 1–3). Next, we review the potential research approaches that would improve the causal evidence base concerning smartphones, social media and childhood and adolescent outcomes, their strengths and weaknesses, and ability to deliver research outputs in a two- to three-year timeframe.

Scope of Report

This report is shaped substantially by the specific remit and constraints of the commission provided by DSIT. We note particular limitations:

- Due to time and scope constraints set by DSIT, as well as the focus of public and policy discussion, we review and consider mostly mental health and wellbeing outcomes. These outcomes establish themselves over longer periods of time, and are therefore influenced by a different range of factors and informed by a different evidence base, compared to more proximal outcomes or behaviours such as contact to strangers, exposure to certain types of content or experiences of bullying.
- While research often focuses on time spent with social media or smartphones, due to its widespread adoption as a measure and potential target of intervention in both policy and research, there is broad agreement that it is not the most meaningful or sufficient measure. Many experts suggest that factors such as the content consumed, the context of use (when, where, with whom, and what is created), and what is displaced (e.g. sleep, meals, homework, play, or in-person interactions) are also relevant to understanding impacts on health and wellbeing.
- We do not examine in detail the influence of design features or other forms of digital engagement, such as gaming.
- We take a primarily public health causal epidemiological perspective, focusing on population-level — not individual-level — outcomes. This means that our recommendations cannot and should not be generalised to individual instances of harm (or benefit). Further, this does not imply that evidence creation from other disciplines, including psychology, social sciences and humanities, or approaches, such as co-creation, co-design and qualitative methods, are not fundamental to progressing our understanding of the impacts of technologies on childhood and adolescence. While these perspectives were not the primary focus of this review, they were actively considered in shaping our approach.
- We focus primarily on the potential harms associated with social media and smartphones, and less on AI chat apps due to a paucity in the research landscape.
- We do not undertake cost-benefit analyses.
- Parts of the report consider both childhood (under 10 years) and adolescence (defined as 10–19 years), yet the primary emphasis in certain sections (such as the evidence review in Appendix 1) is on adolescents, reflecting both the policy relevance of this age group and time limitations.
- We focus predominantly on the academic research literature, and not grey literature such as policy reports, blog posts, civil society documents or focus groups with

affected communities, due to this commission's aim being the improvement of research provision in this area.

The Scientific Consortium involved in this report includes a breadth of disciplinary expertise, encompassing qualitative, quantitative, participatory, and co-design methodologies, which has helped ensure diverse research dimensions were meaningfully reflected. For instance, while we do not explore in depth how to integrate children's and adolescents' voices into the research process within this evidence review (Babbage et al., 2024), we recognise the importance of doing so and have included a brief overview section on this topic later in the report (See 'Involvement of Children, Adolescents and Caregivers'). These limitations in the scope and nature of this report should be considered when interpreting the findings and recommendations presented.

Primary Definitions

We use the following primary definitions, while also providing a Glossary of key terms in Appendix 6. We define:

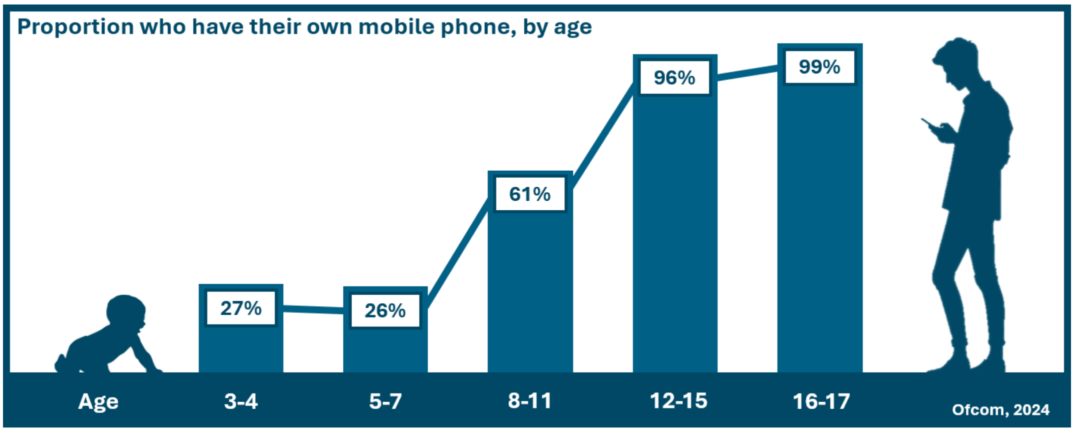
- Social media as 'internet-based, disentrained, and persistent channels of mass personal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content' (Carr & Hayes, 2015).
- Smartphones as portable cellular devices with internet access and capacity to host applications.
- AI chat applications as any chatbot that 'makes the use of digital technology to create systems capable of performing tasks commonly thought to require intelligence' (UK Government, 2019).
- Wellbeing as the state of living well, combining positive emotions, such as happiness, interest and confidence, with effective functioning. This includes developing one's potential, maintaining positive relationships, having a sense of purpose and exercising control over life. While painful emotions are a normal part of life, wellbeing is compromised when these emotions are intense, persistent, and interfere with daily functioning (Huppert, 2009).
- Mental health as 'a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community. Mental health conditions include mental disorders and psychosocial disabilities as well as other mental states associated with significant distress, impairment in functioning, or risk of self-harm' (World Health Organization, 2022).
- Digitalisation as the way many domains of social life are restructured around digital communication and media infrastructures (Brennen & Kreiss, 2016).

Digitalisation of Childhood and Adolescence in the UK

There is no doubt that childhood and adolescence have become heavily digitalised in recent decades. Ofcom statistics show a steady rise in the number of children and young people using the internet. In 2005, 61% of 8–11-year-olds were going online, increasing to 91% by 2015, and reaching 98% according to the most recent data. A similar pattern is seen among 12–15-year-olds, with online usage growing from 67% in 2005 to 96% in 2015, and now reaching 100% of those surveyed in 2024 (Ofcom, 2015; 2024a). By influencing how children and young people spend their time, digitalisation may also impact the nature of childhood and adolescence itself. Indeed, some researchers now argue we have entered a ‘post-digital’ age where distinctions between life on- and offline are no longer appropriate (Taffel, 2016). For adolescents, technology has become so ingrained in their lives that its absence is at times more noticeable than its presence. As children and young people are deeply immersed in the digital world, their development unfolds across both physical and digital spaces in interactive, complex and bidirectional ways (Navarro & Tudge, 2023; Orben et al., 2024).

While younger children mainly use tablets, with the most popular app being YouTube, phone and social media use become more common in adolescence (Ofcom, 2024a). Smartphone ownership rises from 61% of 8–11-year-olds to 96% of 12–15-year-olds (Ofcom, 2024a). This is a substantial increase in smartphone ownership in the past decade, with only 24% of 8–11-year-olds and 69% of 12–15-year-olds owning a personal smartphone in 2015 (Ofcom, 2015). Children and young people use digital technologies to address diverse needs: 68% of UK 8–17-year-olds say social media helps them feel closer to their friends all or most of the time (Ofcom, 2024a), akin to the 69% of US 13–17-year-olds who note that phones make it easier for them to pursue hobbies and interests, and 65% who agree that phones make it easier for them to be creative (Pew Research Center, 2024). Thirty-seven percent of US 13–17-year-olds also note that phones make it easier to develop healthy friendships (Pew Research Center, 2024).

Figure 1. Proportion of children and young people in the UK with personal smartphones, by age. Data taken from Ofcom, 2024a.



However, there are also various drawbacks. 31% of US 13–17-year-olds said phones made developing healthy friendships harder (31% said they made it neither harder nor easier, Pew Research Center, 2024). 44% of UK 16–17-year-olds think their screen time is too high (Ofcom, 2024a), which is similar to the 38% of US 13–17-year-olds who say their phone use is ‘too much’, compared to 51% who believe they spend the right amount of time on their phone (Pew Research Center, 2024). Survey data like this shows that there likely exist individual-level benefits and harms of such technologies.

Parents are also concerned. In the UK, 39% of parents to 3–17-year olds find it hard to control their child’s screen time, compared to 44% who don’t (Ofcom, 2024a). The proportion of parents noting such difficulties rises with the age of the child; 49% of parents of 16–17-year-olds find controlling their child’s screen time difficult (Ofcom, 2024a). Similarly, while 62% of parents to 3–17-year-olds agree that their child has a good balance between screen time and doing other things, that decreases to 55% in parents of 16–17-year-olds (Ofcom, 2024a). There also exists a trend over time. While in 2007, 70% of parents to 5–15-year-olds agreed that the benefits of being online outweighed the risks for their child, that has decreased to 58% 15 years later (Ofcom, 2024a). A US survey found that in 2020 two-thirds of US parents stated that parenting is harder today than it was 20 years ago, with smartphones and social media being referenced as a reason for this change (Pew Research Center, 2020). Moreover, some statistics suggest that certain individuals may be more likely to experience harmful contact or content online. Specifically, children between the ages of 8 and 17 who live with one or more impacting conditions are more likely to be exposed to harmful content online (40% vs 29%) (Ofcom, 2024a).

The State of Science in the Policymaking Process

The Past Five Years of UK Research-Policy Responses

There has been repeated scrutiny about research evidence on the population-level impacts of social media and smartphone use in children and young people. In 2018, the Secretary of State for Health commissioned the UK Chief Medical Officers (CMOs) to report on the effects of screen time on children's health and offer recommendations (Hawkes, 2019). The CMOs' report concluded that there was insufficient evidence to determine whether screens and social media posed a causal risk to children and young people (Davies et al., 2019; Hawkes, 2019). It acknowledged that some studies found a link between screen time and negative outcomes, such as increased anxiety and depression, but that establishing a causal relationship was not possible. The report pointed to issues with the correlational nature of the evidence, including the potential for reverse causality. For example, children and young people who already have mental health issues may be more likely to spend time on social media, which could explain the observed correlation between higher screen time and mental health challenges (Davies et al., 2019).

While the CMOs did not provide concrete screen time recommendations, they referred to the 2018 report by the Royal College of Paediatrics and Child Health (Royal College of Psychiatrists, 2019; Viner et al., 2019), which outlined four key questions for families to consider as a guide when managing screen time: (1) Is screen time in your household controlled? (2) Does screen use interfere with what your family want to do? (3) Does screen use interfere with sleep? (4) Are you able to control snacking during screen time? These questions serve as a framework for families to evaluate how screen time fits into their daily routines and whether it displaces other important activities like sleep, physical exercise, and social interactions.

In 2019, the World Health Organization (WHO) released guidelines recommending limits on sedentary behaviour for children under five (World Health Organization, 2019b). They advised that infants (0–1 years) should not use screens at all, while children aged 2–3 years should have no more than one hour of screen time per day, with less being preferable. While acknowledging the limited quality of available evidence, the WHO highlighted several benefits of reducing the time children spend restrained, whether through screen use or other sedentary activities such as being in a car seat. They found no evidence of harm from reducing screen-based sedentary time and therefore concluded that the 'potential benefits of reducing sedentary screen time and time spent restrained outweigh the possible harms or costs and may increase health equity by improving health outcomes.'

Concerns persisted that the digital world was having, at times, tragic impacts on children and young people (North London Coroner's Service, 2022) and recent explorations of the harms associated with social media usage for children and young people highlight the rapidly evolving nature of individual harms, with Bryce et al. (2023) discussing the rapidly evolving landscape: changing platforms (i.e. TikTok), the development of virtual reality technology and the prominence of algorithm-driven content all pose potential pathways for mental health harms, discussed largely in the context of online sexual risk. However, the report also highlighted the significant methodological, ethical and resourcing challenges involved in researching the extent of harm associated with this growing range of potential exposures.

The Online Safety Act (2023) (OSA) aimed to ensure that platforms prevent children from accessing harmful content categorised as Primary Priority content (e.g. pornography, self-harm and suicide-related material), while allowing age-appropriate exposure to Priority content (e.g. bullying, violence, and substance use). A recent report noted that at least 1 in 12 children reported they had been exposed to content from at least one of these categories (Bryce et al., 2023). Furthermore, the OSA set out to support adult users by promoting greater transparency from major platforms regarding the content they allow, while giving individuals more control over the content they are exposed to. While legislation has now come into force, it is still being implemented and many stakeholders have called for it to be strengthened, particularly after Ofcom published its comprehensive Protection of Children Codes.

The COVID-19 pandemic influenced the science and policy process in this space as platforms became essential for education, social interaction and daily life, highlighting that the screens themselves may not always be inherently harmful, especially to older children (Purba et al., 2024). Instead, their impact depends on the activities and content that children engage with. In fact, digital technologies served as a vital lifeline during the pandemic, helping children stay connected with peers and addressing various developmental needs during isolation (Orben et al., 2020). For example, a study of 1,387 UK 10–15-year-olds found that adolescents without access to a computer had worse mental health outcomes during the COVID-19 pandemic (Metherell et al., 2022).

Yet concerns persisted as the pandemic subsided and the then US Surgeon General, Dr Vivek Murthy, issued a series of advisories expressing concern about the effects of screens and social media on young people, whilst also acknowledging that the evidence remained weak (US Department of Health and Human Services, 2023). Special concern was raised about problematic and excessive use, and individual-level harms. Dr Murthy wrote an open editorial in the New York Times where he called for a health warning, similar to the one on cigarettes, to be placed on social media (Murthy, 2024). Dr Murthy argued that parents and children are currently left to navigate the appropriate 'dose' of social media usage on their own, a task that, in other industries like pharmaceuticals, is handled through established safety checks prior to distribution. While Dr Murthy acknowledged the benefits of social media, he questioned whether they can truly outweigh the substantial harms, which he noted was now evidenced by the scientific literature.

At a similar time, the US National Academies of Sciences conducted a report to document the evidence-based consensus on the relationship between social media and adolescent health by an authoring committee of experts (National Academies of Sciences, Engineering, and Medicine, 2024). Similar to the earlier report from the CMOs, this report emphasised the lack of robust evidence and concluded that, at the population level, it is impossible to determine the overall causal effect of digital technology on youth well-being, while recognising its potential for both positive and negative impacts (National Academies of Sciences, Engineering, and Medicine, 2024). For example, the report did note consistent evidence of social media's negative effect on sleep and that 'given the importance of sleep for emotional regulation and concentration in adolescents, its relation to mental health problems is powerful on its own.' Concerns intensified further in 2024 with the publication of Jonathan Haidt's bestselling book, *The Anxious Generation*, which argued that there is causal evidence of the harm from digital technology on children and young people (Haidt, 2024). His claims have since been challenged by some scholars, who argue that the evidence base is not as strong as claimed (Odgers, 2024; Pearson, 2025; Thorp, 2024).

Recently, a report by the European Commission discussed the relationship between social media use and a range of mental and physical health outcomes (Manolios et al., 2025). The impacts of social media, according to the review, are largely contingent on the type of usage, with 'positive social media uses' reflecting more beneficial outcomes compared to 'negative social media uses'. This review highlights the need for continuous stakeholder engagement to address the needs of children and young people, who do not exist as a homogenous group. The World Health Organization Europe is conducting a similar review of the evidence, which is due to be published shortly following the completion of this report. Efforts to understand the impacts of social media, as such, remain on-going and high priority.

Taking a public health perspective to technological impacts, causality is extraordinarily difficult to prove and much easier to disprove, especially when digital companies are not invested in such evidence creation. It is important to consider the potential consequences of attributing rising mental health issues solely to online harms; such an approach risks overlooking other significant social, economic, and environmental factors that may also be contributing to these trends, and implementing policy changes that might be ineffective, rights restrictive, and have unintended consequences. On the other hand, given the volume of time consumed by digital technologies, and its accelerated rise in our society, researchers have also noted the danger of holding too high an evidentiary bar for starting to test intervention and actions while harms continue to accrue (Casper et al., 2025; Orben & Matias, 2025). By waiting for better evidence, we could be allowing harms to percolate, deeply impacting not just children and young people but our wider society.

Governments have faced increasing pressure to address concerns about social media's impact on mental health, leading to a variety of responses internationally. These responses can generally be grouped into strategies focusing on content moderation, age restrictions, parental controls, addressing potentially addictive design features, and promoting digital literacy (World Health Organization, 2025a). Some examples of this are: France mandating the pre-installation of parental controls on devices to block harmful content (Directorate for Legal and Administrative Information (Prime Minister), 2024); Germany introducing the Youth Protection Act, enforcing strict age-based time restrictions to shield children from certain media (Bundesministerium für Familie, Senioren, Frauen und Jugend, 2021); Australia announcing a nationwide 'ban' on social media use for those under 16 (UNICEF Australia, 2025), and Albania banning TikTok (Associated Press, 2025).

At the same time, parental advocacy groups — such as Smartphone Free Childhood in the UK — have gained substantial traction (Banfield-Nwachi, 2024; Smartphone Free Childhood, 2025). Due to the time it takes for legislative or corporate interventions to take place, while children and adolescents are growing up, such groups argue that we cannot rely on 'top-down' solutions alone.

Across most reports, reviews and commissions examining social media and smartphone use among children and young people — at times reaching conflicting conclusions — two consistent themes clearly emerge. First, there is a widespread call for technology companies to take greater responsibility for making their products and services safer. Identifying the harms caused by commercial products to children and young people should be a priority for digital technology companies, and there is vast consensus that bold and dedicated action is urgently needed. Second, there is common recognition that the existing scientific evidence base, especially with regards to population-level evidence, is weaker, slower and more disjointed than it should be. This is despite repeated calls over the past decade for stronger and more robust studies alongside the rapidly growing concerns in this area. Acknowledging the persistent gap between the evidence being produced and the evidence needed, DSIT has commissioned this report to examine the barriers to high-quality causal research and explore potential solutions.

Understanding Causal Evidence in Research on Digital Technologies and Young People

One major area of contention in the research on new technologies and their impacts on children and young people is whether there is causal evidence of these impacts, and how such evidence can best be delivered. DSIT therefore specifically asked this report to examine 'what methods and data are best suited to understanding the impact that social media and smartphones are having on children and young people, with a particular focus on causal evidence as this has been a major limitation of the data currently available.'

As noted above, this focus restricts our scope to causal inference in particular, even though other forms of evidence creation (e.g. co-creation, youth involvement, self-report) also make important contributions to our understanding of digital impacts. Further, we have defined this remit through a public health and epidemiological perspective, to focus on population-level causal evidence.

Defining Causality in the Context of Digital Research

While causality is central to many arguments in this research area, its definition is not always clear. Causality refers to a cause-and-effect relationship, where one event (the cause) directly leads to the occurrence of another event (the effect). In other words, causality involves a situation where a change in one variable or factor produces a change in another (Pearl & Mackenzie, 2018). The effect would not have occurred without the cause.

For example, in the context of mental health, research might suggest that viewing a specific harmful piece of aggressive content online (cause) leads to higher rates of aggression offline (effect). This would imply a direct cause-and-effect relationship, where exposure to certain digital content contributes to deleterious behavioural effects.

An Epidemiological Approach to Causal Inference

To examine such cause-and-effect relationships, this report draws primarily on a model of causality derived from classical epidemiology, which focuses on individual exposures and population-level effects. This approach offers a structured framework for making causal inferences from observational data, particularly in complex, real-world contexts like digital environments. The work of epidemiologist Miguel Hernán — alongside others such as Donald Rubin, Judea Pearl and James Robins — is central to this approach, providing tools to distinguish true causal effects from correlations.

Hernán (2004) emphasises the importance of counterfactual reasoning, which asks: *What would have happened to the individual if they had not been exposed to the cause?* This method involves imagining an alternative scenario in which the exposure (e.g. social media use) did not occur, in order to estimate its causal effect on outcomes such as mental health. While counterfactuals are conceptualised at the individual level, they are used to infer population-level effects by aggregating these comparisons across many individuals. This allows researchers to draw conclusions about how digital exposures impact broader public health trends. Such approaches are particularly valuable in distinguishing causal relationships from patterns that may only reflect correlation.

Correlation vs Causation: Key Distinctions

Correlation refers to a statistical relationship or association between two variables, where they tend to change together. However, correlation does not imply causation — it simply shows a pattern, not a direct cause-and-effect relationship (Pearl & Mackenzie, 2018). For instance, studies might show a correlation between increased social media use and rising mental health issues, like anxiety or depression. However, this does not necessarily mean social media use is the cause. It could be that individuals with pre-existing mental health conditions are more drawn to social media, or that shared underlying factors, such as loneliness or peer pressure, contribute to both.

The epidemiological approach emphasises the importance of distinguishing correlation from causality by considering confounders (variables that affect both the cause and the effect) and selection bias, both of which can distort observed relationships. In short, causality implies a direct cause-and-effect relationship, whereas correlation only indicates a statistical association, without determining if one variable causes the other. Counterfactual reasoning and causal diagrams provide a more rigorous approach to evaluating causal relationships, ensuring that inferences about causality are grounded in sound reasoning rather than mere associations.

Evaluating Causal Claims: the Bradford Hill Viewpoints

To evaluate whether an observed correlation is likely to be causal, researchers often apply the Bradford Hill Viewpoints — a set of nine principles developed by Sir Austin Bradford Hill in 1965 (Hill, 1965; Shimonovich et al., 2020). These principles provide a structured way to evaluate the strength and plausibility of a causal relationship, particularly when randomised control trials are difficult or unethical to conduct. The nine principles are as follows: 1) Strength of association; 2) Consistency across studies; 3) Specificity of the relationship; 4) Temporality (cause precedes effect); 5) Dose-response relationship (biological gradient); 6) Plausibility of the mechanism; 7) Coherence with existing knowledge; 8) Experimental evidence; 9) Analogy to similar relationships.

Alternative Perspectives: Engineering Approaches to Causality

It is important to acknowledge that epidemiological approaches, as described above, represent only one perspective on causality. These approaches typically focus on how individual exposures — such as time spent on social media — affect health outcomes across a population and are often used to guide interventions aimed at changing user behaviour (e.g. reducing screen time or promoting media literacy).

In contrast, engineering safety research offers a complementary perspective that focuses on the entire system — including the design and functioning of digital platforms themselves. Rather than focusing on individual behaviour, this approach examines how features like algorithms and user interfaces might lead to harmful outcomes at scale. For example, engagement-optimising systems — which aim to keep users on a platform for as long as possible — may inadvertently promote harmful content (Leveson, 2012). While epidemiological models tend to guide behavioural interventions, engineering approaches often aim at platform-level reforms, such as redesigning recommendations systems or altering algorithmic priorities to mitigate harmful content exposure.

Recognising the Value of Interdisciplinary Approaches

Both epidemiological and engineering approaches have their strengths and limitations. While integrating these perspectives could provide a more comprehensive understanding of digital risks and impacts, this was beyond the scope of the current project. Nevertheless, recognising the interplay between individual experiences and systemic design features is crucial for informing future research and developing effective, multi-layered strategies to mitigate harm and promote well-being in the digital age.

The Difficulty Assessing Causal Evidence

Several characteristics of research into the impacts of social media and smartphones on children and young people make it challenging to establish causal evidence, particularly when using a classical epidemiological approach. This approach seeks to quantify individual-level digital technology exposures and link them to population-level outcomes (see also Appendix 3). We review these challenges below, as they in turn highlight some of the general limitations of bio-medical epistemology in this field. These limitations mean that an effective research strategy will likely triangulate or integrate causal approaches with others, such as engineering safety and systems thinking.

While classical epidemiology excels at identifying population-level risk factors, if often translates these insights into policy tools, such as regulation or restrictions. In contrast, an engineering safety (systems) approach offers a complementary perspective that considers the interaction of design features, user behaviour, and broader socio-technical systems (Leveson, 2012). Whereas epidemiology asks, *Is this harmful at a population level?*, engineering asks, *How can we design this to be safer?* By focusing on system architecture, user interface design, feedback mechanisms, and content algorithms, engineering approaches can inform more nuanced and actionable interventions — shifting the conversation from regulation to responsible design.

Further, alongside trying to quantify and understand whether harm exists, we need to accelerate the development and testing of safer products, as well as strategies for users and families to protect themselves from harms and boost benefits (Orben & Matias, 2025).

Dose-response

There is still active debate about whether there is a dose-response relationship between digital technology use, such as social media, and a range of developmental outcomes for children and adolescents such as such as poor mental health outcomes and depressive symptoms (Davies et al., 2019; Kaye et al., 2020; Kelly et al., 2018). A dose-response relationship occurs when incremental increases (or decreases) of the exposure produce incremental increases (or decreases) of the outcome (Hill, 1965). In recent years, social media has often been likened to cigarettes. The harms of cigarette use are underpinned by well-established chemical dose-response relationships, which allow for relatively uniform public health recommendations. Given the variety of activities that one can engage with on social media circumstances do not allow for such uniformity, as social media and smartphone use cover a wide range of activities, each potentially impacting users in different ways (see 'Active Ingredients' below).

Some epidemiological studies have found evidence of dose-response relationships between time spent on social media and specific adolescent health-risk behaviours. For example, research exploring the potential causal relationship between social media and adolescent health-risk behaviours using observational data found time spent on social media was associated with increased risk of cigarette use, e-cigarette use, dual use, alcohol use and binge drinking in UK adolescents in a dose-response manner (Purba et al., 2023b; Purba et al., 2025). Importantly, the findings persisted even after accounting for a range of potential biases, such as missing data and reverse causality. However, while dose-response relationships were observed, the authors note that these associations may have been influenced by confounding factors Further, another found a probably dose-response relationship between more social media use, at least at the extremes, and mental health outcomes (Kelly et al., 2018). However, other studies have found relationships in their data, especially regarding the relationship between social media and well-being outcomes (Przybylski & Weinstein, 2017; Orben et al., 2022). The existence of dose-response relationships in those areas, or their nature, remain inconclusive.

Active Ingredients

Identifying the 'active ingredients' responsible for social media and smartphones' effects on outcomes such as mental health is complex, especially compared to the study of chemical compounds such as cigarettes or alcohol. Time spent using such technologies, the most common exposure measure used in research to determine their impacts, is only a crude conglomerate of many potential active ingredients (content viewed, type of engagement with a platform) and its use can therefore hide important impacts of the technology that — if measured precisely — would be more evident (Kaye et al., 2020). Therefore, while time spent on smartphones or social media may be a key factor in determining some outcomes such as displacement of physical activity, it is likely to be insufficiently granular to understand other outcomes relevant to child or adolescent development.

For example, when examining social media's role in violent behaviour or self-harm, the key factor may be exposure to specific content or discussions (Lavis & Winter, 2020; Purba et al., 2023a). In all, studies need to precisely measure exposure and assess matched corresponding outcomes over appropriate timescales to effectively identify potential causal relationships. This requires a precise alignment between predictors and outcomes: linking 'pro-anorexia' content to knife crime, for example, will likely yield little insight.

In addition to content, platform design and patterns of user interactions may also function as critical 'active ingredients' (Meier & Reinecke, 2021). For example, certain design features — more commonly referred to as affordances — such as the 'infinite scroll' or short-form video formats, may be more relevant when examining outcomes such as feelings of agency or 'addiction' (Brown et al., 2022; Turner et al., 2024). Studying these technological affordances from an engineering safety design perspective can help clarify why and how social media affects mental health and development in diverse ways, and how to design these platforms to be safer (Brown et al., 2022). Policies seeking to address these design features have become popular in many jurisdictions, leveraging existing evidence from both academia and industry (Minnesota Attorney General, 2025).

Limited Access to Objective Data

Independent researchers who aim to measure technology exposures but lack direct access to internal platform data (Przybylski, 2021), predominantly rely on participants' self-reports or time-use diaries, both of which are prone to recall and social desirability biases (Parry et al. 2021; Purba et al., 2023a). Two recent systematic reviews highlight this limitation. Before synthesising the existing evidence on the relationship between social media use and adolescent health-risk behaviours (126 studies), one review found that only five out of 235 social media measures used in the included studies employed data-driven coding, with the majority being self-report (Purba et al., 2023b). The other reviewed the evidence on the relationship between social media use and adolescent internalising symptoms and found that 92% of effect sizes were derived from self-report measures (Fassi et al., 2024)

From a medical epidemiological perspective an accurate and unbiased measure of a precise exposure is very important, and there is now much evidence that self-reported digital technology use (especially time spent) is not that. A growing body of literature suggests that individuals tend to overestimate their phone usage in both retrospective surveys and experience sampling methods (Verbeij et al., 2021), with variations in accuracy also depending on the time frame reference point (Ernala et al., 2020). Possible explanations for this inaccuracy include the frequent fragmented use of social media applications, or the existence of cognitive biases, including recall bias, during the adolescent period (Verbeij et al., 2021). The predominance of such self-report measures of, for example, screen time, therefore, limits the validity of study findings.

As discussed in detail in Appendix 3, this does not mean that self-report measures of digital technology use are not informative. Indeed, simply asking children and young people to reflect and discuss their experiences with digital technologies remains vital. This is particularly important when it comes to understanding if individual experiences are associated with positive, negative or neutral outcomes. For example, current research is considering how negative feelings evoked by online content may be important mediators between digital experiences or exposures and mental health outcomes (Kostyrka-Allchorne et al., 2024). Yet for the most part children and young people's reflections or subjective experiences remain difficult to measure in a uniform way across populations and have not been a focus of research from a classical epidemiological perspective of causality. This has led to an over-reliance on self-report measures that are often used to measure aspects of digital media use best measured objectively, such as what apps are being used, when and for how long. Related work, for example, has observed that while survey measures relating to 'problematic use' are associated with poorer mental health, these relationships reduce considerably when 'use' was replaced with an objective measure of time recorded via a smartphone app (Shaw et al., 2020). This leaves policymakers with a conundrum: it looks like decreasing the time spent on social media might have little impact on mental health whereas addressing social media experiences that elicit negative feelings is more important. Herein lies the challenge, because the latter will involve changes to the former.

In contrast, technology users generate vast amounts of 'objective' data every day through their digital footprints, offering a rich and untapped resource for social media research (Geyer et al., 2022). While app- or phone-based tracking of usage time has become more common in research over the past few years as a response to these limitations, it still fails to capture nuanced aspects of social media use, such as the type of content consumed, that may drive specific effects (Meier & Reinecke, 2021; Purba et al., 2023a). App-based measures of time spent and specific interactions within apps are often difficult to collect, difficult to match up to high-quality longitudinal datasets and remain rare in large-scale longitudinal studies, as any app-based solution requires significant resources to develop and maintain (Di Cara et al., 2023). Application programming interfaces (APIs) provided by companies allow authenticated pathways to get fine-grained user data beyond time spent (Davis et al., 2024). However this is subject to the stability of access provided by social media companies which has already disrupted many research projects (Leightley et al., 2023) — with some scholars noting we are entering a 'Post API' age (Freelon, 2018).

New approaches being developed across the landscape offer potential solutions — albeit not without their own limitations (e.g., they are specific to each digital platform individually and data is restricted to a specific timeframe as most often it is retrospective and not prospective, even though prospective services are now being rolled out). Data donation allows social media users to harness their data subject rights to access their own data, download usage data, and 'donate' it to researchers (Boeschoten et al., 2022; van Driel et al., 2022). This process enables the collection of objective data that can be used to address a variety of important research questions, for example examining the impact of exposure to different types of content on adolescent mental health. The UKRI ESRC has recently funded the UK Smart Data Donation Service whose role it is to ensure there are secure and effective methods to deliver such collection and linkage, but these are only just now being rolled out and implemented. However, even when access to platform data is legally mandated (e.g. under UK General Data Protection Regulation; GDPR), establishing partnerships with industry has proven challenging, and the quality of shared data remains inconsistent (Valkenburg et al., 2024; van Driel et al., 2022).

Individual Differences

Research consistently highlights heterogeneity in social media's impact on children and young people (Beyens et al., 2020; 2021), which we also find in Appendix 1. For instance, social media may have stronger negative effects on younger compared to older adolescents (Orben et al., 2022b), and girls tend to report more pronounced links between social media use and internalising symptoms than boys (Kelly et al., 2018). Further, popular adolescents might receive more online validation, which can reinforce positive psychological outcomes, while those with lower offline popularity may experience more negative effects (Nesi & Prinstein, 2015). When considering health-risk behaviours, research has also suggested that the potential negative effects of social media on outcomes like cigarette use are greater among more socioeconomically advantaged groups, when compared to disadvantaged groups (Purba et al., 2025). These findings highlight the need to not only conduct research at the population level, but at the subpopulation level to understand social media and smartphone impacts.

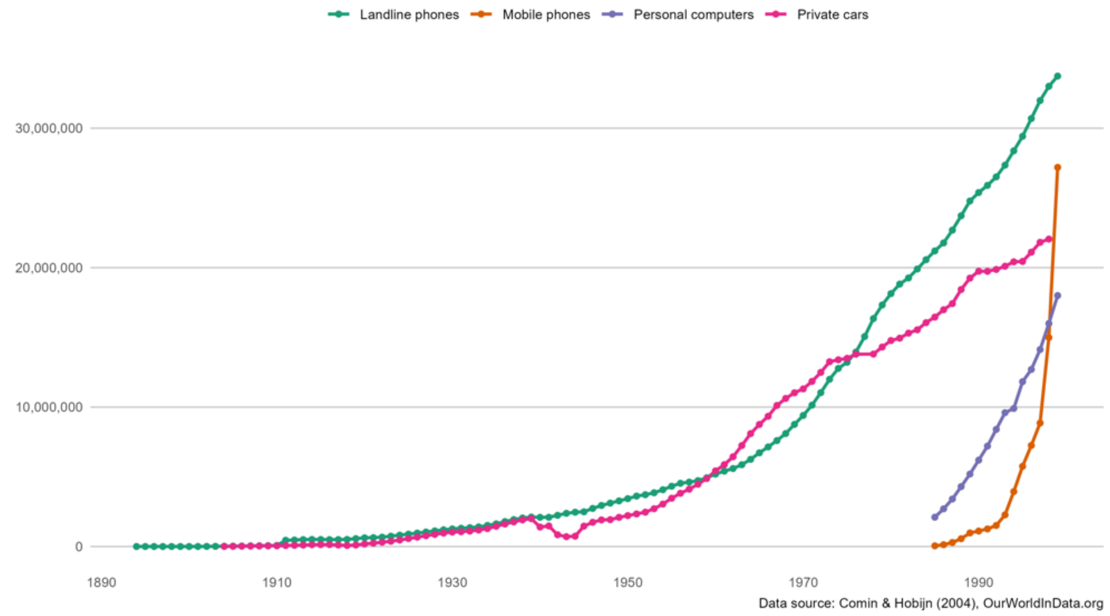
Furthermore, platform algorithm recommender systems ensure that every individual's content exposure on the same platform is different, thus likely contributing to differential experiences (A. Y. Lee et al., 2022). At the same time, the same 'active ingredient' can have very different effects depending on the user's circumstances. This makes it far more difficult to establish clear evidence of causality and — in turn — population-level public health recommendations, as noted, for example, by the CMO reports in 2019 (Davies et al., 2019; Hawkes, 2019; Viner et al., 2019)

Speed of Development and Nature of Products and Services

Another common comparison for social media and smartphone regulation and design safety is cars. Discussions often highlight how society has successfully managed the benefits and risks of cars through regulation and education, including MOT tests, driving licences, traffic laws, and seat belts. It is suggested that a similar approach should be applied to social media and smartphones. This analogy has merit: both cars and digital technologies are complex systems that pose risks and benefits to individual users and wider society, and both require a combination of industry collaboration, best practices, regulation and education to ensure safety.

However, three key distinctions need to be highlighted in this context: 1) the speed of uptake, 2) the stability of services and products and 3) accessibility of platform creation. In terms of speed, it only took two years for TikTok to surpass 15 million users in the UK (Information Commissioner's Office, 2023). This means — especially given the acceleration of progress in AI — that we are now operating in a technological ecosystem that evolves nearly two orders of magnitudes faster than for cars (Figure 2).

Figure 2. Graph depicting technology diffusion in the United Kingdom. Data taken from Comin & Hobjin (2004).



Data source: Comin & Hobijn (2004), OurWorldInData.org

Secondly, cars are relatively stable products. When researchers conduct safety tests on a specific make and model, the design remains consistent, allowing evidence to accumulate over time. In contrast, social media platforms are dynamic and continuously shaped by user interactions. There is no single, fixed ‘make’ of social media. Platforms are highly individualised and evolve in ways that are difficult to track. As a result, one young person’s Instagram experience may be entirely different from another’s, even when using the app concurrently, and both of their experiences of the app will likely differ months later following a change in platform features.

Thirdly, while creating a car requires substantial resources and expertise, social media platforms can now be created by individuals with sufficient but relatively basic and non-exclusive technical knowledge. The UK government’s review of the app store ecosystem found that malicious and poorly developed apps continue to be accessible to users, indicating that some developers do not adhere to best practices when creating apps (Cowls et al., 2023). Further, reviews have found that companies often decide not to research the safety impacts of their products on children and young people, despite the knowledge that children and adolescents use their platforms (Lenhart & Owens, 2021). Importantly, while the automobile industry is governed by safety by default and by design, such regulatory frameworks are lacking in the digital technology sector. This discrepancy exacerbates the challenges in ensuring user safety, further complicating regulatory oversight (Munger, 2019; Orben & Matias, 2025).

While technology is advancing at an unprecedented pace, scientific research and evidence generation remain largely structured in the same way they were a century ago. This is an issue because — as noted above — provision of causal epidemiological evidence of harm from a population perspective is slow due to a range of issues (Orben & Matias, 2025). There are further inefficiencies at multiple stages: securing research funding can take over a year and is not a certainty due to stiff competition for resources, followed by additional delays in setting up grants, obtaining ethical and legal approvals, and collecting longitudinal data. It often takes several years and multiple funding attempts to get a study running. Even when analysis and writing are expedited, the publication process can introduce further delays, meaning that studies may take four or more years to be completed in total. Given the rapid evolution of digital platforms, this timeline is inadequate for producing timely, policy-relevant evidence.

However, policymaking and solutions are still primarily driven from a population epidemiology perspective. Less attention is paid to engineering systems approaches to design and safety as it is for other products (e.g. cars or children's toys). Furthermore, little attention is paid to integrating research and safety processes directly into company research pipelines through regulation. For example, most digital companies already conduct continuous A/B testing to maximise profitability. Approaches have been explored to require those companies above a certain size to include mental health and safety metrics in such experiments, and to publish the findings to the public (Thorburn et al., 2024). While we cannot comment on such policy approaches, we can note the relative inability for current research structures to keep up with evidence need (Orben & Matias, 2025).

Industry Support

Another major challenge in generating evidence in this space is the lack of trust and cooperation between industry, government and civil society (Livingstone et al., 2023a). Over the past decade, public scepticism in the UK has grown about whether digital companies sufficiently prioritise societal and child safety in platform design (Vaccarini et al., 2022). While numerous reports have called for the adoption of safety-by-design principles and stronger protections for children (Livingstone et al., 2023b), meaningful progress has been limited. Some regulatory advancements have been made, such as in the European Union, but in the UK some felt that piecemeal, stop-gap solutions have been implemented (Molly Rose Foundation, 2025; Sellman, 2025). Though now the Online Safety Act is in effect with specific child safety and illegal harms duties.

This stands in stark contrast to other industries, where consumer trust is a high priority for both businesses and regulators. In such sectors, like food safety, safety testing is embedded at multiple levels: companies conduct in-house tests, production lines incorporate safety checks, and independent research centres often funded by a combination of industry and government, such as the Quadram Institute, play a key role in ensuring product safety (Quadram Institute, 2025). To further support scientific oversight, the UK's Food Standards Agency has both a Chief Scientific Adviser and Areas of Research Interest (Food Standards Agency, 2021), helping to reinforce public confidence that products are safe for consumers.

By contrast, in the digital technology sector, reports suggest that companies do little to examine their impact on child user populations, as doing so could expose them to greater regulatory scrutiny (Lenhart & Owens, 2021).

This makes independent research even more critical. Yet, as discussed earlier, researchers lack the necessary support and access to high-quality data to conduct rigorous studies. Much of the independent research conducted involves reconstructing evidence that companies likely already possess but choose not to disclose (Haugen, 2021).

Furthermore, while companies have extensive capacity to test the impact of product and service changes through A/B testing — randomly assigning users to different versions of an app to optimise engagement — this capability is not available to external researchers (Orben & Matias, 2025). The asymmetry in access to data and experimentation tools means that policymakers and the public are often left in the dark, relying on fragmented and outdated evidence rather than the real-time evidence that companies use internally to refine their platforms. Technologists and others have suggested that this gap could be closed by mandating disclosure of this real-time evidence (Lubin & Iyer, 2023; Thorburn et al., 2024), as also covered in the section above. Such changes can potentially be integrated into pre-existing A/B testing mechanisms (Lubin & Iyer, 2023).

Unclear Outcomes and Complex Systems.

A key distinction between the digital world and many other industries is its sheer pervasiveness. It now permeates almost every aspect of society, making it increasingly difficult to separate the digital from the non-digital (Taffel, 2016). Mental, educational, and societal systems are exceptionally complex. Factors such as mental health, youth violence, educational outcomes, workforce engagement, and extreme lone-actor violence are influenced by a vast network of interdependent variables, making single ‘causes’ of changes or trends difficult to pin down (Panayiotou et al., 2023).

The digital world potentially influences nearly all factors already known to impact child outcomes, shaping everything from parental job opportunities and political discourse to information access and social interactions (Orben et al., 2024; Purba et al., 2024). In such complex systems, small changes can produce significant ripple effects, or conversely, have no meaningful impact at all. Moreover, these systems can settle into stable states that require considerably more effort to reverse than was needed to establish them (Borsboom, 2017). For instance, in mental health research, simulations and empirical studies have demonstrated that psychological disorders often emerge from the accumulation of multiple interacting factors (Borsboom, 2017). However, reversing these conditions is not as simple as eliminating the initial contributing factors. Instead, it requires a broader, sustained set of interventions to shift the system into a healthier state (Borsboom, 2017; van de Leemput et al., 2014).

When researchers are asked to provide evidence of the digital world’s impact, they are not dealing with isolated, clear-cut outcomes but rather with large, interconnected systems. Theoretical approaches that seek to expand bioecological models of development into the technological sphere highlight the increasing complexity of influence within digital environments (Navarro & Tudge, 2023). Individual interactions (within physical and virtual microsystems) are shaped by and, in turn, shape broader cultural and systemic forces. There is a renewed emphasis on the macrosystem, acknowledging how cultural norms and subcultural variations influence digital behaviour. As Büchi (2024) notes, these digital practices can produce both concomitant harms and benefits, with macro-level cultural, political and economic conditions introducing substantial nuance and variability in outcomes at the individual level. Shifts in digital use at the societal level have meaningful implications for collective wellbeing, which generates complex, moderating pathways that shape the relationship between digital media use and wellbeing at the individual level.

Thus, while it is possible to gather meaningful evidence in such contexts, establishing definitive causal relationships is significantly more complex (Orben & Matias, 2025). Given this complexity, it may be difficult to reliably assess the effect of the system as a whole. Stronger effects may be easier to find when examining the effects of only specific parts of the system (e.g. engagement-based algorithms) on specific experiences (e.g. unwanted exposure to sexual content).

The Role of Scientists as Independent Safety Testers

While researchers face complex challenges in establishing causal evidence of digital technologies' effects, there is growing public concern that these technologies may be driving or accelerating troubling societal changes. Parental groups are increasingly taking matters into their own hands, working together to limit their children's exposure to smartphones and social media (Banfield-Nwachi, 2024). The Smartphone-Free Childhood Parent Pact, backed by over 11,500 schools in the UK, strongly advocates delaying smartphone use until the end of Year 9 (when youth are aged 13–14 years) and keeping children off social media until they turn 16 (Smartphone Free Childhood, 2025). Some parts of the population are also losing trust in scientific evidence, with certain groups urging action before good quality evidence is available and displaying a distrust of researchers working in this area.

As discussed earlier, childhood and adolescence are sensitive developmental periods during which many lifelong psychological and social patterns are established (Orben et al., 2024; Patton et al., 2016). In other industries, such as pharmaceuticals, even a handful of severe adverse effects on an individual level have been sufficient to prompt the withdrawal of entire product lines. This is however not the case for digital technologies in the current regulatory landscape (Orben & Matias, 2025).

When facing questions about digital technology harms, researchers are often called to examine causal impacts of technology exposures on population levels. However, as noted and discussed above, causal approaches from a bio-medical lens also have limitations. It is important that their investigation complements, and does not displace, other research questions and approaches such as: 1) how do we design, incentivise and enforce safer and healthier digital tools and products or 2) how to we enable children, adolescents and their caregivers to be more informed about digital technologies, and enable them to experience more of the benefits and fewer of the harms? While beyond the scope of this report, we emphasise the need to urgently examine such research questions as well. The best research inference, and quickest progress, will be achieved through the triangulation of research approaches reaching across bio-medical and epidemiological approaches, to other disciplines such as engineering, systems design, social and developmental sciences and philosophy.

Given the stakes, the science-policy ecosystem surrounding digital technologies must be increasingly transparent about its inferential risks (Orben & Matias, 2025). On the one hand, researchers might incorrectly conclude that a technology is harmful when it is not. This could hinder societal progress, lead to unnecessary regulation, and unjustifiably restrict children's and young people's freedoms. On the other hand, false negatives also carry risks: failing to recognise a technology's harms due to insufficient evidence and delaying action to do more research while damage continues to accumulate. Such delays could have significant long-term costs for individuals, society and public health.

At present, it is unclear when, or even whether, causal evidence on the effects of digital technologies can emerge, given the methodological and structural challenges outlined above. Science can be adapted and supported to generate evidence more quickly, effectively, and in ways that are more directly relevant to policy — as put forward by this report. However, we must also acknowledge that, in its current form, operating largely outside of tech companies with little systematic support, scientific research will not always be able to produce definitive causal evidence at the speed necessary to inform policy before new technologies become deeply embedded in society (Collingridge, 1980). Some researchers have argued that precautionary public health responses are therefore needed (Hartwell et al., 2024).

At the same time, history has shown that societies are prone to link emerging technologies to concerns about children and young people, sometimes leading to concerns that are not supported by evidence and result in ineffective policies (Cohen, 1972; Orben, 2020b). Human nature dictates a preference for the status-quo, with individuals demonstrating a heuristic preference for technology originating before their birth (Smiley & Fisher, 2022). Poorly designed interventions can have unintended consequences on children's and young people's rights (United Nations, 2021). As a result, it can be difficult to distinguish between when regulation and intervention are necessary responses to the evolving digital landscape.

These difficult decisions about the level of evidence required for policy action are not limited to social media and smartphones. They will be an ongoing challenge as new, largely unregulated, technologies emerge, often with children and adolescents as early adopters. A recent Ofcom report revealed that children and teenagers in the UK were significantly more likely to have adopted emerging generative AI technologies, with 79% of teens (13–17 years) using them, compared to just 31% of adults (18+ years) (Ofcom, 2024b). Parallel to this, a recent survey found that 79% of respondents believe AI products are inherently unsafe for children, reinforcing growing calls for more rigorous safety checks before new AI tools are widely deployed, even if this slows the pace of innovation (NSPCC, 2025).

In today's digital landscape, independent researchers will continue to play a crucial role as safety testers for rapidly evolving technologies. Given the profound societal impact of digital platforms, it is essential to assess and address the challenges facing the scientific evidence provision system as effectively as possible.

We therefore welcome DSIT's commission to explore funding opportunities for establishing causal evidence on the impact of social media and smartphones over the next two-to-three years. While several viable research approaches exist, they will inevitably be limited to addressing specific and constrained research questions. Further, as noted above, they are limited by our focus on specifically causal evidence, defined from a public health and epidemiological perspective. Broader or more complex inquiries — such as digital technology's overarching role in society — will not be answerable to the level of causality typically required for policymaking and government decision-making. Acknowledging this limitation is crucial when determining the most effective research strategies.

Moreover, the recommendations in this report should be viewed as interim measures. Beyond these immediate steps, a more fundamental, long-term shift is needed in how research in this field is structured and supported. This transformation is essential not only for tackling present challenges but also for positioning the UK as a global leader in online safety and ensuring that future digital ecosystems remain innovative, while prioritising the well-being of younger generations.

Summaries of Standalone Research Reports

Appendix 1: Evidence Review Summary

Appendix 1 presents findings from a two-part evidence synthesis. First, we conducted an Umbrella Review of systematic reviews and meta-analyses examining the relationship between time spent on social media, smartphones and AI chat applications, and adolescent mental health and wellbeing. Second, we carried out a narrative literature review of primary studies, systematic reviews and meta-analyses to explore how content, as well as smartphone or social media restrictions (e.g. school bans), may influence adolescent mental health and wellbeing.

In comparison to other reviews on this topic (Meier & Reinecke, 2021; Sala et al., 2024; Valkenburg et al., 2022), we placed an emphasis on assessing the quality and certainty of the existing evidence base — an essential step for evaluating the strength of causal claims. Specifically, we examined whether included reviews applied the GRADE framework to evaluate evidence certainty and whether they considered the Bradford Hill viewpoints on causality — an established set of principles for assessing causal relationships (Hill, 1965). In addition, we conducted our own risk of bias assessments during the narrative review, using an adapted version of the Newcastle-Ottawa Scale tailored to evaluate each study's capacity to support causal inference (Purba et al., 2023b; Wells et al., 2000). By prioritising these areas, our review offers insights that are particularly valuable for policymaking, where understanding the strength and reliability of evidence is crucial for informed decision-making.

Key findings and recommendations

1. Consistent small correlation between time spent on social media and adverse adolescent mental health: seven systematic reviews investigated the impact of time spent on social media and adolescent mental health outcomes. The methodological quality ranged from critically low (n (number of studies) = 6) to high (n = 1). Across the reviews, there was consistent evidence of a small positive association between time spent on social media and adverse adolescent mental health outcomes, including increased depressive symptoms, internalising problems, and antisocial behaviour. This association also appeared in longitudinal data, which suggests that increased social media use may precede deteriorations in mental health. However, it should be noted that while longitudinal studies can demonstrate temporal order, they do not confirm causality on their own. The small number of reviews (n = 7) and the overall quality of underlying studies, which was relatively low, indicate further research is required before firm conclusions can be drawn.
2. Low certainty of causality: while there is some evidence that greater time on social media may be linked to poorer adolescent mental health, the certainty of this evidence remains low. Most primary studies used cross-sectional designs, relied on self-report data, and lacked diverse samples, limiting their ability to infer causality. Observed associations may also reflect confounding factors, and the potential for reverse causality cannot be ruled out. Experimental studies exploring the effects of social media and screen time reduction interventions show some benefits to mental health

and wellbeing, but none focused on healthy adolescents (the pre-determined focus of our review). High-quality targeted RCTs are needed to increase the certainty of causal claims, particularly if they consistently demonstrate improvements in mental health following reduced use.

3. High heterogeneity in findings: meta-analyses found high heterogeneity (i.e. variability) in the association between time spent on social media and depression and anxiety, and no adequate or consistent explanation was provided for this heterogeneity. Moderators such as age or gender were often examined but typically found no consistent differences by age or gender, suggesting the influence of unmeasured or more complex factors.
4. Limitations of the ‘time spent’ metric: many reviews criticised the use of overall ‘time spent’ on social media as an overly simplistic measure. Individual impacts from social media are likely determined by things other than time spent using it (such as the content consumed, or activities displaced for the individual child), other individual vulnerabilities or inequalities. Several reviews called for a shift toward more nuanced measures of social media, such as type of use, timing of use (e.g. during the night) or content engagement. Several reviews highlighted that the characteristics of social media use for example, content viewed, timing and nature of use may be more important than time spent alone.
5. Content-specific harms: our narrative review found that the type of content consumed on social media plays a key role in mental health outcomes. Positive content and feedback can enhance self-esteem and support mental health, while negative content, exclusion and harmful material are linked to anxiety, social comparison and disordered eating, particularly in vulnerable adolescents.
6. Limited evidence on smartphone and social media restrictions: there were few studies examining the impact of school phone policies (diversely defined in the literature) on mental health or wellbeing in adolescents, with findings being mixed and methods contested. Whereas some showed small and context-dependent benefits of smartphone restrictions for wellbeing, reduced bullying, increased physical activity and improved academic performance, others did not. Very few studies reported negative outcomes. Evidence shows that restrictive school phone policies can have a positive influence on in-school behaviours (e.g. reducing screentime in school and bullying, improving academic attainment and engagement, increasing physical activity during breaks), but there is less clear impact on mental health, wellbeing and other associated outcomes that might be determined also by activities outside of the school environment.
7. Lack of evidence for impact of smartphones and AI chat applications:
we found no systematic reviews exploring the impact of smartphone use or AI chat applications on adolescent mental health. This is likely due to smartphones often being studied as part of broader explorations of ‘screen time’ and the emergent nature of AI technologies.
8. Policy decisions must balance risk with evidence limitations: the lack of high-quality evidence should not be interpreted as evidence of no harm. Policymakers must weigh the risks of delaying action against the risks of acting on a limited evidence base. Thoughtful decisions must consider both potential harms and the current limitations of the science.
9. Need for a National Research Strategy: the overall lack of high-quality, policy-relevant evidence highlights the need for a cross-government National Research Strategy on Online Harms. This should include long-term investment in focused

independent research, improved data access and the development of infrastructure to support timely, rigorous and policy-relevant studies.

10. Fast moving research space: with increasing research interest in this area this evidence base will likely expand and change even in the very near future. In addition, technologies and their uses will develop, making previous conceptualisations obsolete. As such this review should be treated as a 'living' review which should be updated over time.

Appendix 2: Research Activity Overview

Appendix 2 examines funded research activities at the intersection of adolescent developmental outcomes and the use of social media, smartphones and AI chat applications. The key developmental outcomes considered included mental health, wellbeing, physical health, lifestyle behaviours and educational attainment. This synthesis of ongoing and planned research draws on information collected from key funders (including, for example, UKRI) and leading researchers.

Key findings are:

1. Focus on adolescence: most funding is directed towards studies on adolescents (over 10 years), with significantly less investment in research on children and infants (under 10 years). This imbalance likely reflects historical trends, as children have traditionally engaged with social media, smartphones and AI less than adolescents. Furthermore, research involving children presents greater logistical and ethical challenges. However, given the increasing digital engagement of younger age groups, there is a growing need for targeted funding in this area.
2. Focus on mental health and wellbeing: a large part of funded research is focused on mental health and wellbeing, with relatively little attention given to other outcomes such as physical health, lifestyle behaviours and educational attainment. This might be appropriate due to large concerns about mental health and wellbeing in adolescent and child populations but needs to be acknowledged.
3. Few RCTs or natural experiment studies: there are few investments in RCTs or evaluation of natural experiments, with more funding instead focused on improving measurement and observational data analysis.
4. Little research on AI use: the US has made greater investments in studying the impact of AI use, including chat apps, on children and adolescents, while there is a paucity of this research in the UK.
5. Lack of dedicated interdisciplinary research centres: the US, as well as Australia, hosts several dedicated digital media and technology research centres. These centres bring together experts to conduct large-scale, agile and specialised research, an infrastructure that is largely lacking or only replicated at a small scale in the UK. Expanding such research capacity in the UK could strengthen the nation's ability to assess and respond to the evolving challenges of digital media in adolescent development.

Appendix 3: Social Media Research: Limitations and Opportunities Report

Appendix 3 provides a more in-depth summary of the challenges facing research on social media and smartphones, while also exploring areas of potential opportunity. This was co-produced with Scientific Consortium members. Six chapters discuss the challenges to: a) generating causal evidence, b) developing high-quality smartphone and social media measures, c) designing effective intervention research, d) creating and using optimal datasets, e) ensuring work is ethical and responsible, and f) adapting the evidence in response to accelerating technological change. By examining current approaches, identifying gaps in the literature, and considering innovative methodologies to address these, this report provides a more in depth foundation to understand how to best advance research in this area.

Research Question Setting and Prioritisation

Research Question Setting

When wanting to engage in research on this area, it is important to set the appropriate research aims and questions.

Firstly, the aim of the research must be clearly defined. As discussed above, causal approaches rooted in classical epidemiological epistemology have both strengths and limitations, making them more suitable for addressing some research aims and questions than others. For instance, they tend to prioritise the investigation of the impacts of individual-level exposures on population-level impacts rather than the impacts of individual-level exposures on individual-level outcomes. If the objective is to understand individual-level harm (e.g. in a specific individual) or to develop short-term interventions that enhance digital environments, improve safety or offer parents and young people practical, real-time tools to navigate challenges, then estimating causal population-level impacts should not be the primary focus. Recommended scientific approaches would therefore vary depending on the aim of the research commissioner, for example, whether they are government officials, technologists, parents, litigators examining individual harms, etc.

If the priority is to generate causal evidence on the effects of social media and smartphone use on populations of children and adolescents in the next two to three years (as stated by this commission), research must begin with a well-defined question that is scientifically testable. This requires identifying a specific exposure and outcome pairing, if taking an approach focused on causal inference.

There are numerous possible exposures to consider. For instance, researchers might investigate the age at which children first access, own or use smartphones or social media, or the type of content consumed (especially certain types of harmful or problematic content). Other areas of interest could include interactions with so-called ‘addictive designs’ or usage during key times of the day, such as school hours, late at night, or during mealtimes. The impact of school-wide or country-wide bans on social media or smartphones, as well as other regulatory interventions, could also be explored. Each of these predictors requires a distinct research project and approach.

The range of potential outcomes is equally broad. Researchers might focus on self-reported well-being, clinical diagnoses such as anxiety, depression or eating disorders, academic performance, or behaviours such as bullying, violence, sleep or self-harm. The timeframe of interest is also fundamental to the type of study being run. Understanding whether social media influences mood within minutes or has long-term developmental effects over several years would require different methodological approaches.

Another key consideration is the study population. If researchers decide to study individuals as the unit of assessment, they must decide whether to examine the general adolescent population or focus on those most at risk, such as children with pre-existing mental health or neurodevelopmental vulnerabilities, those in care, or those living in isolated or crisis-affected areas. Developmental stage and environmental factors are also crucial (Orben & Blakemore, 2023; Valkenburg & Peter, 2013). However, researchers can also study communities or other types of groups (such as schools) as units of assessment which would need a different approach.

Furthermore, researchers must determine how to account for the complexity of real-world behaviours. Digital media not only influences children and young people but is also shaped by their emotions and behaviours in a bidirectional manner (Panayiotou et al., 2023; Büchi, 2024). There is ongoing debate, and subsequent longitudinal research, about whether digital experiences merely reflect offline realities or amplify them (Kostyrka-Allchorne et al., 2024). For example, studies show that most children who experience cyberbullying also face bullying in offline settings (Przybylski & Bowes, 2017). On a similar note, phones can act as a conduit for both cyberbullying and peer rejection, whilst also fostering a sense of connection and belonging: meaning the direct impact of smartphone bans on child mental health is not clear cut, and the ethics of subsequent research must account for this (Campbell et al., 2024). Similarly, exposure to harmful content can have negative effects that are expressed online and offline.

Research Question Prioritisation Methodologies

With a multitude of potential causal research questions, a critical challenge is determining which to prioritise. For long-term discovery and curiosity-driven science such prioritisation can be done within research teams, informed by strong theory (see 'Theory Building' section below). Yet for short- and medium-term research intended to inform policy, this requires stronger collaboration between researchers, policymakers and other stakeholders. Researchers may not always be aware of the most actionable research questions, as some topics may be more relevant for policy or intervention than others. The type of study needed will differ depending on whether the goal is to evaluate a ban on social media for under-16s, assess the impact of certain types of content, or measure the effects of screen time on developmental outcomes. Furthermore, as researcher expertise is oftentimes specialised, successful collaboration between different types of researchers — such as digital media, public health and mental health researchers — is of value. Further such collaboration can highlight emerging areas of concern that require study.

There is no universally agreed-upon process for setting research priorities at a national level. However, one influential model for prioritising research comes from the James Lind Alliance (National Institute for Health and Care Research, James Lind Alliance 2025), a UK-based non-profit established in 2004 by NIHR. Its goal is to align research priorities with the needs of patients, carers and clinicians. The Alliance facilitates Priority Setting Partnerships (PSPs) that identify and rank unresolved research questions, known as 'evidence uncertainties', based on their real-world importance.

The PSP process begins by collecting input from affected communities (in the medical literature this is often patients, carers and clinicians, but these will be different for our topics of interest) to identify knowledge gaps. These uncertainties are then prioritised through structured consensus-building, leading to a top ten list of research priorities. This process can incorporate multiple approaches, with Lund et al. (2022) suggesting four: expert consultation, stakeholder engagement, literature review and ranking.

Once priorities are set, they are promoted to key stakeholders, including research funders, scientists and groups of affected communities. This approach has demonstrable efficacy in this research space, with Hollis et al. (2018) successfully using this method to identify ten research priorities related to the safety and efficacy of digital technology interventions in comparison with face-to-face interventions in mental health research and treatment.

Recent studies have adapted this framework for use with children and young people, albeit in different topic areas than the one discussed here. For example, Aldiss et al. (2023) demonstrate that the methodology is largely analogous when applied to younger age groups. By ensuring that both the language and the purpose of the research were age-appropriate and accessible, this approach has shown demonstrable success in generating research priorities with children and young people. For more information on involving children and adolescents see 'Involvement of Children, Adolescents and Caregivers' section.

Research Question Prioritisation for Policy

A key recommendation for research prioritisation under any applied Research and Development funding from DSIT is to focus on research that can result in actionable outcomes that are most relevant to policy decision-making over the next two to three years. Research should be designed to inform interventions that can be implemented using existing or new policy levers within the department or across government, and it should measure outcomes that are of highest strategic importance for policy impact.

Table 2 below outlines potential areas of interest across digital technology types, forms of exposure, outcome measures, population groups and subgroup analyses. We would recommend a prioritisation exercise is completed by DSIT, and by any other research funder or commissioner, where each is ranked in terms of priority and urgency (low, medium, high), based on their relevance to current policy priorities. For DSIT, to align with their brief, this would be thinking about the next two- to three-year timeframe, but for others this could be longer or shorter term. These priorities will need to be informed by the priorities of DSIT and other key policy stakeholders, as well as potential consultation with affected communities. They are subject to short term change.

For example, a trial prioritisation exercise by a subset of our team showed that the potential research question on how removing social media completely, or partially in certain settings or times (e.g. at night) impacts the mental health of adolescents might be a high research and development investment priority for the next two to three years. As policy needs continue to evolve, such a recommendation should however be considered time-sensitive and subject to change. Our trial prioritisation exercise was also specific to current policy need, and did not consider what research should be invested in now to help future policy decisions that are less urgent at present. For example, one could argue that investing in impacts of AI applications might be an important investment to target current and future policy concerns.

It cannot be overstated that the ultimate success of any research commission by DSIT in this area will depend, in part, on setting the right research question — which in turn will allow researcher collaborations to determine the right research methodology and approach.

Table 2. Recommended research question priority setting table for policymakers and other research commissioners.

Outcome	**Priority**	**Urgency**	**Ranking**
Technology			
Social media			
Smartphones			
AI applications			
Other technology			
Exposure			
Time spent: continuous outcome			
Time spent: total removal/ban			
Time spent: partial removal/ban (certain setting, e.g. school)			
Time spent: partial removal/ban (certain time, e.g. at night)			
Content: harmful content			
Content: other types of content			
Activity: posting content			
Activity: passive scrolling			
Activity: social comparison			
Addictive design features			
Other exposure metric			
Type of Outcome			
Mental health			
Wellbeing			
Educational attainment			
Lifestyle habits			
Violence and crime			
Hate and extremism			
Physical health			
Other outcome metric			
Population			
Infants (Under 5 years)			
Children (5–9 years)			
Adolescents (10–18 years)			
Young adults (19–24 years)			
Other population			

Subgroup Analyses			
Sex			
Age			
Disability			
Ethnicity			
Socio-economic circumstance			
Urban/Rural			
Care experienced			
Sexual orientation			
Gender identity			
Religion			
Other subgroup			

Potential Research Methodologies

Below we review seven potential methodologies for obtaining causal evidence of the impact of social media and smartphones on child and adolescent outcomes in the next two to three years. Specifically, we consider the benefits, challenges and potential ethical considerations of systematic reviews, qualitative methods, observational data analysis on pre-existing datasets, observational data analysis on augmented pre-existing datasets, ecological momentary assessment studies (EMAs), natural experiments and RCTs.

Again, we note that we specifically focus on classical epidemiological perspective due to the scope of this commission. As a result of this limited scope, other relevant approaches to enhance digital safety such as engineering systems design are not covered. In addition, we do not cover standalone new long-term data collection (e.g. new cohort studies) due to the inability to deliver standalone long-term longitudinal data collection in the provided two to three year timeframe. Instead, we frame discussions of new longitudinal data collection in terms of developments and data linkage in existing cohorts.

Table 3 below summarises our reviews' conclusions on each method's ability to obtain causal evidence of the impact of social media, smartphones and AI chat applications on child and adolescent developmental outcomes in the next two to three years. This is a simplified version of a summary table that can be found in Appendix 7, which gives further information on our classification mechanism demonstrated here in Table 3.

Table 3. Evaluation of research methods overview.

Method	**Ability to get to causal evidence**	**Ability to run study in two to three year timeframe**	**Flexibility to changing policy priorities and technologies**	**Ethical concerns**	**Cost**
Systematic reviews	Low	High	Low	Low	Low
Qualitative methods	Low	High	High	Low	Low
Observational analysis using	Medium	High	Medium	Low	Low

existing national data assets					
Augmenting existing observational or cohort datasets	Medium/ High (with potential to upgrade to high if high-quality digital trace data is linked)	Medium	Medium	Medium (with potential to upgrade to high if sensitive digital data is linked at scale)	High
Ecological Momentary Assessment studies	Medium/ High (with potential to upgrade to high if high-quality digital trace data is linked)	High	High	Low (with potential to downgrade to medium or high if sensitive digital data is linked at scale)	Medium
Natural experiment studies	High (with potential to downgrade to low if no appropriate natural experiment is found)	Medium	Low	Low (with potential to downgrade to medium if new data collection if needed)	Low (with potential to downgrade to medium if outcome measures are costly to collect or multiple evaluations are carried out)
Randomised Controlled Trials	High	Medium (with potential to downgrade to low if complex design is needed)	Low	High (with potential to upgrade to medium or low if RCTs of purely digital short-term interventions are run)	High (with potential to upgrade to medium if RCTs of purely digital short-term interventions are run)

***Note.* The colours in the table represent the relative strength of each methodology in a given category. A green cell indicates that the characteristic or value in that cell is considered a strength in that specific context, rather than indicating a high or low value.**

As noted above, each research question of interest can have a different recommended research method. In our assessment we prioritised the research question of how removing social media completely, or partially in certain settings or times (e.g. at night) impacts the mental health of children and adolescents, due to our judgement of its high policy priority.

In summary, the methods with the strongest capacity to generate causal evidence (see column 1 in Table 3) are the evaluation of natural experiments and the implementation of RCTs. Both approaches could be completed within two to three years, although only if less complex study designs are prioritised and ethical concerns are minimal. However, they are relatively inflexible in responding to shifting policy priorities and tend to incur medium to high costs.

Standard large-scale RCTs are typically more expensive and pose greater ethical and practical challenges. Nevertheless, they can be conducted directly within the UK population, which enhances the relevance and applicability of the findings. Smaller-scale RCTs, as discussed under ‘Method 7: RCTs’ below, are a feasible alternative and may help mitigate some of these concerns. In contrast, natural experiment evaluations are generally more cost-effective and ethically straightforward, though their feasibility depends on the occurrence of relevant policy changes or events in comparable populations, along with the availability of high-quality data to assess outcomes. If natural experimental evaluations of international policy changes are prioritised, this would mean that DSIT will inherently have to wait for such evaluation to take place before being able to decide whether to take similar action.

If generating robust causal evidence is a priority for DSIT's Research and Development investment, we recommend a dual approach that supports both RCT and natural experiment evaluation methods. This strategy would balance risk, cost and impact. It is particularly important given that our Research Activity Overview Summary (Appendix 2) indicates very limited support, and planned support, for such methodologies within the current research landscape.

As outlined in our Evidence Review (Appendix 1), natural experiments and RCTs offer the best potential for improving causal claims regarding the links between digital technology use and child outcomes. However, if this goal is not central to DSIT's priorities, alternative methods may be more suitable. For example, causal modelling of pre-existing data can make progress in this direction if designed appropriately, as well as qualitative methods and ecological momentary assessments (EMAs) which provide less robust causal inference but are more adaptable to evolving policy needs and generally involve lower costs. As noted in Appendix 2, these types of studies are already more commonly supported within the research landscape.

Additional recommendations, particularly for longer-term investment not covered by the scope of this report, include enhancing the quality and scope of digital technology data within large-scale UK observational cohort studies. This is especially the case for new investments such as the EOP-S cohorts and the Adolescent Health Study. Linking longitudinal data to high quality measures of digital engagement, and including high-quality self-report measures for more subjective perceptions of use, would provide a flexible and sustainable foundation for advancing research and improving the evidence base over long periods of time.

Further, there is agreement across the Scientific Consortium that there exist important cross-cutting foundational investments in theory building and the involvement of children, adolescents and caregivers in research that should not be overlooked as a vehicle to improve research quality and effectivity in the longer term and keep up with accelerating and novel technological change.

Method 1: Systematic Reviews of Pre-existing Literature

Approximate total cost of project: £250,000–£400,000

Major factors that determine cost level:

1. Size of literature under review.
2. Number of different sub-analyses requested.
3. Use of GRADE methodology.

An essential method for informing policy is the systematic synthesis of existing literature to address specific causal questions. This can be achieved through a systematic review, which involves a structured search and narrative synthesis of findings, or a meta-analysis, which quantitatively combines effect sizes from multiple studies to estimate an overall effect. While these approaches are observational and do not generate new data, they represent the gold standard for evaluating the strength, consistency and reliability of evidence across pre-existing studies. When conducted rigorously, systematic reviews and meta-analyses provide valuable evidence for policy decisions, helping to identify patterns, assess potential biases and contribute to causal inference by highlighting areas of consensus, divergence and critical gaps in the research.

The focus of a systematic review must be on a well-defined exposure, with the research question structured using the PICO framework (Population, Intervention/Exposure, Comparison, Outcome). To ensure transparency and minimise selective reporting bias, the review protocol should be pre-registered with PROSPERO or a similar registry (National Institute for Health and Care Research, 2025b). This step helps mitigate bias by committing to the review's methodology and scope before the research process begins.

The review should, where possible, prioritise studies with stronger causal potential, such as randomised controlled trials (RCTs) over non-randomised studies, as potential biases are greater for non-randomised studies (Cochrane, 2025a). In addition, included studies should be evaluated for their alignment with established causal inference frameworks, while also considering structured approaches to evaluating causality such as the application of Bradford Hill principles (Hill, 1965; Shimonovich et al., 2020). For example, a recent method drawing on principles of process tracing proposes assessing each Bradford Hill principle based on its uniqueness and definitiveness — whether supportive evidence cannot be easily explained by alternative factors, and whether contradictory evidence strongly undermines the causal claim (Shimonovich et al., 2024). This can enhance the transparency and rigour of causal assessment in systematic reviews, particularly of non-randomised studies. Alongside these considerations, studies should also be assessed for risk of bias using well-established Cochrane endorsed tools such as the Cochrane Risk of Bias 2 (RoB 2) Tool for randomised trials or the ROBINS-E tool for non-randomised studies (Cochrane, 2025b; Higgins et al., 2024; Shimonovich et al., 2024).

To strengthen causal inference, meta-analytic techniques should be employed if possible. For example, meta-regression can be used to assess whether study-level factors, such as exposure dose, population characteristics or intervention duration, contribute to variations in effect sizes. By accounting for these moderators, this technique helps isolate the impact of the key variable (e.g. exposure to specific types of content on social media) and strengthens the evidence for a meaningful relationship.

Furthermore, the GRADE (Grading of Recommendations Assessment, Development, and Evaluation) system provides a structured approach to assess the quality of evidence in systematic reviews (Guyatt et al., 2011). It evaluates factors such as study design, risk of bias, consistency of findings and precision of estimates. GRADE allows researchers to provide clear recommendations about the strength and reliability of the evidence, which is crucial for making informed policy decisions.

Benefits of Approach

Systematic reviews offer two key benefits. First, they are a cost-effective alternative to research designs that require the collection of primary data. By aggregating findings from multiple studies, they enhance statistical power, allowing for the detection of trends and patterns that may not be evident in individual studies. In addition, they provide a comprehensive overview of the existing evidence, helping to identify gaps in the literature and guiding future research priorities.

Challenges of Approach

The reliability of systematic reviews and meta-analyses is directly dependent on the quality of the studies they include. Poor-quality studies can skew results and make them unreliable and unhelpful. As discussed in previous sections, much of the existing literature in this research area suffers from methodological limitations (e.g. observational studies with self-reported measures), meaning that systematic reviews will not fully overcome these issues. Since GRADE transparently assesses the quality of included studies, its adoption should be prioritised for reviews intended to inform policy decisions (Guyatt et al., 2011). Furthermore, there are relatively few studies addressing key policy-relevant questions, such as the impact of social media bans, further limiting the utility of this method in informing concrete policy decisions.

However, systematic reviews are not inherently causal; they approximate causality by synthesising existing evidence. In fields where studies vary significantly in design, methodology and outcome measures, meta-analysis becomes particularly challenging. This is especially true in longitudinal research, where diverse modelling methods make comparisons difficult. Moreover, high heterogeneity in the data would prevent a meta-analysis, thus requiring a shift to narrative synthesis, which, while useful, lacks the standardisation and comparability offered by quantitative meta-analytic techniques.

To address these challenges, frameworks like GRADE and Cochrane Risk of Bias tools are essential for evaluating a study's ability to make causal inferences. As discussed, GRADE evaluates the quality of evidence based on factors such as risk of bias, consistency and the precision of the data, explicitly identifying whether studies provide sufficient evidence to draw causal conclusions (Guyatt et al., 2011). The Cochrane Risk of Bias tools similarly assess the risk of bias in randomised and non-randomised studies, helping to determine whether the design and conduct of a study allow for valid causal interpretations (Cochrane, 2025b; Higgins et al., 2024). These tools are critical for ensuring that the studies included in systematic reviews are capable of supporting reliable, causal inferences — vital for evidence-based policymaking.

Ethical Considerations

Systematic reviews are generally considered to have low ethical risk, as they do not involve primary data collection. To ensure transparency and consistency, preregistration of the review process and adherence to standardised guidelines, such as the PRISMA guidelines, are essential (Page et al., 2021b). Additionally, conflicts of interest should always be declared, and to minimise bias, quality assessments should be double-coded by at least two reviewers.

Method 2: Qualitative Methods

Approximate total cost of project: £250,000–£600,000

Major factors that determine cost level:

1. Type of qualitative research methods applied.
2. Diversity and representativeness of populations studied, and the proportion of which is ‘hard to reach’ (e.g. care experienced children).

When implemented effectively, qualitative research such as in-depth interviews, focus groups and ethnographic studies can play a crucial role in advancing causal understanding by complementing other research methods. Qualitative research makes two central contributions specifically to research questions regarding causal inference. First, it allows the refinement of causal hypotheses by uncovering underlying mechanisms and contextual factors that shape observed relationships. Second, it allows the generation of new theories or evidence that can later be tested in studies explicitly designed to establish causal links. While it does not directly produce causal evidence, it provides critical further information needed to advance the field. A rigorous qualitative research process would involve multiple, iterative stages designed to maximise its contribution to causal inquiry.

A wide range of engaging qualitative approaches could be employed to investigate the impact of social media and smartphones on adolescent mental health including focus groups, interviews, diaries, observational studies, offline/online ethnography, content analysis (especially important for policy analysis or guidance), visual elicitation methods (including photo elicitation and card sort tasks) and oral elicitation tasks (e.g. think aloud protocols) (Goodyear & Bundon, 2021). The precise approach used (e.g. inductive, deductive, hybrid and analytical) should be driven by the research question being investigated, for example, if exploring the experiences of an underexplored group of young people then inductive would be more appropriate, but for theory building hybrid is often more appropriate.

There are a range of analytical approaches that can be employed in qualitative methods including thematic analysis, IPA, content, framework, case study, narrative, grounded theory and epistemological. The choice of analysis will be driven by the research question, sample and the context. Analyses commonly identify recurring patterns, themes and explanatory mechanisms that are developed from participant responses. This process may involve coding transcripts, clustering related concepts and mapping emergent themes onto existing theoretical models. See, by way of example, Goodyear et al., 2019; Goodyear & Armour, 2021.

Qualitative studies should be conducted with stakeholders relevant to the causal question of interest. The precise design should be informed by theories of change to systematically identify potential underlying mechanisms and confounding factors. To strengthen causal inference, qualitative findings can be systematically compared with evidence from other methods such as interventions, natural experiments or longitudinal observational data analysis. This mixed-methods approach enables the triangulation of evidence: qualitative data can help contextualise and interpret quantitative results, revealing mechanisms or moderators that may not be apparent in large-scale datasets. Conversely, quantitative data can be used to validate qualitative findings by assessing their generalisability and prevalence across broader populations. Some methods are inherently mixed methods by design, such as the Card Sort Task for Self-Harm which was co-created with young people to enable them to describe their subjective journey to self-harm (Townsend et al., 2016). The results can be analysed qualitatively (Bilello et al., 2025; Lockwood et al., 2020) or quantitatively (e.g. by using sequence analysis (Townsend et al., 2016; Wadman et al., 2017)),

Benefits of Approach

Qualitative approaches offer three key benefits. First, they offer insights into participants' perspectives and concerns that cannot be obtained otherwise. This is valuable when researching a new topic to discover the terms in which people think and express themselves, to reveal unexpected patterns or concerns, and to identify differences among participants. It is especially valuable when working with sensitive topics and/or disadvantaged or vulnerable groups (including children). Qualitative approaches contribute to knowledge in their own right, and have their own standards of robustness and validity. Second, when incorporated in a mixed-methods research design, they can also generate rich primary data that can provide in-depth information regarding the underlying mechanisms between an exposure and an outcome, thereby contributing to the validity of the study and trouble-shooting researchers' misconceptions, inappropriate wording or unexpected results. By integrating qualitative findings into causal frameworks, researchers can develop new and testable hypotheses for subsequent quantitative and causal studies, ensuring that future experimental and observational research is better aligned with real-world complexities that are rife when considering social media and smartphone use.

Third, they amplify the voices of user groups with unique perspectives on online harms without taking a top-down perspective based on researcher or policymaker assumptions. Qualitative methods allow researchers to explore how individuals experience and interpret digital environments, providing a nuanced understanding of behavioural drivers and social dynamics that quantitative studies may overlook. For example, interviews can provide initial information on why certain populations may be more vulnerable to the negative effects of social media, how specific platform features influence engagement patterns, or what contextual factors mediate the relationship between smartphone use and mental health outcomes. Such approaches can also elucidate the meaning of quantitative findings. For example, adolescents may spend extended periods of time on social media because they want more social connection, or they are subject to peer pressure, or they are seeking escape from a negative situation or emotion. By capturing lived experiences and emergent themes, qualitative research can help ground other causal approaches in real-world complexities, ultimately enhancing the design and interpretation of subsequent experimental and observational studies.

Qualitative methods may also be relatively low-cost when compared to interventions or large-scale observational research, and careful recruitment can compensate for the limitations on representativeness that often characterises quantitative approaches, especially as regards 'hard-to-reach' groups.

Challenges of Approach

Qualitative research provides another means of understanding causality, while not providing causal evidence itself (e.g. by exploring sequences, pathways and/or patterns in behaviours or outcomes from participant perspectives), that requires robust processes for ensuring quality and rigour (e.g. authenticity, transparency, fairness and coherence [with theory] (Goodyear & Bundon, 2021; Townsend et al., 2016; Tracy, 2010). Qualitative research introduces a higher degree of subjectivity compared to experimental or statistical approaches, requiring strategies to enhance the quality (also referred to as validity or reliability) of the research process (Smith & McGannon, 2018; Tracy, 2010).

The depth of engagement required in qualitative research also makes it a time-intensive process, often involving extensive interviews (focus group and individual), observations, content and visual analysis, and/or engagement with artefacts (e.g. card sorts, creative materials produced). To generate meaningful data with participants, concerted time is required by researchers to build trust and relationships to facilitate the sharing of opinions, thoughts and feelings, and to develop honest responses (equally to minimise othering). See by way of example: Smith et al., 2023.

While qualitative methods yield rich, contextually grounded evidence, they typically focus on smaller samples compared to quantitative methods, that are less representative and generalisable to broader populations in comparison to other methods (Smith, 2018). Furthermore, research outcomes are highly dependent on sample composition, meaning that careful consideration must be given to participant selection, recruitment strategies and potential limits in representation (Wood et al., 2023).

Furthermore, the beliefs and prior experiences of both researchers and participants must be considered. While researcher bias can be mitigated through strategies such as reflexivity and pre-registering qualitative hypotheses (Karhulahti et al., 2023), participants' responses may also be shaped by dominant cultural narratives. For example, young people may internalise negative societal messages about social media use, which can affect how they interpret and report their experiences, and this raises challenges for distinguishing between perceived and actual effects (Black et al., 2024a).

Addressing these challenges requires methodological rigour to enhance validity and reliability. A number of criteria can be employed, including transparency in data collection (e.g. pre-registration of analytical plans), reflexivity in analysis, member sense checking, co-production at all stages of the study and triangulation with other evidence sources (see an example of co-produced registered focus groups with young people; Hickman Dunne et al., 2025; see, for an overview of approaches, Hickman Dunne et al., 2025; Lloyd et al., 2024; Tracy, 2010). One key strategy is the use of multiple coders to cross-check themes, helping to minimise individual researcher bias and ensure that the findings reflect the participants' experiences. To reduce social desirability bias, i.e. that participants may disclose what they think the researcher wants to hear, researchers should design open-ended, non-leading questions and foster a safe, non-judgemental environment where participants feel comfortable sharing their experiences. Conducting focus groups within communities can improve access to hard-to-reach populations, ensuring that diverse perspectives (particularly those from marginalised or underrepresented groups) are included.

Ethical Considerations

This approach is considered to have low to medium ethical risk, depending on the approach, population and sensitivity of the topic. Several risk mitigation strategies should be considered. First, parental consent and the assent of young people should be obtained (these can be via opt-in or opt-out dependent on the level of perceived risk (Kucirkova et al., 2024)).

Second, distress and safeguarding protocols must be in place. For example, researchers must consider the potential emotional impact of discussing sensitive topics related to online risks, but also consider the challenges with discussing sensitive topics in a group setting (in focus groups). The context of data collection is also key, including the spaces used (school, home, online, clinic) and the researcher profile (including relationship to participants, training and familiarity). Therefore, participants should be adequately supported, with clear safeguarding measures in place especially for children and young people, such as access to counselling resources or referrals to relevant support services. Schools are ideal places to conduct one to one interviews or focus groups, as they have clear safeguarding and support systems in place, and all schools have a designated safeguarding lead with pathways of communication to home and support services. This also includes providing participants with the right to withdraw during and after the research process, and de-briefing participants. Steps relating to confidentiality also need to be transparent, such as if a participant discloses sensitive information and/or the researcher becomes aware of a safeguarding issue. See Randhawa et al., 2024 for an overview of safeguarding adolescents in digital mental health research in schools.

Third, researchers must consider the value and challenges of making qualitative data openly available. For example, safeguarding duty to adolescents must be ensured, and the difficulty in fully anonymising qualitative data must be considered (Tamminen et al., 2021). In such cases, explicit parental consent and young person assent must be obtained and data must be carefully anonymised and deposited in databases with appropriate restrictions (e.g. UK Data Service, 2022).

Method 3: Observational Analysis Using Existing National Data Assets

Approximate total cost of project: £400,000–£800,000

Major factors that determine cost level:

1. Type of observational data analysis applied (which will determine expertise and size of team required).
2. Number of different analyses requested.
3. Data access costs for observational datasets.

Another method is the analysis of pre-existing observational data from cohort studies, health surveys, or administrative datasets without adjusting or augmenting these assets. The UK is home to some of the world's leading cohort studies on children and young people, such as the Avon Longitudinal Study of Parents and Children (ALSPAC), the Millennium Cohort Study (MCS), Understanding Society, and Born in Bradford. These studies have been instrumental in advancing knowledge on child and adolescent development. ALSPAC, for instance, has tracked a cohort of over 14,000 children since their birth in the early 1990s, while the Millennium Cohort Study follows 19,000 children born in 2000–2001, providing rich longitudinal data on various aspects of life, from health to education. The study aims to understand the factors that influence health and development, particularly during early childhood, and to improve health outcomes in diverse, disadvantaged communities.

Research approaches can leverage such pre-existing investment in the UK's data ecosystem to enable researchers to track trends and identify patterns that develop over time, offering unique perspectives into long-term outcomes. For instance, researchers can examine temporal relationships between social media exposure and key outcomes, such as mental health, lifestyle behaviours, or educational attainment, providing valuable evidence for understanding how digital media shapes child and adolescent developmental outcomes over time.

While observational studies do not inherently establish causality, advanced causal inference methods, such as target trial emulation and directed acyclic graphs (DAGs), can strengthen causal claims by accounting for confounding variables and simulating experimental conditions. Furthermore, existing cohorts also act as an invaluable resource for evaluating the impact of large-scale shifts in the environment in natural experiments (i.e. policy changes), through providing participant-level data before and after the change.

A Target Trial is a hypothetical randomised trial that cannot necessarily be conducted, but is used in the field of causal epidemiology to enhance the robustness of planned observational analyses. Observational data are used to emulate the target trial and thereby have many of the key features of randomised trials required for causal inference (e.g. comparability of exposed and control groups) (Hernán et al., 2022). This approach clarifies causal questions, reduces biases (e.g. confounding, selection, measurement and information biases), and enhances transparency. By explicitly defining design choices, it improves reproducibility and comparability with randomised trials (Hernán et al., 2022). The approach involves articulating the causal question which is framed as a protocol for a hypothetical randomised trial. If conducted, researchers should seek to align their trial with the upcoming *TrAnsparent ReportinG of observational studies Emulating a Target trial (TARGET)* guideline (Hansford et al., 2023).

A primary limitation in existing evidence is the lack of transparency regarding confounder selection and the use of theory-free statistical criteria and algorithms to inform selection (Heinze et al., 2018). Few of these conventional approaches specifically consider each variable's role in relation to the exposure and outcome, and it is often unclear why certain variables were selected for consideration and others not. Thus, reported associations are uninterpretable, highlighting the need for DAGs. With development supported via subject knowledge, existing evidence and input from youth and policymakers, DAGs can allow for the explicit illustration of hypothesised causal pathways.

Benefits of Approach

Using pre-existing observational datasets offers a range of key benefits. First, this method is cost and time effective, as it eliminates the need for new data collection, and it reduces participant recruitment and personnel costs.

Second, these datasets are particularly valuable due to their large sample sizes, which enhance statistical power and support the generalisability of findings across diverse populations. In addition, the large sample sizes improve the ability to analyse subgroups, including vulnerable populations, providing more detailed understanding into how diverse groups may be affected by digital media. Many of these studies regularly collect self-reported and subjective data on digital media usage, including smartphone ownership, social media account usage and screen time, alongside a variety of developmental outcomes such as mental health, academic performance and behavioural patterns.

Third, these methods offer a unique opportunity to identify early risk factors linked to social media use and to explore the long-term effects of digital exposure across various stages of development. Furthermore, they enable researchers to track pathways over extended timescales, including how social media use interacts holistically with multiple other determinants of health outcomes, providing a more nuanced understanding of how digital media influences adolescent development and well-being.

Observational data analysis approaches could be used to assess a multitude of research questions using such data, and this combined with the use of DAGs would act to produce high quality transparent research which would be well-placed to inform policy.

Challenges of Approach

While pre-existing observational data offers many benefits, there are several challenges that limit its utility for addressing research questions in the two to three year timeframe. The primary limitation here is the lack of high-quality and precise digital trace data collection within UK cohorts and other data collection initiatives. This point is addressed directly below (in Method 4).

However, subsidiarily, it is important to note that many of the established cohort and household panel surveys are limited to specific samples which have aged over time and are now adults or young adults, making this group not suitable to address research questions of interest. For example, participants in ALSPAC are now approximately 33 years old, while participants in MCS are 23 years old. In the past years various new cohort studies have therefore been funded including the Adolescent Health Study (UKRI, 2024), and three DfE funded cohort studies comprising an early years, primary school, and secondary school cohort (Bernardi et al., 2023; Ipsos, 2025; National Centre for Social Research, 2025).

Conducting a high-quality observational data analysis generally takes at least 1.5 years, and data collection for several of these cohorts is still in the initial stages (for example, recruitment letters for ‘Growing up in the 2020s’ were sent out in January 2025). As a result, it is unlikely that this specific subset of new cohorts will be able to deliver the required insights within the two to three year timeframe requested by DSIT when considered in isolation.

There are also critical limitations to consider that relate both to this method and to Method 4 (Observational Analysis of Improved Pre-existing Data). Observational data cannot provide experimental controls, whereby researchers randomly assign adolescents to different levels of social media use. Use of the Target Trial approach could address this limitation in part. Further, observational data is susceptible to confounding variables, i.e. factors (e.g. age, sex, family conflict, life stressors, personality traits) that causally influence both the exposure (e.g. social media use) and the outcome (e.g. mental health), potentially distorting the results and making it difficult to determine direct causal effects. However, use of DAGs as well as researcher participation in UK Cohort survey consultations to ensure adequate data on confounding variables is collected could act to address this limitation in part.

Data from observational studies is typically collected on an annual basis, which can be problematic for studying phenomena that unfold over shorter time periods (e.g. days or months), such as the impact of exposure to negative content online on adolescents’ mood. The use of longitudinal data is not highly agile or adaptable, as incorporating new questions or adapting the study design to address emerging research questions is often a slow and difficult process. Finally, the long-term nature of these studies can present challenges in maintaining participant engagement, leading to high attrition rates that can reduce the generalisability and reliability of the findings. These limitations are further compounded when digital trace data is incorporated, as ethical concerns, data access restrictions and data sparsity can limit both feasibility and validity (Al Baghal et al., 2020).

Ethical Considerations

There are generally few ethical concerns associated with the analysis of pre-existing observational data, as the data has already been collected and is typically managed by established research teams with appropriate infrastructure in place to address any potential issues. Nonetheless, it is essential that participants are made fully aware of the informed consent processes and their right to withdraw from the study if needed. Personal data should be anonymised or de-identified before storage and analysis to safeguard participant privacy. Additionally, strict adherence to GDPR regulations must be ensured, particularly regarding participant rights, data retention and data protection protocols. Regular audits and ethical reviews should be conducted to ensure compliance with privacy and data security standards throughout the research process.

Method 4: Augmentation and Improvement of Existing National Data Assets

Approximate total cost of project: £500,000–£1,500,000

Major factors that determine cost level:

1. Type of linkage mechanism (e.g. commercial apps or use of pre-existing public funded infrastructure like the UK Smart Data Donation Service).
2. Number of participants linked (i.e. full cohort or only a random selection).
3. Amount of linkage points (if permission for data linkage cannot be given on an ongoing basis, it might need to be updated at certain time thresholds).
4. Infrastructure and personnel costs for different large-scale datasets.
5. Alignment of digital trace data collection with pre-existing data asset strategic priorities (e.g. facilitation of a cohort’s digital trace data collection roadmap).

Another promising avenue for investment is the targeted augmentation of pre-existing high-quality cohort or household panel datasets outlined above. This approach can significantly increase the value of prior data investments by improving both the quality and specificity of digital exposure measures. This has been identified as a key limitation in Method 3. After augmentation, analytic pipelines outlined in Method 3 can be employed but with the potential for radically improved evidence generation.

Data augmentation in this context falls into three broad priority tiers with reference to efficiency: with each descending tier, immediate impact is reduced and potential costs are increased.

A top priority, taking a public health approach, would be to augment high-quality pre-existing data products with precise and objective retrospective measures of digital behaviour (e.g. social media, smartphone and AI chat app use histories). Various mechanisms allow researchers to obtain a copy of an individual’s digital history (sometimes referred to as data donation), and to fuse this history to all pre-existing data that is held regarding that individual (e.g. self-report measures and health records within a cohort study). By fusing retrospective digital trace data to pre-existing data, this strategy immediately enhances the potential of observational research to address causal research questions regarding amount of use or content consumed without the costs and delays associated with collection of future (prospective) waves of data.

A secondary priority would be to augment ongoing and novel data collection with the precise and objective prospective measurement of digital behaviour. In contrast to the strategy outlined above, this prospective work would involve the integration of novel data collection strategies into cohorts and other large-scale data collection efforts with the aim of tracking future (rather than prior) behaviour in a high-quality way. These measures could be of time spent on digital devices or specifics apps, as well as specific content viewed and interactions (e.g. likes, comments).

Both strategies outlined above directly address the common limitation of cohort studies, where exposure measures are often imprecise, reliant on self-report rather than objective data, and limited to specific (e.g. annual) time-points, enabling more accurate and impactful conclusions about the effects of digital technologies on various outcomes.

However, it is important to highlight a tertiary priority: to make sure studies are integrating high-quality self-report measures for those aspects of digital technology use that cannot be measured objectively (e.g. children's reflections, priorities and concerns). As these are less relevant from a causal inference perspective, they will be covered in less detail below, but should not be considered unimportant for research in this area.

Methods of Objective Data Collection

There are a range of different methods that could be used to collect objective digital media use data. To collect objective time spent on smartphones or social media, devoted tools such as the Effortless Assessment Research System (EARS) app can be installed on phones. These applications harness the sensors installed in smartphones to collect objective, naturalistic data including physical activity, geolocation, sleep, phone use duration and even natural language use (Lind et al., 2023; Van Berkel et al., 2023). Related systems focus specifically on the time spent using specific apps and associated interactions (Geyer et al., 2022). Most of this data can be collected retrospectively for 1–2 weeks or prospectively when a participant downloads and runs a data collection app (Geyer et al., 2022). Importantly, such sensing tools, after installation, collect data passively, which reduces effort burden on participants and therefore corresponding data loss through attrition, however these applications can be seen as invasive. Further consideration to the invasive nature of these methods of data collection are discussed in the 'Ethical Considerations' section below.

Other methods involve the collection of screenshots from the device directly. The Human Screenome Project (Brinberg et al., 2021) gathers regular screenshots (e.g. every five seconds) of the phone screen, creating a vast dataset on user phone behaviour with high ecological validity. However, there are large-scale ethical and legal concerns with these methods, making them — in our judgement — not applicable for use in national cohort assets. Less invasive methods require more input from participants, such as the provision of screenshots of pages of interest such as 'screen time' or 'battery usage' (Gower & Moreno, 2018). However, obtaining screenshots taken by participants themselves can prove cumbersome, which can limit the time periods of data collection as well as the samples of participants used.

Participants may find the use of some or all of these apps overly intrusive. In addition and irrespective of method, all still require some participant engagement at the outset to ensure apps are installed and running. The apps also require regular maintenance and updates so they will continue to operate in the long term.

Innovative approaches to collect objective data about content engaged in on social media include data donation. Data donation takes advantage of the rights conferred by GDPR, granting individuals the ability to request and receive an electronic copy of their personal data held by data controllers. To comply with these rights, many data controllers (e.g. social media companies) allow users a mechanism with which to request and receive a copy of their personal data. We do not cover the use of APIs that are not aligned with GDPR (i.e. are not linked to data donation) as these are unstable and, in our opinion, too risky of a prospect for DSIT investment in how they are designed currently (Leightley et al., 2023).

In 'data donation', participants obtain and donate these data for research purposes. Research infrastructure now exists which can facilitate this donation process, while also granting users autonomy in deciding which aspects of their data to share, and clear information about how the data will be used (Boeschoten et al., 2022; van Driel et al., 2022). Data donation can be used retrospectively, with participants donating past data. In theory, this data may go back an extended period of time (i.e. several years, or to the birth of an account). However, it is important to note that facilities for data donation are provided by the data controllers themselves, and thus are subject to provider-specific technical issues. For example, there have been data quality issues for data from some social media firms such as TikTok not extending far beyond a few weeks (Valkenburg et al., 2024), and challenges in determining whether features in data are empirical differences or errors in the sampling procedure as data provision process is not transparent for researchers.

There now exist new data portability APIs that are provided on the basis of new regulations in the EU that require continuous data transfer to third parties from companies (these are therefore not traditional APIs where companies themselves control who has access, but where user rights force access). To our knowledge, the regulation does not require such data portability APIs to be available to UK users, but some companies have granted such access — such as TikTok. These APIs are much easier to use for participants than data donation methods, where they have to request their data from a company and often wait a few days until it is received before they can donate it to researchers. Instead, they often operate by just asking a user to log-in and provide consent for data transfer/donation. Such APIs don't only decrease the burden of data donation processes, making this method more scalable in future, but raise the prospect of prospective data collection with a participant consenting for ongoing data donation into the future. Yet this has yet to be implemented within an academic context in practice. While there are no methods specific to AI chat app use, similar methods to the aforementioned can be augmented to collect data both about frequency of AI use, time spent using it and specific interactions (Brinberg et al., 2021).

Such new approaches to collecting digital data represent innovative ways to access rich, objective social media data but only approximate the richness of objective usage data accessible to internal company researchers. Although sharing user data with independent researchers will involve establishing how best to preserve privacy, researchers as well as policymakers have called for infrastructure to facilitate external access to data on the scale accessible to social media companies (Davidson et al., 2023).

Benefits of Approach

By augmenting existing longitudinal data with digital footprint data, a core limitation of current large-scale national 'crown jewel' data investments, especially in addressing critical policy questions about social media, smartphone and AI chat app use, can be effectively addressed. This enhancement builds on the advantages outlined in Method 3, strengthening the ability to approximate causal effects through techniques such as DAGs and other causal approaches. With this improved data, researchers will be equipped to conduct more granular longitudinal studies, enabling them to explore, for instance, how specific patterns of social media usage are linked to mental health changes over both short and long-term scales.

This approach builds on foundations laid by some cohorts that have qualitatively explored the risks of adding digital footprint data. Their findings generally indicate that participants find data-linkage acceptable, particularly when it is clearly shown to support population data science that benefits the public good. Crucial to this acceptability is the distinction participants make between trustworthy, well-governed research and the misuse or lack of personal control over similar data in other contexts. Trust in the cohort and affiliated organisations also plays a key role (Di Cara et al., 2020; Shiells et al., 2020).

Going beyond this, some cohort studies, such as Born in Bradford and ALSPAC, are already piloting the inclusion of objective social media use metrics in their datasets. For example, the Born in Bradford Age of Wonder Cohort will be trialling the collection of TikTok data donations this year as part of a wider study conducted by University College London. Cohort studies such as ALSPAC have been enriched through data linkage to external sources — including GP records, hospital statistics and education records — and have also explored approaches such as linking Twitter (now X) data to their cohort through the platform's API (Davis et al., 2024; Tanner et al., 2023). While large-scale data are not available for this yet, there is an opportunity to leverage these tests, especially if rolled out across a larger sample in the next year (Al Baghal et al., 2020).

Indeed, looking to the future, there is significant potential in some of the newer cohort studies if they introduce better digital technology use data, particularly those that a) go beyond subjective self-reports for measures of technology use better measured objectively (e.g. time spent, apps used, content consumed) and b) integrate high-quality self-report measures for technology use that is more subjective and reflective.

Despite this, many of these studies face funding constraints and have expressed concerns that digital data collection might need to be deprioritised in favour of ensuring large-scale participant recruitment and retention. For instance, the 'Growing up in the 2020s' cohort has begun gathering digital data on a subset of their sample, monitoring app usage and the time spent using each one. However, it remains uncertain when and how this data will be made available to the wider research community.

Challenges of Approach

Many of these approaches involve high participant burden, as they often require individuals to install tracking apps, enable continuous background data collection, or repeatedly complete in-the-moment surveys such as ecological momentary assessments. There is also the potential time-lag between data requests and when this data is subsequently provided to the participants for them to donate to researchers, requiring careful management of participants to ensure data is donated. These methods can be intrusive, time-consuming and may raise concerns about privacy and data security, leading some participants to opt out entirely or disengage partway through. As a result, there is a risk of potential low participant representativeness, particularly for the most intensive or invasive data collection methods, which may exclude individuals from more vulnerable or less digitally savvy groups. In this context, integrating digital trace data collection into a cohort study or large-scale survey represents an opportunity cost. Both the individuals leading data assets, and the stakeholders to whom they answer, must balance the relative importance of collecting digital trace data against — for example — health or financial data. A key challenge is understanding the pressures placed upon these decision-makers and creating digital data collection opportunities in such a way that strategic benefits outweigh costs.

Indeed, implementing these approaches at scale — especially within large, nationally representative cohorts — is logistically complex and financially demanding, requiring significant investment in infrastructure, participant support and data processing. For instance, the high volumes of digital data that are inherent to observational datasets present logistical challenges with regards to data storage, management and analysis. Further, in previous large-scale study investments that relied on APIs to access digital data, company refusal caused substantial challenges for data acquisition (Leightley et al., 2023), and recent data donation studies have noted incomplete data packages being provided (even though others have not noted such issues), for example from TikTok (Valkenburg et al., 2024).

Donated digital data is often ‘found’, i.e. not created for research, and could be of limited value, it could also be degraded easily (e.g. if sharing is stopped or limited by digital companies). This fragility extends to many digital data collection methods more broadly: because they often rely on third-party platforms and infrastructure, digital companies can unilaterally alter, block or deprecate access, making these methods risky and potentially unsustainable for long-term, large-scale cohort studies. Analysing messy digital footprint data is also difficult and typically requires complex data processing pathways to be useful. Unsupervised machine learning can identify patterns and outcomes in such complex data, but it is predictive rather than explanatory, so it does not reveal what is specifically driving the effects. Further investigation would be needed to understand the underlying mechanisms.

Moreover, prospective digital data collection will take time, and such data collection over multiple years may not be possible in the intended two to three year period. It is likely that an investment for evidence creation in this time period will either have to focus on long-term retrospectively collected data (which is relatively novel and untested as a data collection strategy in this context), short-term outcomes (e.g. collecting digital data linked to ecological momentary assessment), or medium-term data (e.g. three data collection waves, each six months apart and 1.5 years to write-up and analyse data).

Ethical Considerations

The use of smartphone applications as well as data donation to track participant behaviours also raises significant ethical and privacy concerns. For example, traditional conceptualisations of ‘informed consent’ in psychological research rely on obtaining consent about data which is relatively impersonal and thus it is straightforward for participants to understand associated privacy risks. In contrast, ecological data about phone use, when aggregated and analysed with advanced statistical methods, may allow for inferences to sensitive information participants do not realise they are revealing (Shaw et al., 2022) — such as when patterns of content viewed can be associated with mental health status, political ideology or sexuality. Researchers must therefore take additional steps to ensure informed consent at all stages of the process, and to ensure that data is appropriately secured. Novel data donation infrastructure can help address informed consent by explicitly asking for consent, showing participants their data and allowing participants to actively decide which aspects of their data to share, providing participants with greater education and autonomy (Yap et al., 2024). Finally, there also exist ethical logistical concerns in handling existing data custodianship and participant consent.

Risk Registries

It also needs to be noted that serious adverse outcomes (harms) from online activity are unlikely to be captured prospectively by small observational cohorts or RCTs. These events might include self-harm, suicide, referral for mental health assessment and treatment etc. There are a few options to target this specific issue.

For example, a structured reporting system for these events would require an Online Harms Mental Health Observatory — which could function on similar basis to the Yellow Card reporting system for medicines adverse events run by the MHRA (Medicines and Healthcare Products Regulatory Authority). The Alan Turning Institute has established an ‘Online Harms Observatory’, although there is no current linkage of this data to physical or mental health data (Alan Turing Institute, 2025). Reports could be made online by any member of the public, young people, parents, teachers or health professionals etc. All reports would be followed up to be assessed for seriousness, causality and requirements for platform regulatory/enforcement action.

A related approach to online harm surveillance could utilise existing UK health datasets (e.g. UK BioBank) with consented populations who could donate passive digital activity data. A more indirect approach to online harms surveillance (avoiding ethical concerns of linking data at an individual level) is to link online risks (platform surveillance) to existing public health data within a digital observatory to identify potential causal relationships with methods including geographic matching, temporal matching and demographic cohort matching.

Method 5: Ecological Momentary Assessment Studies

Approximate total cost of project: £300,000–£500,000

Major factors that determine cost level:

1. Smartphone EMA app (cost per participant) and whether objective tracking assessment is required.
2. How participants are incentivised.
3. Analyses required and linkage to other objective data.
4. Expertise knowledge.

Another promising and emerging avenue for investment is the use of intensive longitudinal assessment methods, such as Ecological Momentary Assessment (EMA): also referred to as Experience Sampling Method, daily diary or ambulatory assessment. These approaches involve self-report diary techniques that capture individuals' real-time, naturally occurring experiences, symptoms and contextual factors as they unfold in daily life. Typically, data are collected via dedicated smartphone apps that prompt individuals to complete brief surveys (usually lasting a few minutes) several times a day while they go about their routines.

Unlike traditional cohort studies, EMA relies on a more intensive longitudinal design aimed at capturing dynamic phenomena that are expected to fluctuate over shorter periods (within days or weeks). This enables researchers, for example, to explore moment-to-moment relationships between factors such as time spent on social media, or specific platforms, and outcomes including sleep, attention, lifestyle behaviours and mood. EMA is less suited to capturing more stable outcomes (e.g. academic attainment), which evolve over longer timescales. However, given that child and adolescent development and mental health are complex, characterised by an interplay of processes that occur at multiple timescales (see e.g. Ram et al., 2014), EMA can still offer significant value.

For example, EMA data can be linked with data sources of longer-term outcomes, whether they be administrative (e.g. academic and attendance data sourced from schools or the National Pupil Database (NPD)) or collected for research (e.g. cohort data). EMA can also be embedded within broader longitudinal designs, with traditional assessments administered before and after the EMA period to contextualise short-term processes within broader longer-term developmental outcomes (Chiang & Lam, 2020). This approach is particularly useful in identifying how momentary social media experiences may contribute to shifts in mental health or progression toward clinical diagnosis. For instance, Fried et al. (2023) combined repeated EMA and traditional assessments to identify individuals at risk of developing depression. EMA can also be used to explore developmental processes and potential causal mechanisms through a burst design — that is, repeated EMA windows nested within a longitudinal framework (Chiang & Lam, 2020; Ram et al., 2014).

EMA studies can be time-contingent with assessments scheduled at fixed or random points in the day, or event-contingent, with assessments triggered by specific events (Dejonckheere & Erbas, 2022). The latter is particularly promising for exploring young people's immediate responses following social media exposure.

While EMA studies alone do not establish causality, as with Method 3, their temporal design can enhance causal inference when paired with appropriate methods (e.g. DAGs) and experimental designs, and control for confounding variables. Additionally, EMA can be integrated with objective measures of social media use, such as platform and time tracking and data donation (as discussed in Method 4), allowing for closer real-time examination of digital behaviours and experiences. Similarly, EMA can be combined with objective health data (e.g. via wearables), including sleep and physical activity (Burnell et al., 2022).

Benefits of Approach

EMA methods offer several advantages. First, by capturing individuals' momentary mental states (e.g. 'I feel happy right now'), they significantly reduce recall bias associated with retrospective reporting (Heron et al., 2017). This is especially valuable when examining the effects of social media use among adolescents with pre-existing mental health difficulties, who are more likely to recall past experiences in a negatively biased manner (Bone et al., 2021). EMA is also well-suited, and may be more appropriate, for assessing momentary responses to specific exposures, such as body image concerns following real-time social media interactions (Krug et al., 2020).

Second, EMA enhances ecological validity by collecting data in real-life environments, such as the home or social settings, capturing emotions, behaviours and contextual details as they naturally occur (Russell & Gajos, 2020). This can include information about what individuals are doing, who they are with, and what platforms they are engaging with. When combined with objective data (e.g. screen time, data donations, sleep quality, physical activity) EMA can thus help highlight potential real-time causal mechanisms for further explorations in experimental designs.

Third, EMA facilitates the creation of rich short-term datasets. For instance, a 14-day design with five prompts per day results in 70 data points per individual, which far surpasses the annual waves of assessment typical of traditional cohort studies. This allows researchers to move beyond group-level or simple within-group analyses to examine within-person changes that occur throughout a day, enabling a more individualised approach. Such designs are particularly valuable for identifying unique vulnerabilities, conducting single-case analyses, and monitoring real-time intervention effects (Myin-Germeys & Kuppens, 2022). For example, EMA can help determine optimal digital engagement time tailored to individual adolescents.

Challenges of Approach

Despite their unique affordances, EMA methods present key challenges. First, EMA, as with other longitudinal designs, is still correlational and thus remains a less effective method in making causal claims, without the use of experimental designs and appropriate modelling (e.g. DAGs). Second, intensive EMA designs typically require smartphone access. While most adolescents own a smartphone, access is significantly lower among younger children with only 27–61% under 11 owning one (Ofcom, 2024a) which can limit recruitment and introduce sampling bias.

Third, the reliance on smartphones for EMA studies, while convenient, creates a methodological paradox when the research focus is on the potential harms of smartphone use: the smartphone becomes both the variable under study, and the tool for conducting the study. This may lead to recruitment barriers and biased samples, for example, it may deter participation from those trying to reduce screen time and may raise concerns among schools and parents, who may be hesitant to support smartphone-based research (Perowne & Gutman, 2024). Relatedly, frequent notifications may burden participants and reduce compliance (Dejonckheere & Erbas, 2022; Wen et al., 2017). It is therefore a high effort data collection which, depending on the design, can result in substantial participant burden and raises concerns regarding smartphone use and data security. These challenges must therefore be weighed against the strengths of the approach and addressed through appropriate mitigation strategies, for example, ensuring co-production of design and methods, to support successful and unbiased recruitment (Van Roekel et al., 2019).

Fourth, EMA poses methodological challenges. School restrictions on smartphone use prevent data collection during school hours (Heron et al., 2017). While this can be addressed by scheduling the assessments before and after school, it limits the ability to examine potential school-related mechanisms (e.g. bullying, social exclusion) that may be important in understanding causal social media and smartphone mechanisms. Furthermore, a lack of validated EMA measures often forces researchers to develop new questions or adapt existing cross-sectional measures (Fritz et al., 2024), potentially compromising momentary sensitivity and validity.

Finally, as with other methods (see Method 4 for details), linking EMA with objective digital or health data presents challenges, particularly when dealing with complex data, such as data donations. This process requires expertise in data management, linkage and analysis, as well as financial investment, participant engagement (e.g. providing data donations, using wearables), and secure, transparent and efficient data processing. Without these the richness and validity of the data may be compromised.

Ethical Considerations

EMA is considered a medium-risk method. Privacy and consent issues vary depending on the study design (e.g. use of audio recording), topic sensitivity and whether passive smartphone or other objective digital or health data are collected (Kirtley, 2022). Transparent communication with young people and their parents is essential, outlining what data will be collected, how it will be stored and how confidentiality will be maintained. Collecting and/or linking to existing objective digital or health data can be perceived as invasive and raises significant security concerns. This requires careful planning and additional safeguards to ensure ethical, transparent and secure data collection and management (see Method 4).

Accessibility is another key concern, as not all young people have access to a smartphone or may face compatibility issues. One solution is to provide participants with research-specific devices, ensuring equal opportunity to participation and increasing sample representation. However, this raises challenges around smartphone use, for example, restricting access to only the EMA app would be required, and comes with substantial financial cost.

Participant burden is a key consideration in EMA studies. The length, frequency and timing of EMA assessments must be carefully designed to minimise fatigue and avoid disrupting adolescents’ daily routines such as school and sleep. Involving young people, parents and schools in the design process can help ensure feasibility and acceptability.

For individualised EMA designs, researchers must determine whether responses will be monitored in real time and establish clear safeguarding and risk management protocols. These plans must be communicated to both participants and their parents (Kirtley, 2022).

Regardless of design, participant support should be prioritised, including clear safeguarding measures and embedded signposted access to support within the EMA app. Participant burden must also be carefully weighed against potential benefits (Kirtley, 2022). GDPR-compliant EMA apps must be used, and robust ethical oversight — including informed consent procedures and confidentiality protections — is crucial throughout.

Method 6: Natural Experiment Studies

Approximate total cost of project: £500,000–£1,000,000

Major factors that determine cost level:

1. Whether there is pre-existing data available to monitor impact of natural experiment (e.g. https://datamind.org.uk/, and efforts to track mental health data in Wales and England).
2. If the natural experiment has not yet occurred, but will, substantial costs can arise if more data collection is required.

Another promising avenue for investment is the use of natural experiments, where real-world events or policy changes create conditions that resemble experimental and control groups. These naturally occurring interventions provide an opportunity to examine the effects of social media and smartphone use on child and adolescent developmental outcomes in a way that mimics experimental research. By capitalising on external changes (such as shifts in legislation, platform restrictions, school-level bans or variations in technology adoption) researchers can study the causal impact of digital media on developmental outcomes.

The defining strength of natural experiment evaluations lies in their ability to approximate randomisation. When exposure to a given intervention (such as a social media ban) is determined by external factors rather than individual choice, the groups that experience the intervention and those that do not can be compared with reduced risk of confounding. This makes it possible to isolate the effect of social media or smartphone exposure from underlying individual differences. Unlike traditional observational studies, which may be vulnerable to bias from self-selection or unmeasured confounders, natural experiment studies provide stronger causal inference by ideally using quasi-random variation.

Natural experiment studies are particularly well-suited for evaluating large-scale national policy changes that cannot feasibly or ethically be studied through interventions or RCTs. For example, nationwide age restrictions on smartphone use, nationwide restrictions or bans in schools, changes in platform moderation policies, or nationwide regulations affecting children's access to social media all create opportunities to study the broader population-level effects of digital engagement. Such studies allow researchers to assess both the intended and unintended consequences of policy shifts, offering valuable further evidence for future regulation and intervention strategies (Craig et al., 2017). Updated guidance from the MRC/NIHR discusses the process of identifying and appraising opportunities for a natural experiment evaluation and working out a feasible and appropriate design (Craig et al., 2025). Further, natural experiment studies have been endorsed by the UK Government as a means to evaluate the effects of digital health products/services, however as suggested, finding credible natural experiments can be challenging (UK Office for Health Improvement and Disparities, 2020).

Benefits of Approach

Natural experiments offer two key benefits. First, this method allows for the study of direct effects of social media and smartphone use, particularly in contexts where traditional experimental methods are impractical or unethical. This approach strengthens causal inference through use of real-world events that create quasi-randomised exposure conditions, reducing bias from self-selection and unmeasured confounders without requiring direct experimental manipulation.

If appropriate data collection of the outcomes of interest (e.g. through administrative data on school performance, or health data; or longitudinal population or cohort studies) are in place, the evaluation of a natural experiment might not need additional primary data collection, which reduces the cost of it. However, often the specific and proximal outcomes are not available, due to a lack of data collection or linkage on national scale, making some primary data collection necessary. New outcome data can be collected to make the most use of a natural experiment, for example by tracking outcomes with high-quality measures before and after an intervention, but natural experiments can often also be analysed using pre-existing administrative, survey or digital trace data. This makes them highly cost-efficient.

Many of the most pressing research questions, such as the impact of nationwide social media restrictions in schools or changes in platform policies, cannot be studied through controlled experiments, making natural experiments an important alternative.

Challenges of Approach

Unlike planned experimental studies, natural experiments rely on external events or policy changes that may not arise in a way that is useful for causal inference. Researchers are limited in evaluating those natural experiments that have already occurred and will therefore always be behind current activity. While providing particularly good opportunities for causal inference, this method is therefore less forward-looking, and research questions cannot be determined solely based on policy need but also based on availability of appropriate natural experiment occurrences.

Another major limitation is the availability of high-quality, high-frequency data. Natural experiments are most informative when outcome measures are captured at regular intervals before, during and after the event. They also need to be captured in ways that are reliable and comparable. However, in many cases, the necessary data infrastructure is lacking. While administrative datasets can provide some important information, they often lack the granularity required to assess nuanced changes in behaviour, mental health, education or well-being. For example, standardised educational or health records may not capture short-term fluctuations in social media engagement or mental health that are critical for understanding causal mechanisms.

Some natural experiments may take place in regions where data collection is not feasible. Further, if the event takes place in a non-English-speaking country, researchers must translate and validate measures across multiple languages, adding complexity to study design. Cross-country comparisons require consistency in measurement tools and methodologies, which can be difficult to achieve.

High quality natural experiment evaluations require a high degree of researcher expertise to do well and good quality natural experiments that allow for valid inference. A natural experiment cannot fully eliminate the possibility of unmeasured confounding variables. While they reduce some forms of bias compared to traditional observational studies, they do not offer the same level of experimental control as randomised trials. Researchers must rely on statistical methods such as difference-in-differences analysis or instrumental variable approaches to strengthen causal claims, but these methods require assumptions both to be identified by expert researchers and evaluated.

Finally, in some cases, policymakers or organisations may restrict access to relevant data, preventing researchers from conducting a comprehensive independent analysis. Further, natural experiments are inherently embedded in the broader context of child and adolescent lives, which will be impacted by other concurrent changes (e.g. other legislative changes) making further assumptions needed to pinpoint the sole causal impact of the natural experiment of interest.

Ethical Considerations

Natural experiments pose lower ethical risks, as they do not involve researcher-imposed interventions. Instead, participants are observed within existing conditions. If additional data is collected appropriate ethical consent needs to be sought and safeguarding measures must be in place.

Since studies will often rely at least on some pre-existing data, it may not be feasible or necessary to obtain direct consent from participants. Researchers must take care to ensure that data is anonymised or de-identified to protect participant privacy while maintaining the integrity of the research. Further ethical concerns arise when studying vulnerable populations, such as children and adolescents.

Natural experiment evaluations often also rely on administrative or third-party data sources, which may be subject to ethical and legal restrictions regarding access and use. Full compliance with data protection regulations, such as GDPR, is essential. Researchers must navigate data-sharing agreements carefully, ensuring that all collected information is used responsibly and in line with participant rights.

Method 7: RCTs

Approximate total cost of project: £2,000,000–£4,000,000

Major factors that determine cost level:

1. Whether feasibility/acceptability study is needed before main RCT.
2. Type of RCT applied (e.g. changing a single design feature on a technology versus a removal of a technology as a whole).
3. Single or multi-arm RCT (i.e. if studying one or multiple exposures/interventions).
4. Simple or cluster RCT (i.e. if decision is made to randomise individuals versus schools).
5. Complex interventions (i.e. if multiple interventions are delivered at once, e.g. restriction plus digital literacy intervention).

RCTs are widely regarded as the gold standard for establishing causal relationships, making them a powerful tool for investigating the impact of social media use on adolescent developmental outcomes. This approach involves randomly assigning participants (or groups of participants, e.g. classes, schools) to different intervention arms, allowing researchers to assess the effects of specific variables while controlling for confounding factors due to random allocation. Interventions can be designed to mimic potential policy changes or recommendations, or to tap into potential causal mechanisms. Like most of the study designs above, RCTs can measure influences on both primary outcomes (e.g. mental health and well-being) and secondary outcomes (e.g. educational attainment, lifestyle habits and physical health). RCTs are also best able to assess common populational level outcomes rather than rarer but serious individual level events (see 'Risk Registries' above).

A well-designed RCT ensures that both observed and unobserved characteristics are evenly distributed across groups, meaning any differences in outcomes can be directly attributed to the intervention rather than external influences. The inclusion of a control group provides a baseline for comparison, while a multi-arm approach allows researchers to test multiple causal pathways, or interventions, within a single study. For example, in the Science and Policy workshop, one team developed a multi-arm RCT where the intervention arms focus on digital literacy training, child-led device restrictions and externally imposed limits. By varying these conditions, researchers can examine the nuanced effects of different intervention components (digital activity) on adolescent development (Hollis et al., 2017). However, RCTs can also be smaller in scale, for example implementing a specific intervention on a phone to increase 'friction', such as by inserting a one-second pause before a certain social media app is opened, or by changing the user interface (Grüning et al., 2023; Lyngs et al., 2024).

When applying RCT methods in the social media field, unique methodological considerations arise (Murphy et al., 2024). For example, attitudes and actions regarding social media are deeply embedded in a cultural zeitgeist, so that it is difficult to isolate randomised 'actions' from the way they will be culturally interpreted. Unlike 'placebos' in medical RCTs, which separate treatment from psychological associations, interventions such as abstaining from social media are intrinsically associated with corresponding societal and cultural meanings such as participants' beliefs that they are doing something admirable and healthy. Further, given that social media often permeates multiple aspects of an individual's life — including their social life, as well as news consumption and entertainment — conclusions from RCTs will have to account for how various compensatory behaviours may contribute to effects at different timescales.

Benefits of Approach

RCTs offer three key benefits. The biggest strength of RCTs is that they are designed to eliminate bias and confounding, thereby isolating the causal effect of an intervention. Second, they provide a controlled environment to pilot test mechanisms before broader roll out, such as in the case of policies. The researcher is able to control the exact nature of the intervention that is delivered, meaning well-crafted designs can aim to directly link to relevant causal pathways. Third, they allow for the comparison of multiple interventions within the same study (yet this is not specific to RCTs as it can also be done in traditional observational and natural experiment studies). For example, if an RCT is testing several digital interventions (e.g. screen time reduction, digital literacy training, notification blocking), researchers can directly evaluate the relative effectiveness of each approach under the same conditions. Different interventions can be targeted at a range of current policy considerations (e.g. social media reduction, social media removal, social media blocks at certain times). Platform RCTs are an extension of multi-arm RCTs which allow new interventions to be added as they emerge to existing protocols and ethical approvals, however they require large infrastructure investments that while currently under consideration by funders in the mental health field have not yet been established (Gold et al., 2022).

Challenges of Approaches

While RCTs are the gold standard for causal inference, there are limitations to RCTs and experimental studies.

Firstly, there are ethical implications of investigating certain conditions (e.g. exposure to self-harm content) or outcomes (i.e. adolescent alcohol use) in a trial setting, thus RCTs are not always feasible. As researchers are directly intervening on children and young people's lives there are specific ethical limitations to what sort of interventions they can feasibly apply. For example, it might well be unethical and not pass ethical review to provide young children with phones to assess their impact or to expose them to certain harmful content.

Furthermore, RCTs are often risky and costly, meaning that it is common to have pilot and feasibility trials to mitigate the risk of issues to do with the acceptability of the intervention or feasibility of its deployment. For example, a recent RCT on a family screen time intervention detailed in Appendix 1 (Schmidt-Persson et al., 2024) had very low uptake across families, even when they said they were interested in the study, making it difficult to assess whether the intervention would be feasible and applicable at larger scale. This means that having a large-scale RCT ready within two years is extremely difficult (e.g. it was managed during COVID but is not the norm in other circumstances), and would require exceptionally focused remits and expert teams to achieve. In a fast-moving area, as in online safety, a large investment in an RCT can be risky, as the study can be out of date by the time it is completed, e.g. as policy priorities have shifted.

There is also the risk that the results of RCTs, even when on representative samples, do not generalise. For example, the effects of a national technology restriction implemented across all schools may differ significantly from those observed when the same policy is introduced in only a handful of pilot schools. For example, in the latter case, pupils, staff and parents might perceive the intervention as unfair or stigmatising, potentially leading to greater resistance or resentment. By contrast, a nationwide rollout could normalise the change, reducing feelings of being singled out and possibly increasing acceptance and compliance. It could also be that the first schools are exceptionally motivated as being the first of a national campaign, leading to more positive outcomes.

Recruitment also poses further challenges. Many RCTs struggle in biases in recruiting, as certain families or individuals wanting to cut down on their technology use are more likely to sign up to interventions, and may already be experiencing more negative effects of smartphone use prior to intervention, ultimately biasing results. Further, due to recruitment issues, intervention periods are often, although not exclusively, shorter — especially historically when it comes to technology interventions.

Such studies also often remove technology use from children or adolescents lives to assess their impact. This assumes that removing exposure to technology is approximately the opposite of using it, which oversimplifies reality. Short-term interventions (e.g. two-week abstinence periods) cannot replicate the lifelong, cumulative effects of digital media use and its influence on society. In addition, RCTs typically assess short-term changes, meaning they may not adequately capture long-term developmental consequences.

Network effects play a crucial role and the research question of interest to the RCT needs to be considered: i.e. do they want to target individual changes in technological behaviours that test individual effects or group-level changes that target group-level effects. This decision needs to be weighed up against the cost and nature of the study. For example, the consequences of abstaining from smartphone use will depend on the broader social context. An individual who quits while everyone else continues using it may experience negative effects, such as social exclusion. However, if an entire community disengages, the effects could be different. It might therefore be valid to call for cluster RCTs where, for example, whole schools or classrooms engage in the same part of the RCT.

Ensuring that studies are sufficiently powered to detect meaningful effects is particularly difficult when interventions require participants to be grouped within school settings or specific communities. The more intervention arms are included, the more complex the study becomes, both in terms of logistics and statistical analysis. This will also have cost implications, with RCTs being expensive to run at a high-quality level.

Ethical Considerations

As noted above, there will be a limit to the interventions that will get ethical approval to test, even interventions that restrict social media or smartphone use fully may inadvertently worsen mental health for some individuals, which needs to be assessed. Hence, adverse event monitoring should be included within any RCTs.

Privacy and data security are also critical concerns. Any collected data should be securely stored, with anonymisation measures applied before researchers gain access. Informed consent must be obtained from participants and, in the case of children, from their parents or guardians. Researchers must also remain transparent about study aims, potential risks, and participant rights, ensuring compliance with ethical and legal frameworks, such as GDPR.

Cross-cutting Foundational Research Investments

The Scientific Consortium further discussed two cross-cutting foundational investments in research that would benefit fundamental research efforts in this area: improved theory building and the involvement of children, parents and caregivers. We detail these below.

Theory Building

Approximate total cost: £200,000–£1,000,000

Major factors that determine cost level:

1. What type of methodology is used (e.g. Delphi studies, focus groups, interviews).

2. Requirement to build theory on systematic literature reviews.
3. Follow up consultation once framework is developed.
4. Ongoing maintenance costs due to quickly developing field.

Theory building in research refers to the process of developing frameworks or models that explain how and why certain phenomena occur. It involves identifying key concepts, defining the relationships between them, and generating testable hypotheses. Strong theory building helps researchers move beyond describing patterns to understanding underlying mechanisms. This area of research is marked by a significant gap, with conceptualisations and theoretical frameworks often lacking clarity and consistency. It can be inductive, emerging from data and existing studies — or deductive, based on existing theories that are refined or extended. A well-defined theoretical framework is important to help set and prioritise research questions, as well as clarify causal pathways, prevent duplication of research efforts, and ensure that research outputs are relevant to both stakeholders and policymakers. One recent example of this was conducted by Sonuga-Barke and colleagues (2024a), who develop a clinically and developmentally informed theoretical framework for the relationship between digital activity and depressed mood.

An interdisciplinary and mixed-methods approach is critical in this case, drawing information from a range of disciplines, spanning not just the sciences but social sciences and humanities to create a comprehensive systems model that applies across different fields and enables the identification of causal mechanisms through which online harms might occur. This approach would require regular updating based on new evidence and evolving technologies.

Benefits of Approach

Investing in this approach holds three key benefits. First, it would establish a strong theoretical foundation, ensuring a clear conceptual framework and consistency across the research in the field, whether observational, intervention-based, or mixed-methods. Second, it would allow for co-production of theoretical models with children and young people, stakeholders and scientific experts, informed by scoping literature reviews and consensus building around the evidence base in the field. Consensus building, for example through Delphi methods, can help policymakers gauge researcher opinion across a polarised field. Thirdly, it could help to draw links across different technology permutations, helping to generate robust research which focuses on underlying causes rather than surface-level and changeable features of technology platforms. Finally, it would allow for the identification of relevant research questions to investigate and prioritise, as well as laying the foundation for, exploring the impacts of emerging technologies, enhancing the speed at which subsequent research and policy can respond to potential harms.

Challenges of Approach

This approach is a foundational requirement for effective research, which would improve research in this area in the long term. However, theory building, in and of itself, will not directly lead to causal evidence in the next two to three years. Instead, theory building provides a long-term pathway to clarify the correct, most important/urgent or most effective causal questions and interventions to conduct in subsequent work, ensuring research produces robust causal evidence. Developing extensive theoretical models with input from a range of experts in varying disciplines, as well as children and young people, is expected to be of moderate cost and time intensive.

Ethical Considerations

The lack of primary data collection in theory building means there are few ethical risks. However, a high-quality execution of this approach will involve co-production with children and young people and those with lived experience (e.g. which will come with ethical considerations. It will also be important that the researchers involved are diverse and from a range of perspectives and disciplines to minimise bias.

Involvement of Children, Adolescents and Caregivers

Approximate total cost: £10,000–£50,000 (depending on research methods)

Major factors that determine cost level:

1. Whether involvement is a one-off session or a sustained programme of activities.
2. Whether activities are online, face-to-face or hybrid (transport and accommodation costs).
3. PPIE staff time to support involvement sessions (at least two staff per session).
4. Costs for third sector partners to support participants as needed.

Participatory research — variously termed 'Co-production', 'Patient and Public Involvement (PPI)', 'Public and Patient Involvement and Engagement (PPIE)', or simply 'Involvement', and hereby referred to as PPIE — encompasses a range of activities designed to support the inclusion of people with lived experience across academic disciplines, approaches and methods. When conducted well, such involvement can lead to more robust, appropriate, meaningful and impactful research, including in RCTs (Selman et al., 2021), systematic reviews (Agyei-Manu et al., 2023), intervention or tool development (Babbage et al., 2024; Grant et al., 2020) and qualitative studies (Dewa et al., 2021).

Despite this, formal impact evaluations of involvement are still relatively rare, and the value or necessity of such evaluation is debated within health and clinical research (Wilson et al., 2015). However, some evidence shows that across various conditions and participatory approaches, involvement of individuals with lived experience of the condition under study in an RCT is significantly associated with improved enrolment (Crocker et al., 2018).

In youth mental health research specifically, a recent systematic review of 19 studies involving young people (aged 10–26) found that PPIE improved the relevance of research questions, study materials and dissemination. However, systematic evaluation of PPIE outcomes remained inconsistent (McCabe et al., 2023). Notably, none of the included studies evaluated the quantitative impact of youth participation on either study outcomes or outcomes for the young people involved.

These findings reinforce conclusions from earlier research showing that youth participation can enhance the relevance and trustworthiness of mental health studies, while also highlighting a persistent lack of standardised frameworks or tools for evaluating the effectiveness of participatory methods (Mawn et al., 2015). In response to this gap, tools such as the GRIPP2 checklist have been developed to support the consistent reporting of involvement (Staniszewska et al., 2017). Nevertheless, a recent systematic review in the context of patient safety found that PPIE was still infrequently reported using the GRIPP2 framework (Hammoud et al., 2024).

The involvement of children and adolescents has become an increasingly recognised principle in social media research, ensuring that studies are relevant, timely and uphold children's rights (United Nations, 2021). In 2023, the Digital Futures Commission, led by Professor Sonia Livingstone, summarised 18 previous consultations to call for a shift from doing research 'on' children to doing research 'with' children (Livingstone & Mukherjee, 2020). Their synthesis found that, first, children value both sociable and imaginative play, whether offline or online. The significance of free, self-directed play, without excessive adult supervision, is highlighted, and the benefits of this transcend the medium in which it is conducted. In particular, the benefit of digital play as means of both solitary and social play are noted.

Regarding privacy and data security, a recent study on young people's engagement with data donation highlights a general sentiment of comfortability in donating their data to researchers, contingent on several conditions, such as the legitimacy and trustworthiness of the research and researchers involved (Yap et al., 2024). With regards to platform design and innovation, children and young people criticised features that expose them to harmful content and set unrealistic expectations. In turn, children and young people called for safer designs, including transparent data usage, default privacy settings and more comprehensive reporting tools. Furthermore, children and young people argue that the burden of responsibility for safer usage is unfairly placed on the consumer and should instead lie with social media companies and their platforms.

Recently, a UKRI commission designated 'Digital Youth with Sprouting Minds' has evidenced the benefit of co-producing their research on a larger scale and has demonstrated that is possible to involve children and young people in all stages of the research lifecycle across a range of study designs from analysis of pre-existing cohorts qualitative studies to intervention development and RCTs (Babbage et al., 2024; De Alcântara Mendes et al., 2024; Khan et al., 2024; Kostyrka-Allchorne et al., 2023; Williams et al., 2023; 2024).

The Importance of Involvement and Key Methods

Involving children and adolescents in relevant research is especially important, yet their access is often restricted by adult gatekeepers, such as ethics committees, parents and professionals. Whilst such gatekeepers exist to protect children, they may unintentionally suppress children's voices. Experts advise that children should be viewed as social actors that can take a conscious role in the decision to participate in research, rather than being the passive subjects of the research process. This would require communicating effectively with children about research, and ensuring they understand the nature and consequences of participation. This is especially important when potential participants are considered vulnerable, or the topic of research is sensitive (Powell & Smith, 2009).

Effective and meaningful involvement requires funding in accordance with NCCPE guidelines (NCCPE, 2025; National Institute for Health and Care Research, 2025a). Ideally involvement should be incorporated throughout the lifecycle of research from development to dissemination. In youth mental health participatory research three common phases have been identified: 1) setting the scene, 2) employing a cyclical or iterative process and 3) acknowledging the impact of cultural context (Lloyd et al., 2024). It is also vital that experienced involvement experts are costed into funding applications to support children and young people in working with researchers on mental health topics and that potential pathways to clinical support are identified and provided as necessary. Detailed examples of supporting effective involvement in digital youth mental health have been described by Babbage et al. (2024).

We give a short, and non-comprehensive, overview of different options to involve children and adolescents in research below. Given the above discussion, it is vital that all involvement is reported and evaluated in terms of the impact on participants and the impact on the research design and outcomes. Using an established tool such as the GRIPP2 is recommended (Staniszewska et al., 2017).

Research Advisory Panels

Research advisory panels position children and young people, as well as other key stakeholders such as parents and teachers, as co-creators rather than passive subjects of research. Young people are involved in all stages of a project shaping research questions, choosing observational methods, producing materials and interpreting data. This can be achieved across a range of methods including surveys and experiments. Secondary data analysis is particularly pertinent with regards to qualitative data, where children and young people can ensure the questions in focus groups/interviews are age/experience appropriate but also offer interpretations of findings that reflect real life experiences. Such methods provide a platform for participants to express their unique, subjective perspectives and experiences in their own words. In constructing a safe and supportive research environment, qualitative research offers nuanced, rich evidence into the lived experience of children and young people, empowering them as experts and respecting their agency.

Advisory panels can also provide feedback on consent procedures, and how to handle sensitive topics. An example of such efforts can be seen in Yap et al. (2024) and Hickman Dunne et al. (2025). The UKRI funded programme grant ‘Digital Youth’ involves co-creation with young people through the ‘Sprouting Minds’ Young Person Advisory Group (Digital Youth, 2025) and two young people are included as co-investigators on the grant.

Formalised Committees and Research Advisors

There are also more centralised youth advisory processes. The Youth Parliament Select Committee is an initiative led by the National Youth Agency, supported by the House of Commons and jointly funded by Parliament and the Department for Culture, Media and Sport. The 12 committee members, aged between 14 and 19 support the government’s efforts to integrate youth voices and perspectives with ongoing and future research.

With regards to the impacts of social media, the Youth Select Committee has recently published a report investigating the links between social media and youth violence (Youth Select Committee, 2025). Throughout the course of its enquiry, the Committee explored the regulation of social media, the role of schools and other institutions in promoting digital literacy, as well as the role of the police. They made several recommendations for government and relevant authorities. Their report has now been sent to government for an official report.

Similarly, the National Children's Bureau Young Research Advisors (YRAs) are a diverse group of children and young people from 7–18, as well as a group of children and young people with additional needs up to 25, who play an active role in ongoing research. The YRAs receive ongoing training on research methods, ethics and policy issues. They carry out a range of roles including: 1) advising on research methods and tools, 2) carrying out primary research activities such as peer research, 3) interpreting research findings and 4) exploring research priorities. Cohort studies like Born in Bradford also have their own standalone youth advisory board and co-creation systems.

Ensuring Safe and Equitable Involvement in Digital Youth Mental Health Research

There are, therefore, significant benefits of involving young people in research, but it is vital to involve them early and sustainably in the entire research process from start to finish (this requires significant resources) and should be an important factor in considering the nature and type of investment required to sustain robust participatory science in this field. It is important that wellbeing and safety is central in youth involvement work. Ideally, researchers should agree ways of working with young people up front and co-create a document reflecting this, which the entire research team then signs up to (Babbage et al., 2024).

Researchers should intentionally recruit young people from diverse backgrounds (including those from minority ethnic groups, lower socioeconomic circumstances and different education levels) to ensure research is not skewed towards a narrow demographic — working with third sector partners enables this (Digital Youth, 2025). They should regularly gather feedback from young people on how involvement is working and adapt processes based on their input. In addition it is vital to document and report in detail how young people influenced research decisions, not just that they were involved (Babbage et al., 2024).

Further recommendations include: use accessible, visually engaging materials (e.g. infographics, collaborative online platforms like Miro boards). Offer flexible ways to participate — such as contributing offline, asynchronously or through low-barrier methods like chat or polls, as this can really boost involvement. This helps to facilitate a co-production mindset where young people are treated as active co-designers and co-researchers, rather than as subjects of research. Ensure they can meaningfully influence major decisions about study design, recruitment, intervention tools and dissemination. Decide in advance how decisions will be made by the team to manage expectations (Babbage et al., 2024).

Anticipate that discussions about social media, smartphones and mental health could surface distress or unintended consequences. To mitigate against this, have accessible support in place during workshops (such as in-session clinical support or crisis service access). Prioritise safety and wellbeing in youth involvement by implementing a wellness plan for every young participant, including emergency contacts, self-care strategies and clear safeguarding protocol (Babbage et al., 2024). Conduct mood check-ins before and after sessions (e.g. via a Visual Analogue Scale) to monitor emotional impact (Townsend et al., 2016).

Finally, align youth involvement with Responsible Research and Innovation (RRI) principles to ensure research serves public interest, includes diverse perspectives and actively anticipates potential harms (Babbage et al., 2024; De Alcântara Mendes et al., 2024).

Conclusion

Robust research on online harms has long been recognised as essential to inform high-quality policy and effective interventions. Many policy reports, such as those from the UK CMOs (Davies et al., 2019), US Surgeon General (US Department of Health and Human Services, 2023) and National Academies of Sciences (National Academies of Sciences, Engineering, and Medicine, 2024), have highlighted the need for better research evidence, especially that which is causal in nature examining population-level impacts.

Providing such evidence is challenging due to the rapidly evolving and increasingly complex technological landscape, the inherent difficulty of establishing causal relationships, limited access to data and infrastructure, and a fragmented, reactive approach to the funding of and investment in research. Yet the challenge to provide timely evidence is growing, not receding, particularly as powerful technologies such as generative AI are developed by companies whose commitment to children and adolescents' safety remains publicly contested.

Our systematic umbrella review of the evidence on the relationship between social media use and adolescent mental health found consistent negative correlations, with greater time spent on social media associated with poorer mental health outcomes. However, the evidence base is marked by significant limitations, including the predominance of low-quality primary studies. While experimental and quasi-experimental designs have the potential to substantially strengthen our ability to make causal claims about the impact of time spent on social media, our accompanying narrative review did not identify any experimental studies that had specifically reduced or altered time spent using social media or smartphones among healthy children or adolescents and measured their resulting changes to wellbeing or mental health.

This is an important evidence gap to fill, but our review of what research has and is being funded showed a lack of current or planned experimental and quasi-experimental studies on children and adolescents. It also found limited research investment on younger children and other subgroups potentially most as risk, and a relative absence of research on the impacts of AI in childhood and adolescence.

This report was commissioned to identify opportunities for targeted investment in research projects capable of generating stronger causal evidence on the effects of smartphones and social media on populations of children and young people within two to three years. For this we recommend a dual approach investing in both RCTs and natural experiment evaluations. While each method comes with trade-offs and limitations, including cost, feasibility and responsiveness to changes in policy interests, they can be implemented within the necessary timeframe if chosen research designs are not overly complex. Natural experiment evaluations, though often more cost-effective, are limited by access to the right data to track outcomes and the likelihood of the right natural experiments occurring. RCTs, while more complex, offer greater design control and can be tailored for relevance in the UK context, but are often more costly and difficult to implement.

Establishing causal relationships in this research area is difficult, and our report also notes that the inability to locate good-quality causal evidence of social media and smartphones' impact on children and young people does not mean that harm is not being caused, especially at the individual-level. Alongside research to produce higher-quality causal evidence of the impact of technologies on child and adolescent populations, we must therefore also ensure we research and promote interventions and policy changes to equip individuals, families and communities with tools and strategies to navigate a dynamic and challenging digital environment that is constantly evolving and creating new opportunities for harm. This also means acknowledging it will not just be how much time children and young people spend on social media or smartphones, but how they engage with them, their content and context, as well as the activities they might be displacing, that will be central to understanding their wider impact. Such work will best be done through interdisciplinary research going beyond traditional epidemiology, drawing on a diversity of fields and approaches and including efforts to improve theory and co-create research with affected communities. Where causal inference is not the main objective, more flexible and lower-cost methods, such as qualitative research and other types of studies such as ecological momentary assessments, are therefore also potential areas for research investment.

Strategic investment in this research area to generate better evidence over the next two to three years is necessary and welcome, but also insufficient for longer-term efforts to ensure better online safety. If the UK is to lead globally on online safety over the next decade, a more strategic, long-term vision will also be essential to develop, for example through the establishment of a national research strategy on online harms. This means moving beyond reactive, one-off investments and towards ambitious, sustained investment in research centres, programmes or networks. Improving and harmonising the measurement of digital technology use within the UK's flagship cohort studies now would also maximise the value of existing world-class research investments, enabling the creation of unique and innovative data assets for assessing online harms in future.

The paucity of good quality evidence found throughout our report illustrates the need for ongoing inquiry into how young people engage with constantly shifting digital technologies. Research, prevention and intervention will always need to evolve and progress to keep up with the rapid changes we are experiencing as a society. Accelerating the pace of scientific work while upholding rigour is critical if we are to ensure that children and adolescents can grow up in a digital world that supports their health, development and wellbeing.

Appendix 1: Evidence Review Summary

February 2025

Acknowledgements

Team contributions

Ioanna Fokas: Conceptualization, Investigation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Visualization, Data Curation; **Lukas J. Gunschera**: Conceptualization, Investigation, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Supervision, Validation; **Brandon Davidson**: Validation; **Matthew Richards**: Validation; **Zhuo Yao Yap**: Project Administration; **Amrit Kaur Purba**: Conceptualization, Methodology, Writing — Reviewing and Editing, Supervision, Funding Acquisition; **Amy Orben:** Conceptualization, Writing — Original Draft Preparation, Writing — Reviewing and Editing, Supervision, Funding Acquisition.

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Competing Interests Declaration

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/disclosure-of-interest/. In the interest of full transparency, the completed forms are provided in full in Appendix 8.

The corresponding author is AO (amy.orben@mrc-cbu.cam.ac.uk), who is also the guarantor of this review. AO affirms that the manuscript is an honest, precise and transparent account of the review reported, with no important aspects of the review omitted. Any discrepancies from the review as planned (and, registered) have been explained.

Peer Review

We received one round of external peer review by Michael Rich (Harvard Medical School), Jacqueline Nesi (Brown University), Adrian Meier (University of Erlangen-Nürnberg), Ravi Iyer (University of Southern California), Zach Rausch (New York University) and Jessica Packer (University College London). Peer review proformas are available on reasonable request and pending approval from the reviewers.

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Data Availability Statement

Data analysed were based on published data. Template data forms, data extracted from included studies and other materials are available from the corresponding author on reasonable request. The study protocol is published on Prospero: https://www.crd.york.ac.uk/PROSPERO/view/CRD42025641338 (PROSPERO ID: CRD42025641338).

Executive Summary

This report presents findings from a two-part evidence synthesis. First, we conducted an Umbrella Review of systematic reviews and meta-analyses examining the relationship between time spent on social media, smartphones and Artificial Intelligence (AI) chat applications, and adolescent mental health and wellbeing. Second, we carried out a narrative literature review of primary studies, systematic reviews and meta-analyses to explore how content, as well as smartphone or social media restrictions (e.g. school bans), may influence adolescent mental health and wellbeing.

Key findings and recommendations

1. Consistent small correlation between time spent on social media and adverse adolescent mental health: seven systematic reviews investigated the impact of time spent on social media and adolescent mental health outcomes. The methodological quality ranged from critically low (n (number of studies) = 6) to high (n = 1). Across the reviews, there was consistent evidence of a small positive association between time spent on social media and adverse adolescent mental health outcomes, including increased depressive symptoms, internalising problems and antisocial behaviour. This association also appeared in longitudinal data, which suggests that increased social media use may precede deteriorations in mental health. However, it should be noted that while longitudinal studies can demonstrate temporal order, they do not confirm causality on their own. The small number of reviews (n = 7) and the overall quality of underlying studies, which was relatively low, indicate further research is required before firm conclusions can be drawn.
2. Low certainty of causality: while there is some evidence that greater time spent on social media may be linked to poorer adolescent mental health, the certainty of this evidence remains low. Most primary studies used cross-sectional designs, relied on self-report data and lacked diverse samples, limiting their ability to infer causality. Observed associations may also reflect confounding factors, and the potential for reverse causality cannot be ruled out. Experimental studies exploring the effects of social media and screen time reduction interventions show some benefits to mental health and wellbeing, but none focused on healthy adolescents (the pre-determined focus of our review). High-quality targeted randomised controlled trials (RCTs) are needed to increase the certainty of causal claims, particularly if they consistently demonstrate improvements in mental health following reduced use.
3. High heterogeneity in findings: meta-analyses found high heterogeneity (i.e. variability) in the association between time spent on social media and depression and anxiety, and no adequate or consistent explanations was provided for this heterogeneity. Moderators such as age or gender were often examined but typically found no consistent differences by age or gender, suggesting the influence of unmeasured or more complex factors.
4. Limitations of the ‘time spent’ metric: many reviews criticised the use of overall ‘time spent’ on social media as an overly simplistic measure. Individual impacts from social media are likely determined by things other than time spent using it (such as the content consumed, or activities displaced for the individual child), other individual vulnerabilities or inequalities. Several reviews called for a shift toward more nuanced measures of social media, such as type of use, timing of use (e.g. during the night) or content engagement. Several reviews highlighted that the characteristics of social

media use for example, content viewed, timing and nature of use may be more important than time spent alone.

5. Content-specific harms: our narrative review found that the type of content consumed on social media plays a key role in mental health outcomes. Positive content and feedback can enhance self-esteem and support mental health, while negative content, exclusion and harmful material are linked to anxiety, social comparison and disordered eating, particularly in vulnerable adolescents.
6. Limited evidence on smartphone and social media restrictions: there were few studies examining the impact of school phone policies (diversely defined in the literature) on mental health or wellbeing in adolescents, with findings being mixed and methods contested. Whereas some showed small and context-dependent benefits of smartphone restrictions for wellbeing, reduced bullying, increased physical activity and improved academic performance, others did not. Very few studies reported negative outcomes. Evidence shows that restrictive school phone policies can have a positive influence on in-school behaviours (e.g screen time in school, reducing bullying, academic attainment and engagement, physical activity during breaks), but there is less clear impact on mental health, wellbeing and other associated outcomes that might be determined also by activities outside of the school environment.
7. Lack of evidence for impact of smartphones and AI chat applications: we found no systematic reviews exploring the impact of smartphone use or AI chat applications on adolescent mental health. This is likely due to smartphones often being studied as part of broader ‘screen time’ and the emergent nature of AI technologies.
8. Policy decisions must balance risk with evidence limitations: the lack of high-quality evidence should not be interpreted as evidence of no harm. Policymakers must weigh the risks of delaying action against the risks of acting on a limited evidence base. Thoughtful decisions must consider both potential harms and the current limitations of the science.
9. Need for a National Research Strategy: the overall lack of high-quality, policy-relevant evidence highlights the need for a cross-government National Research Strategy on Online Harms. This should include long-term investment in focused independent research, improved data access and the development of infrastructure to support timely, rigorous and policy-relevant studies.
10. Fast moving research space: with increasing research interest in this area this evidence base will likely expand and change even in the very near future. Further, technologies and their uses will develop, making previous conceptualisations obsolete. As such this review should be treated as a ‘living’ review which should be updated over time.

Overview

The pervasive use of social media and smartphones during adolescence is reshaping adolescent development in unknown ways. In response to claims that such activity negatively impacts mental health and wellbeing, there has been a rapid increase in research being carried out on this topic. To summarise the emerging findings, and assess the quality of evidence, we carried out two reviews.

Our primary focus was an umbrella review, also known as an overview of reviews, investigating the relationship between time spent using social media, smartphones and AI chat applications and adolescent mental health and wellbeing. In this systematic review of pre-existing systematic reviews and meta-analyses, we synthesised findings according to the preferred reporting items for overviews of reviews (PRIOR) guidance (Gates et al., 2022), while also taking into account PRISMA guidance (Page et al., 2021a). By focusing on a specific research question — selected for its conceptual relevance to current policy proposals aimed at potentially restricting time spent on these technologies through bans, limits or usage recommendations — we were able to conduct an in-depth synthesis, assess the quality of the evidence and offer a focused interpretation across three research objectives.

To supplement the umbrella review and address two core limitations — that time spent does not account for content viewed and that systematic reviews might be missing important experimental studies — we completed a pre-registered search of Google Scholar to identify both primary literature, systematic reviews and meta-analyses on the relationship between content viewed on social media and adolescent mental health and wellbeing. We also completed a search of the evidence for research on the relationship between smartphone and social media bans and adolescent mental health and wellbeing. While the search was pre-specified, it was not conducted systematically, and as such, we synthesised findings narratively. Consequently, this narrative review offers a broader overview rather than a detailed, in-depth analysis.

The results from both searches provide an overview of the current findings on the impacts of social media, smartphone and AI chat application use on adolescent mental health and wellbeing. Additionally, the review considers the quality of the evidence, its limitations and the broader implications of these findings.

Umbrella Review of the Relationship Between Time Spent on Social Media, Smartphones and AI Chat Applications and Adolescent Mental Health and Wellbeing

Background

Adolescence is widely recognised as the developmental period between childhood and adulthood that begins with puberty and ends with independence from parents or guardians (Steinberg, 2010). It constitutes a critical period for neurodevelopment: one in which the brain is particularly sensitive to social feedback and environmentally induced changes (Blakemore & Mills, 2014; Larsen & Luna, 2018). Key social behaviours emerge, including sensitivity to social exclusion, increased salience of social stimuli, and increased peer orientation (Andrews et al., 2022; Blakemore & Mills, 2014; Sawyer et al., 2018).

Understanding normative behaviours during adolescence is a prerequisite for understanding abnormal development (Larsen & Luna, 2018). This is particularly important given that adolescence is a time when major psychopathology begins to emerge (Solmi et al., 2022). During this period, adolescents undergo changes that predefine adult trajectories.

The unique importance of social stimuli during this stage in development demands the careful consideration of evolving social contexts, especially the rising use of digital technologies, with regards to adolescent wellbeing. In an increasingly digitalised world, socialisation during adolescence now occurs as much online as it does face-to-face. Reports indicate that 95% of adolescents have access to a smartphone, with nearly 20% saying they are online ‘almost constantly’ (Anderson et al., 2023). Digital interactions are ubiquitous in the social life of adolescents, bringing with them a series of benefits and challenges that are both novel and unique (Nesi et al., 2021).

There is still much debate in the academic literature about whether digital technologies such as social media and smartphone use impact the mental health and wellbeing of young people. This ongoing debate is characterised by conflicting findings (Jensen et al., 2019; Orben et al., 2022b) and varying interpretations of similar data (Ferguson et al., 2025; Kelly et al., 2018), highlighting the complexity and uncertainty surrounding this issue.

In turn, there has been a rapid surge in research examining the impact of digital technologies on mental health and wellbeing, including a growing number of systematic reviews and meta-analyses. Valkenburg et al. (2022) observed that in recent years, over 300 primary studies on social media use and mental health and wellbeing have been published annually, with 22 reviews emerging in 2020 and 2021 alone (Valkenburg, 2022). This pace has only accelerated over the past four years, underscoring the need for updated evidence syntheses to inform timely and effective policy decisions.

Across the medical sciences, there has been a marked increase in both primary research and integrative systematic reviews, even within highly specialised areas (Bastian et al., 2010). This proliferation of evidence can be overwhelming, making policy decision-making increasingly difficult. In response, umbrella reviews, also known as ‘reviews of reviews’, have become commonly adopted. These reviews collate and synthesise existing systematic reviews and meta-analyses to provide a comprehensive overview of findings within a field.

As they build on systematic reviews, umbrella reviews are often regarded the highest level of evidence synthesis available (Choi & Kang, 2023).

Many existing reviews do not systematically assess the quality of the underlying evidence — a critical shortcoming, given that such evaluations are a core requirement of the A Measurement Tool to Assess Systematic Reviews 2 guidelines (AMSTAR-2; Shea et al., 2017). Furthermore, as highlighted by Purba et al. (2023b), individual study risk of bias assessments are rarely included, significantly limiting the ability of these reviews to support causal inferences.

Given the vast and rapidly growing body of literature — including numerous narrative reviews, systematic reviews, and meta-analyses — an umbrella review was selected as the most appropriate methodology for this project. This approach allows for a comprehensive synthesis of existing evidence on the impacts of social media, smartphone and AI chat application use on child and adolescent development outcomes.

In collaboration with the Research Consortium and DSIT multiple potential research objectives were assessed considering time constraints and policy relevance. It was agreed that the review would focus on synthesising evidence related to the association between time spent on digital platforms and adolescent mental health and wellbeing.

While time spent on digital technologies is often considered a simplistic measure of digital engagement (Kaye et al., 2020), it remains central to many current and proposed policy measures — such as bans, restrictions or usage recommendations — making it a critical focus for this evidence synthesis. Our review focused on six key objectives related to the impact of time spent on digital technologies — specifically social media, smartphones and AI chat applications — on adolescent developmental outcomes. These objectives were grouped into three key areas:

Social media and adolescent developmental outcomes:
Objective 1a: To assess the relationship between time spent on social media and adolescent mental health outcomes.
Objective 1b: To assess the relationship between time spent on social media and adolescent wellbeing outcomes.

Smartphone use and adolescent developmental outcomes:
Objective 2a: To assess the relationship between time spent on smartphones and adolescent mental health outcomes.
Objective 2b: To assess the relationship between time spent on smartphones and adolescent wellbeing outcomes.

AI chat applications and adolescent developmental outcomes:
Objective 3a: To assess the relationship between time spent on AI chat applications and adolescent mental health outcomes.
Objective 3b: To assess the relationship between time spent on AI chat applications and adolescent wellbeing outcomes.

Methods

We followed the Preferred Reporting Items for Overviews of Reviews (PRIOR) guidance (Gates et al., 2022), and the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines (Page et al., 2021a). This study was registered with PROSPERO: https://www.crd.york.ac.uk/PROSPERO/view/CRD42025641338 (PROSPERO ID: CRD42025641338) (see Appendix 1.1). See Appendix 1.2 for both PRIOR and PRISMA checklists.

Search Methods for Identification of Reviews and Eligibility Criteria

MEDLINE, the Cochrane Database of Systematic Reviews (CDSR), and PROSPERO were searched for manuscripts appearing between 1 May 2007 (first global social media platform, 'Facebook', launched) and 1 January 2025 using a comprehensive search strategy (see Appendix 1.3). These databases were selected for their relevance and strong standing within the fields of psychology, medicine and public health. MEDLINE was also included for its coverage of social science literature, reflecting the interdisciplinary nature of this research area. IF completed the searches and review selection against eligibility criteria. In case of uncertainty, inclusion was discussed with LG and AO to make final decisions.

No filters were applied based on study type or geographical location. Only studies in the English language were considered for inclusion, as time constraints prevented the translation of non-English language studies. We defined systematic reviews and meta-analyses as those employing a pre-specified, systematic search strategy established prior to conducting the initial search.

We also screened reference lists of relevant systematic reviews and consulted subject matter experts to identify any additional, planned, ongoing or unpublished studies. In addition, we reviewed four previous umbrella reviews that addressed similar research questions and examined the included reviews and meta-analyses to ensure comprehensive coverage and avoid omissions (Cunningham et al., 2021; Dickson et al., 2018; Sala et al., 2024; Valkenburg et al., 2022).

We did not include additional primary research studies; that is, we did not conduct a separate search of the primary literature to identify studies not already captured in existing reviews. However, primary research studies were examined in the accompanying narrative review (see 'Supplementary Literature Review').

Inclusion and exclusion criteria

Participants

Inclusion

This umbrella review focused on the adolescent population, defined as individuals aged 10–19 years, in line with the World Health Organization's (2019a) age classification. Systematic reviews or meta-analyses (hereafter referred to as 'reviews') that included broader age ranges were eligible for inclusion if the mean age of participants fell within the 10–19-year age range. If the mean age was not reported, we calculated the midpoint of the age range provided to assess eligibility.

Exclusion

We excluded any reviews where the population of interest did not fall between the ages of 10–19 years. We further defined ‘fell between 10–19 years’ as between 10.00 and 19.00 years after registration.

Exposure

Inclusion
This umbrella review focused on time spent using social media, smartphones and AI chat applications. The following definitions applied:

- Social media defined as ‘internet-based, disentrained, and persistent channels of mass personal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content’ (Carr & Hayes, 2015).
- Smarthones defined as portable cellular devices with internet access and capacity to host applications.
- AI chat applications defined as any chatbot that ‘makes the use of digital technology to create systems capable of performing tasks commonly thought to require intelligence’ (Department for Science, Innovation and Technology, 2019).

Exclusion

- Studies examining internet/computer/media activities other than social media, smartphone and AI chat application use.
- Studies examining social media, smartphone and AI chat applications as a recruitment method.
- Studies examining ‘problematic’ use of social media, smartphones and AI chat applications. This decision was based on ongoing concerns about the validity of how problematic use is defined — terms like ‘problematic’ or ‘addictive’ are often applied inconsistently and lack clear theoretical grounding and an objective and accurate measurement method.
- Studies investigating social media dating platforms.

Outcome(s)

The outcomes of interest were mental health and wellbeing.

Inclusion
Studies that measured clinical outcomes (diagnoses of mental health disorders) and specific clinical symptoms (internalising, fear of gaining weight, restriction of food intake) were included as measures of mental health. All measurement methods of outcomes were considered for inclusion, including standardised questionnaires, self-report, measurement of online activity, categorical diagnoses from physicians, reports from parents, guardians and peers, self-report and physiological measures.

Exclusion
Studies that focused on subclinical phenomena related to mental health problems (body image) were excluded as measures of mental health. Studies that focus exclusively on clinical populations with pre-existing diagnosed mental health disorders unrelated to social media use were excluded to ensure that outcomes are directly linked to the effects of social media. If these reviews examined one or more of the primary outcomes they were considered for inclusion if relevant data could be extracted.

Study type

Inclusion
Systematic reviews and meta-analyses.

Exclusion
Editorials, commentaries, primary research studies, conference abstracts and non-peer-reviewed papers.

Additional specification after PROSPERO registration

After the initial search, we found it necessary to further refine our inclusion criteria. Rather than imposing a single definition of 'time spent on social media/smartphones/AI chat applications', we adopted the definition assumed by each review author. This approach was taken due to the lack of consistency in the way social media use was defined across studies, and to prevent excluding potentially relevant studies. We excluded measures focused on frequency of use, specific behaviours (e.g. posting a certain number of pictures) or exposure to content. We did not include studies examining outcomes related to body image or appearance satisfaction.

We also included studies that examined broader measures of social media/smartphone/AI chat application use (e.g. frequency or content), measures beyond just mental health and wellbeing (e.g. health risk behaviours), or wider age ranges (e.g. general population samples), if they included a separate evaluation of the relationship between time spent on social media/smartphones/AI chat applications and adolescent mental health or wellbeing which could be extracted. For meta-analyses, this additionally required the inclusion of a standalone analysis dedicated to this research question. Meta-analyses covering wider research questions (e.g. both adult and adolescent populations) were included if they reported subgroup analyses or moderation results specifically isolating the research question of interest (e.g. a meta-analysis for adult and adolescent populations with age as a moderator and reported results for the adolescent age subgroups separately).

Selection of Reviews

Records were de-duplicated in Zotero (Corporation for Digital Scholarship, 2023) and imported to Covidence software for screening (Covidence, 2025).

Data Extraction

Data were extracted in Microsoft Excel by the lead author (IF*) and BD* separately. Titles of primary studies were extracted to determine primary study overlap. Data extraction fields are presented in Appendix 1.4. IF* and AO* discussed any cases where IF* and BD* disagreed or where further effort was needed to identify or clarify missing or unclear information.

*Author Key: IF – Ioanna Fokas; BD – Brandon Davidson; AO – Amy Orben.

Primary Study Overlap Assessment

We analysed the extent to which primary studies overlapped between the included reviews and meta-analyses, following recommendations by Lunny et al. (2021). We created a citation matrix visualising primary study overlap (Appendix 1.5). We then calculated the Corrected Covered Area (CCA) according to the formula below, which corrects for biases introduced by the number of reviews included, study size and redundant or inflated data from repeated conclusions (Lunny et al., 2021). While there is no established standard by which a certain level of CCA should exclude certain reviews from evidence synthesis, it is a measure that can be used as an indicator that findings may be biased or overly inflated due to high primary study overlap. We calculated pairwise CCA measures between each review, serving to highlight the reviews with particularly high levels of overlap.

$$\mathrm{CCA} = \frac{(\text{Total study occurrances} - \text{Number of unique studies})}{(\text{Number of reviews } \times \text{Number of unique studies}) - \text{Number of unique studies}}$$

In the instance of high study of overlap, we used the Alberta Research Centre for Health Evidence (ARCHE) decision tool for inclusion of systematic reviews in overviews of reviews of healthcare interventions (Pollock et al., 2019). As recommended by ARCHE, the most recent and high-quality systematic reviews were prioritised for interpretation and analysis. Recency is defined by year of final search completed. Quality, also known as risk of bias, assessment of reviews is discussed below.

Quality Assessment of Reviews

Quality assessment was conducted independently by IF, MR/BD and an independent reviewer (JP), using an adapted version of the AMSTAR-2 tool (Shea et al., 2017). Any discrepancies in the quality assessment rating between the three reviewers was resolved by a third reviewer (LG).

Risk of Bias of Included Studies

We made efforts to identify the risk of bias and quality assessment measures taken in the primary studies of included reviews, extracting data on the assessment tool used in the reviews themselves, guidance/checklists used, and the authors interpretation of quality.

Reporting Bias Assessment

It was important to also assess whether publication bias, the systematic overrepresentation of significant findings in the published literature, determined which studies were reported in the reviews. We therefore compiled for each review, if available, their reporting bias or small study bias assessments (e.g. funnel plot and funnel plot symmetry tests (Egger et al., 1997)).

Certainty Assessment

To assess certainty of evidence in the systematic reviews we identified whether authors utilised the Grading of Recommendations, Assessment, Development and Evaluation (GRADE) criteria (Schwingshackl et al., 2021) or considered the Bradford Hill viewpoints for making causal claims (Hill, 1965). The former provides a systematic approach to evaluating certainty of evidence in systematic reviews, whilst the latter are a series of principles used to assess evidence of a causal relationship between cause and effect in epidemiology (Guyatt et al., 2008; Hill, 1965).

Data Synthesis

We conducted a narrative synthesis of the findings included under our specified inclusion criteria, prioritising more recent and higher quality reviews as outlined above. We summarise the heterogeneity and moderator analyses reported in each review and synthesise these narratively to explore potential sources of heterogeneity. We did not undertake any additional sensitivity or heterogeneity analyses.

Results

Review Selection

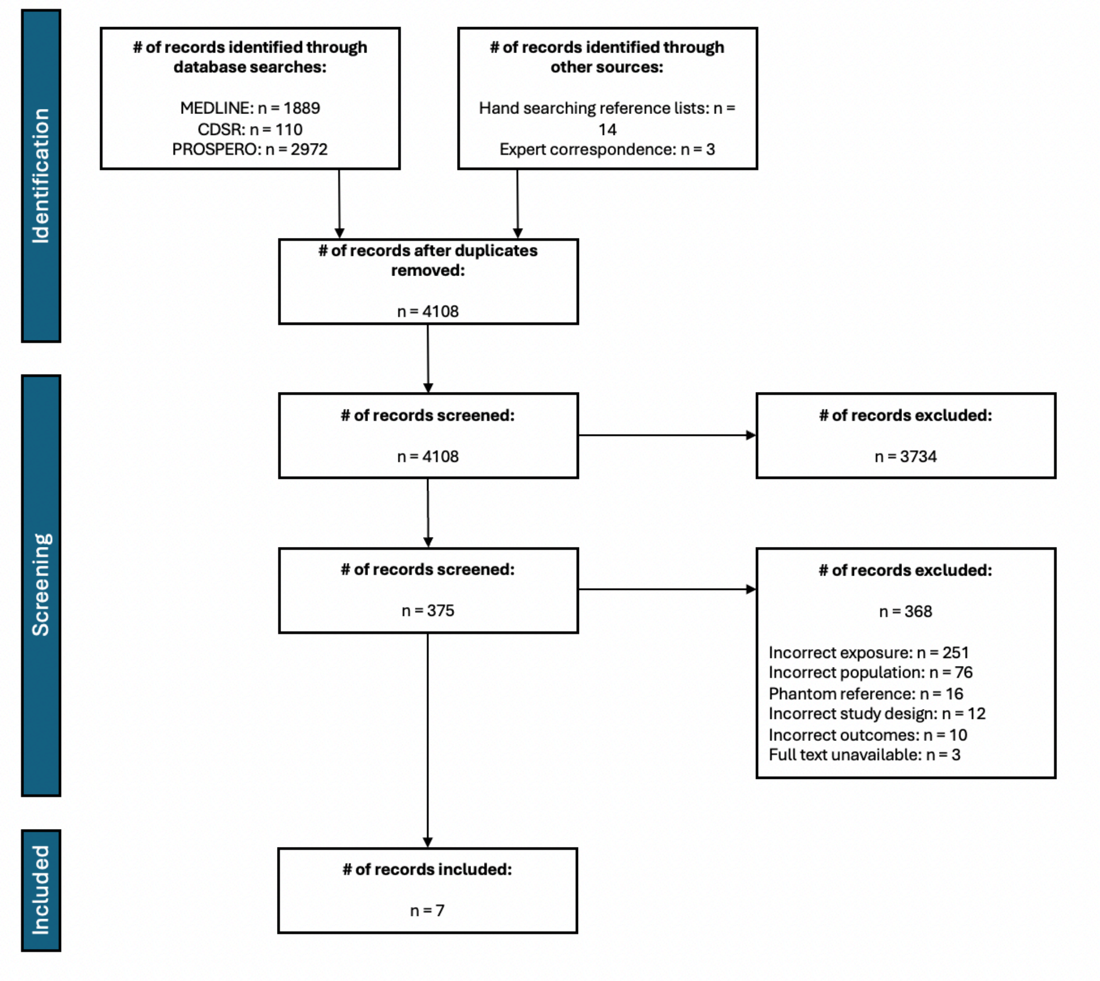
Figure 3 summarises the review selection process in accordance with the PRISMA guidelines (Page et al., 2021b).

Our database search yielded 4,971 items. Following deduplication, the lead reviewer (IF) screened 4,108 items by title and abstract. Of these, 3,734 were excluded and 375 progressed to full text screening. On full text screening, 368 were excluded with reasons including: incorrect exposure, incorrect population, incorrect outcome, incorrect study design and the existence of phantom references (citations or references that appear in citation databases but cannot be traced to an actual source). Three full texts were unavailable, and were excluded after efforts to reach the authors were unsuccessful.

The final sample included seven reviews. Characteristics of included reviews are presented in Appendix 1.6.

We further considered each review included in four pre-existing umbrella reviews on this research area (Cunningham et al., 2021; Dickson et al., 2018; Sala et al., 2024; Valkenburg et al., 2022), and provided a reason for exclusion or inclusion based on our pre-specified population, exposure and outcome criteria for each (see Appendix 1.7).

Figure 3. PRISMA flow diagram of the screening process.



Legend: MEDLINE = Medical Literature Analysis and Retrieval System Online, CDSR = Cochrane Database of Systematic Reviews

Primary Study Overlap Assessment Results

CCA analyses was used to guide evidence synthesis. The calculated CCA for the studies was 0.056, classed as a moderate amount of overlap (Lunny et al., 2021; Pieper et al., 2014).

We also reviewed overlap between studies. Following the ARCHE tool (Pollock et al., 2019), reviews with very high overlap (CCA > 15%) (Pieper et al., 2014) and lower methodological quality were deprioritised to reduce the risk of inflating findings due to redundancy. If studies had the same overarching quality rating we prioritised those with the least AMSTAR categories which were rated as 'no', i.e. not a 'yes' or 'partial yes' (Appendix 1.8). For example, M. Liu et al. (2022) had an overlap of 17.78% with Ferguson et al. (2025), 19.7% with Fassi et al. (2024) and 21.1% with Ivie et al. (2020). Based on quality ratings and search recency, Fassi et al. (2024) was prioritised over both M. Liu et al. (2022) and Ferguson et al. (2025), Ferguson et al. (2025) was prioritised over M. Liu et al. (2022), and M. Liu et al. (2022) was prioritised over Ivie et al. (2020). Full details of the CCA calculations and review prioritisation process can be found in (Appendix 1.5).

Characteristics of Reviews

All seven reviews were found to investigate Objective 1, i.e. time spent on social media and adolescent mental health and wellbeing. All reviews investigated mental health as an outcome (Objective 1a), while two investigated mainly mental health but also some general wellbeing measures (Objective 1b). Due to the lack of standalone studies for Objective 1b, we decided to report all results collectively under the heading of Objective 1.

No systematic reviews or meta-analyses were found which addressed Objective 2, investigating time spent using smartphones and adolescent mental health and wellbeing, nor Objective 3, investigating time spent using AI chat applications and adolescent mental health and wellbeing. We therefore do not report any results for these objectives.

Five of the reviews used meta-analysis (Cunningham et al., 2021; Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; M. Liu et al., 2022; Purba et al., 2023b), one also carried out a Synthesis without Meta-Analysis (SWiM), an approach to narrative synthesis recommended by Cochrane (Cochrane Training, 2025; Purba et al., 2023b) and one was solely a narrative synthesis (Keles et al., 2020).

One out of seven reviews included studies where participants were less than 10 years or more than 19 years of age. In this case, the mean age of the sample was taken and, if between 10–19 years, subsequently included in the review. If the mean age was not provided, we took the mean of the provided age range. All included reviews assessed both male and female adolescents.

The reviews examined specifically depressive symptoms (n = 3), more general internalising symptoms which included depressive and anxiety symptoms (n = 1), antisocial behaviour (n = 1) and broader generalised measures of mental health and wellbeing (n = 2). Reviews employed validated measurement tools to record symptomology, including the Centre for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977) the Short Mood and Feelings Questionnaire (SMFQ; Angold et al., 1995), Beck's Depression Inventory (BDI; Beck et al., 1961), the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2011), the Children's Depression Inventory (CDI) (Kovacs, 2013), the Differentiation of Self Inventory (Skowron & Schmitt, 2003), the Hospital Anxiety and Depression Scale (Zigmond & Snaith, 1983), the Yale-Brown Obsessive Compulsive Scale (Goodman et al., 1989), as well as clinical diagnostic cut-offs.

Outcome: Antisocial behaviour

Purba al. (2023b) examined the association between social media use and antisocial behaviour (as well as various other health risk behaviours not included in the scope of this review) in adolescents aged 10–19 years. The review was rated as high quality according to our AMSTAR-2 assessment — making it the only review in this synthesis to receive that rating. The researchers carried out a systematic review of the literature between 1997 and 2022, finding six studies investigating the relationship between time spent on social media and antisocial behaviour. These studies all demonstrated harmful associations following the application of vote counting procedures (95% CI = 61.0 to 100.0%, participant n = 51,611, sign test p = 0.03). A meta-analysis of the included studies found a positive standardised mean difference of 0.14 (CI = [0.13, 0.14]).

Outcome: Internalising symptoms

While internalising symptoms can include depressive symptoms, they can also encompass a wider variety of outcomes such as anxiety symptoms or more general internalising symptom assessments. In a meta-analysis exploring the association between social media use and internalising symptoms in both clinical and non-clinical populations, Fassi et al. (2024) found a small positive and significant correlation between time spent on social media and internalising symptoms ($r = 0.12$, 95% CI = [0.09, 0.14]; $p < .001$; $I^2 = 98.0\%$). They also found that this effect size did not vary significantly between those adolescents diagnosed with anxiety or depression, and a general population reporting on their internalising symptoms. The review included a larger age range than others (they defined adolescence as an extended period from 10–24 years; the review was included in our umbrella review as the mean of this range is 17 years) and therefore included substantially more studies than the other reviews (56 studies with 117 effect sizes). The review was rated as critically low quality based on our assessment.

Fassi et al.'s (2024) review included 24 longitudinal studies which were treated as correlational in the meta-analysis due the large variations in methods of analysis. However, the review conducted a structured synthesis of their effect directions. Among the 24 longitudinal studies that examined time spent on social media in relation to anxiety, depression or internalising symptoms at a later time point, 38% (nine studies) reported no overall association and 4% (one study) found a negative relationship between time spent on social media and adverse outcomes limited to a subgroup of moderate social media users. A further 33% (eight studies) found a positive longitudinal relationship, with greater time spent on social media associated with higher internalising symptoms at a later time point. The remaining 25% (six studies) reported a positive relationship only for specific subgroups: girls only (three studies); adolescents using social media for more than three hours daily (one study); individuals with generally high social media use (one study); and in one study, for girls at one time point and boys at three time points.

Outcome: Depressive symptoms

In a meta-analysis investigating the correlational relationship between time spent on social media and depressive symptoms across a general population including adolescents and adults, Cunningham and colleagues also found a small but statistically significant pooled correlation of $r = 0.11$, 95% CI = [0.086, 0.13], $p < 0.001$ (Cunningham et al., 2021). The review was rated as critically low quality based on our assessment. A non-significant moderation analysis ($Q = 3.40$, $p = 0.065$) found weaker associations in those studies collecting data from only adolescents ($r = 0.02$, $n = 6$) rather than only adults ($r = 0.11$, $n = 24$).

M. Liu et al. (2022) carried out a systematic review and meta-analysis of 26 primary studies, the majority of which (21 studies) were cross-sectional and five were longitudinal. The review was rated as critically low quality based on our assessment. Across a total of 55,340 participants between 11–19 years of age, they found that time spent on social media was significantly associated with a higher risk of depression as measured by a series of validated diagnostic tools (pooled Odds Ratio (OR) of 1.59, 95% CI = [1.44, 1.77], $p < 0.001$) (M. Liu et al., 2022). There was little difference between the results of the cross-sectional (OR = 1.61, 95% CI = [1.44, 1.81]) and longitudinal studies (OR = 1.57, 95% CI = [1.44, 1.71]). A dose response analysis was completed across four studies, finding a linear dose response relationship where each hour of social media use was predicted to increase depression risk by 13%.

Three reviews specifically assessed the relationship between time spent on social media and depressive symptoms. Ivie et al. (2020) systematically reviewed and meta-analysed 12 primary studies (11 studies cross-sectional, one study longitudinal) reviewed up to 2020. The review was rated as critically low quality based on our assessment. They found a small but significant positive correlation (harmful association) between adolescent social media use and depressive symptoms ($r = 0.12$, 95% CI= [0.04, 0.20], $p < 0.01$).

Outcome: Generalised mental health and wellbeing

A systematic review and meta-analysis by Ferguson et al. (2025) reviewed 46 primary studies relating to time spent on social media and broad mental health and wellbeing outcomes, finding a standardised beta coefficient of $\beta = 0.061$ (95% CI = [0.047, 0.075]). Moderation analyses of gender, study year, study type (i.e. cross-sectional vs longitudinal) or adoption of methodological best practices were not significant. The review was rated as critically low quality based on our assessment.

Keles et al. (2020) completed a systematic review of the literature on the relationship between time spent on social media and depression, anxiety or psychological distress in adolescents, finding mixed effects across six studies. Four found positive correlations between time spent on social media and worse mental health outcomes or more psychological distress in samples from Australia (O'Dea & Campbell, 2011), Europe (Tsitsika et al., 2014), Canada (Sampasa-Kanyinga & Lewis, 2015) and China (Yan et al., 2017). Two samples in Australia (Blomfield Neira & Barber, 2014) and Serbia (Banjanin et al., 2015) found no relationship. The review was rated as critically low quality based on our assessment.

Risk of Bias of Reviews and Primary Studies

Reviews

Based on the AMSTAR-2 criteria (see Appendix 1.8 and Appendix 1.9), six of the included reviews were considered to be of 'critically low' quality (more than one critical flaw with or without non-critical weaknesses) (Cunningham et al., 2021; Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; Keles et al., 2020; M. Liu et al., 2022) and one review was found to be of 'high' quality (no critical weaknesses) (Purba et al., 2023b). Key critical domains that reviews failed on were (i) inadequate justification for study design inclusion and (ii) failure to account for risk of bias when interpreting the study results.

Primary studies

We also synthesised how the reviews evaluated the quality or risk of bias of their included primary studies. For example, Purba et al. (2023b) evaluated risk of bias using an adapted version of the Newcastle-Ottowa Scale (Wells et al., 2000) which facilitated assessment of a study's ability to make causal inferences. Considering the six studies investigating antisocial behaviour, three were rated high risk of bias, one moderate and two low risk of bias.

Fassi et al. (2024) used the Quality of Survey Studies in Psychology Checklist to assess the quality of included primary studies (Moyer & Finney, 2005): 55% (n = 78) of studies were of acceptable quality while the remaining 45% (n = 65) were of questionable quality. Studies were primarily marked down due to a lack of justification for their sample size, low evidence for the validity of their measures, lack of description of key demographic characteristics and lack of debriefing at the end of data collection.

Ivie et al. (2020) assessed primary study quality using the National Institute of Health Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies (National Institute of Health, 2021). The tool provides a total score between 0–18 to each study, and the included studies scored between 15–18, however no further interpretation was provided. Keles et al. (2020) used the same assessment tool but provided quality ratings (good, fair, poor) rather than scores. Three studies were rated poor, one rated fair, and two rated good. Most studies were downgraded due to their cross-sectional design, lack of demographic information or lack of sample size justification. Poorer studies were further downgraded due to poorly defined and invalid measures of exposure or outcomes.

M. Liu et al. (2022) assessed study quality referencing the Meta-analysis of Observational Studies in Epidemiology (MOOSE) (Stroup, 2000) and the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) (Von Elm et al., 2007) guidelines. They gave studies points for appropriate selection of participants, valid measures of time spent on social media, valid measures of depression, handling of confounds, design issues and statistical methods. The maximum score was eight, and studies ranged from scoring three to seven, with 19 studies (73%) scoring over five. No further interpretation of these scores was provided.

Ferguson et al. (2025) evaluated study quality using criteria they had developed previously (Ferguson et al., 2022). The review found that the use of validated measures of mental health was common (92–95%), as well as use of basic control variables (64%, i.e. gender, age, family environment and baseline outcomes in longitudinal studies). However, studies were marked down for not including multiple respondents (19%), lack of pre-registrations (5%), no querying for hypothesis guessing (1%) and no distractor questions (0%). No synthesised quality rating for individual primary studies was provided. Cunningham et al. (2021) did not provide any evaluation of risk of bias of primary studies.

Synthesis of Results

All meta-analyses identified a small, positive correlation between increased social media use and more adverse mental health outcomes in adolescents including depressive symptoms (Cunningham et al., 2021; Ivie et al., 2020; M. Liu et al., 2022), internalising symptoms (both depressive and anxiety symptoms) (Fassi et al., 2024; Ferguson et al., 2025) and antisocial behaviour (Purba et al., 2023b). In a narrative review of six studies, four found a relationship to decreases in mental health (Keles et al., 2020). Higher quality and more recent reviews (e.g. Purba et al., 2023b) were prioritised in our synthesis of results.

A review of effect directions of longitudinal studies by Fassi et al. (2024) highlighted that most studies (58%; n = 14) found a positive longitudinal relationship with greater time spent on social media associated with higher internalising symptoms later in time across the whole sample or a subgroup, while 38% (n = 9) reported no association and 4% (n = 1) finding a negative relationship.

Heterogeneity

Heterogeneity analyses were only applicable for meta-analyses, and five of them found high heterogeneity in study designs across included studies (Cunningham et al., 2021; Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; M. Liu et al., 2022), while one, considering antisocial behaviour, found low heterogeneity ($I^2 = 13.98\%$) (Purba et al., 2023b). All included meta-analyses used random effects models, with heterogeneity ranging from $I^2 = 72.6\%$–$I^2 = 98.8\%$.

When considering depression or internalising mental health outcomes, heterogeneity was consistently high across all reviews. For example, Cunningham et al. (2021) ($I^2 = 96.65\%$), Ferguson et al. (2025) ($I^2 = 98.8\%$) and Ivie et al. (2020) ($I^2 = 97.38\%$) all found similarly high levels of heterogeneity. This also aligned with Fassi et al. (2024) who found high heterogeneity ($I^2 = 98.0\%$) when accounting for sample type (clinical vs community sample; no heterogeneity analysis was reported without this moderation).

M. Liu et al. (2022) reported high heterogeneity overall ($I^2 = 72.6\%$) and across cross-sectional studies ($I^2 = 75.3\%$) but low heterogeneity for the five longitudinal studies ($I^2 = 0\%$). This exceptionally low rating requires further scrutiny but could underscore the potential benefits of longitudinal studies in this area. Yet it conflicts with the substantial range of results found in Fassi et al.'s narrative assessment of 24 longitudinal studies, where a range of outcomes was reported.

Moderators

Several reviews carried out subgroup analyses to identify possible moderators of the relationship between time spent on social media and mental health outcomes (Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; M. Liu et al., 2022). Overall, only one review (rated as 'critically low' quality in our risk of bias review above) found substantial moderators or subgroups that could explain the high levels of heterogeneity found (M. Liu et al., 2022), and the significant moderators this study found were not replicated across most of the other studies in the sample, including those of higher quality.

Five studies found few or no moderators. In Purba et al. (2023b), subgroup analyses by development status of the study setting (e.g. high vs low-middle income), study design (e.g. cohort vs cross-sectional) or social media category also did not find any important differences when investigating antisocial behaviour. Fassi et al. (2024) found no significant moderators of the high heterogeneity across sample type (clinical vs community), mental health outcome, COVID-19, participant age or sex when investigating internalising symptoms. Ivie et al. (2020) completed subgroup analyses indicating that neither age nor sample size accounted for any of the high heterogeneity between studies when investigating social media use and depressive symptoms.

Ferguson et al. (2025) found no significant moderation by sex, best research practices, study year, participant age, citation bias in studies, study type (correlational vs longitudinal) or method to measure time spent using social media. The only significant moderator they found was the type of dataset, with bespoke or dissertation datasets finding smaller effect sizes than national datasets. Cunningham et al. (2021) found that year of publication, and whether studies included only social media users or also non-users, were not significant moderators, while whether participants were recruited through social media was (with higher effect sizes for those participants recruited via social media).

Keles et al. (2020) did not perform formal moderation analyses but noted that three of the primary studies performed some group comparisons. Banjanin et al. (2025) found no moderation by age or gender, while Tsitsika et al. (2024) found a significant effect of age (with younger heavier social media users finding a stronger relationship) and Neira and Barber (2014) found that female adolescents might be more negatively impacted than males. The only study to find substantial moderating effects was M. Liu et al. (2022) who isolated significant moderating effects by age (over 14s have higher OR), gender (pooled OR for adolescent girls was 1.72, compared to 1.2 for boys) and measure of depression. The review, however, did not find significant moderating effects for world region, measure of time spent on social media or sample size.

Reporting Bias

Overall, the evidence for reporting bias was mixed. One review identified evidence of publication or small study bias (Ferguson et al., 2025), one reported weak evidence (M. Liu et al., 2022), three found no evidence (Fassi et al., 2024; Ivie et al., 2020; Purba et al., 2023b), and two did not conduct such analyses (Cunningham et al., 2021; Keles et al., 2020). As a result, we cannot draw firm conclusions either for or against the presence of reporting bias. Cunningham et al. (2021) found evidence of publication bias through visual inspection, revealing an asymmetric funnel plot, and Egger's test indicating significant asymmetry. The trim-and-fill method suggested that 14 studies may be missing due to this bias. Similarly, there was evidence of missing studies in Ferguson et al. (2025) with Egger's Regression ($p = 0.021$) and trim-and-fill (missing studies $n = 4$) suggesting potential for publication bias.

M. Liu et al. (2022) found weak evidence of publication bias: Begg's test did not show significant publication bias ($p = 0.986$), Egger's linear regression test showed some publication bias ($p = 0.039$), yet no trimming was required during the nonparametric trim-and-fill method. Fassi et al. (2024) and Ivie et al. (2020) found no evidence of small study bias using the same methodology, with Ivie et al. (2020) also completing a p-curve analysis. Due to insufficient data, Purba et al. (2023b) only assessed publication bias for the outcome sexual risk behaviour, where results suggested some publication bias ($p = 0.04$; bias towards the null), however insufficient data precluded investigation of other outcomes including antisocial behaviour. Keles et al. (2020) also did not provide any assessment.

Evidence Certainty

To evaluate how the included reviews assessed the certainty of evidence and, more specifically, considered causal inference, we examined whether they employed the GRADE framework to assess the certainty of evidence and considered Bradford Hill viewpoints for causation (Guyatt et al., 2008; Hill, 1965).

To evaluate how the included reviews assessed the certainty of evidence and, more specifically, considered causal inference, we examined whether they employed the GRADE framework to assess the certainty of evidence and considered Bradford Hill viewpoints for causation (Guyatt et al., 2008; Hill, 1965).

Only one review, Purba et al. (2023b), applied the GRADE criteria to assess the certainty of the evidence. This review examined nine health-risk behaviours: 1) alcohol use, 2) drug use, 3) tobacco use, 4) electronic nicotine delivery system use, 5) unhealthy dietary behaviour, 6) inadequate physical activity, 7) gambling, 8) antisocial behaviour and 9) sexual risk, as well as the risk for multiple of these health-risk behaviours to co-occur. In line with the GRADE framework, the study team's policy advisory group ranked these behaviours in order of importance, and the top seven prioritised behaviours were alcohol use, drug use, tobacco use, electronic nicotine delivery system use, sexual risk behaviour, gambling, and multiple risk behaviours. This did not include antisocial behaviour, the outcome of interest in this review. Across these priority outcomes, the authors reported harmful effects on alcohol use with low certainty, and very low certainty for the remaining outcomes. These ratings were largely attributed to the observational nature of the included studies and the high risk of bias, partly due to inadequate adjustment for confounding variables and poor measurement of social media use. Additionally, the study team conducted a post-hoc GRADE assessment for exposure to content displaying health risk behaviour (vs no exposure) and unhealthy dietary behaviour because of the substantial difference in quality of evidence observed (four randomised controlled trials); where they reported moderate GRADE certainty.

None of the reviews explicitly cited Bradford Hill, yet several (Ivie et al., 2020; Keles et al., 2020; M. Liu et al., 2022; Purba et al., 2023b) considered the principles in their discussions, as outlined below. Several reviews (Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; M. Liu et al., 2022; Keles et al., 2020) raised concerns about the methodological quality of the included studies. These concerns align with Bradford Hill's *strength* and *consistency* viewpoints, as common issues included reliance on self-reported measures of time spent on social media, the predominance of cross-sectional designs, and the scarcity of RCTs. Fassi et al. (2024) explicitly cautioned against making causal inferences, citing reverse causality, which aligns with the *temporality* viewpoint in Bradford Hill's framework — emphasising the importance of time order in establishing causality. This concern was echoed by Ivie et al. (2020), Keles et al. (2020), M. Liu et al. (2022) and Purba et al. (2023b).

M. Liu et al. (2022) suggested that social media use could be a risk factor for mental health, noting a possible *dose-response* effect, which aligns with the *biological gradient* viewpoint. However, they acknowledged limitations in the control variables used and concluded that causal conclusions could not be drawn. Both Ivie et al. (2020) and Purba et al. (2023b) raised the possibility that the observed associations may be driven by unmeasured common risk factors (e.g. pre-existing mental health conditions), thus invoking the need to consider *confounding* factors.

The reviews also highlighted the need for more robust research designs, with Ivie et al. (2020) and Purba et al. (2023b) advocating for experimental studies to better establish causality, which relates to the *experimental evidence* criterion of Bradford Hill. Additionally, M. Liu et al. (2022) and Purba et al. (2023b) called for more objective data on time spent on social media (e.g. via future access to user data from social media platforms), supporting the need for higher-quality data to reduce bias and improve reliability.

Regarding *heterogeneity*, many reviews noted the high variation in study results, with several (Cunningham et al., 2021; Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020) suggesting that unmeasured moderating variables (e.g. timing of social media use, such as night time use) could influence the outcomes, addressing the *consistency* and *specificity* viewpoints. The lack of demographic detail in several studies further hindered the analysis of moderating factors such as gender identity and ethnicity, which are essential for understanding *specificity*.

Finally, some authors commented on the small effect sizes observed (Cunningham et al., 2021; Ferguson et al., 2025; Ivie et al., 2020). Cunningham et al. (2021) and Ferguson et al. (2025) suggested that these small effects might lack clinical significance, which relates to the *strength* criterion. Ivie et al. (2020) compared these findings to other mental health risk factors, such as stress, concluding that the effects of social media use were weaker comparatively. However, Purba et al. (2023b) highlighted that consistent associations across both correlational and longitudinal study designs, especially when adjusted for baseline measures of outcomes, may indicate a genuine underlying relationship, thus addressing *temporality*, *strength*, and *biological gradient* in Bradford Hill's framework.

Discussion

Summary of Findings

This umbrella review synthesised the findings of systematic reviews and meta-analyses investigating the effects of time spent on social media, smartphones and AI chat applications on adolescent mental health and wellbeing.

We found no systematic reviews addressing the effects of time spent on smartphones or AI chat applications on adolescent mental health or wellbeing outcomes. The absence of such studies likely reflects both a lack of research in novel but emerging technologies such as AI chat applications and the tendency for smartphone use to be subsumed within broader 'screen time' variables. As a result, the specific effects of smartphone use remain indistinct from those of other digital media such as television, computers and tablets.

In contrast, we identified five systematic reviews linking time spent on social media to mental health, and two linking it to both mental health and wellbeing. Given the overlap in outcomes, we analysed these collectively. The methodological quality of the included reviews varied: six were rated 'critically low' (Cunningham et al., 2021; Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; Keles et al., 2020; M. Liu et al., 2022), and one 'high' (Purba et al., 2023b). Despite several reviews being of poor quality (often characterised by limited transparency or inadequate reporting) enough were of moderate to high quality to permit a reasonably reliable synthesis. Priority was given to higher quality and more recent reviews in our narrative synthesis and interpretation of results.

The reviews examined a range of mental health outcomes, including depressive symptoms, internalising symptoms, antisocial behaviour and wellbeing. The quality of primary studies underlying these reviews consistently raised concerns. For example, Purba et al. (2023b), Fassi et al. (2024) and Keles et al. (2020), reported that approximately 50% of included primary research studies were of poor or questionable quality. Other reviews reported point ratings of study quality without interpretation, though similarly indicated substantial heterogeneity in primary study quality ratings. There is an overreliance on self-report measures of social media use: Fassi et al. (2024) note that 92% of their effect sizes were derived using self-report measurements rather than objective measurements of social media use, which have been shown by meta-analyses to be of poor quality (Parry et al., 2021).

Overall, this low study quality was acceptable for further analysis but should be considered on interpretation.

Evidence of publication or small study bias was inconsistent, with some reviews suggesting a bias against null findings and others finding no such evidence. Most studies relied on cross-sectional designs and self-reported measures of social media use. Few provided detailed demographic information. Several reviews emphasised that time spent on social media is an inadequate measure in isolation and that other factors, such as type of use, timing of use (e.g. night time use) or nature of content, may be more informative (Fassi et al., 2024; Ferguson et al., 2025; Purba et al., 2023b). Purba et al. (2023a) later highlighted that this methodological limitation may stem from limited access to data, underscoring the need for social media companies to share data with researchers. Furthermore, in the absence of real-time data, they emphasised the need to develop generalisable, validated measures of social media use which differentiate between activities performed and content consumed to improve comparability across studies and to better understand the most harmful aspects of social media for youth.

Of the included reviews, six were found to be of critically low quality (Cunningham et al., 2021; Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; Keles et al., 2020; M. Liu et al., 2022). Of particular importance for the aims of this review, these included all reviews pertaining to the mental health outcomes of anxiety and depression (broader internalising disorders), with the one high quality review pertaining to antisocial behaviour (Purba et al., 2023b). These methodological limitations affect both internal and external validity and constrain the extent to which causal inferences can be drawn.

Despite these limitations, all included reviews found small but consistent positive associations between time spent on social media and adolescent adverse mental health outcomes/mental health problems. Fassi et al. (2024) found that these associations extended to about a third of longitudinal data, with time spent on social media predicting increased internalising diagnoses at subsequent time points. An additional 25% of longitudinal studies in their review found such longitudinal relationships for specific subgroups of adolescents.

However, while there is therefore aligned longitudinal data, conclusions need to be drawn with caution. A review of longitudinal studies investigating the relationship between adolescent screen time and mental health found mixed results, and small effect sizes, for studies concerning the longitudinal mental health impacts of social media use (Tang et al., 2021). As this review defined social media use broadly as time or frequency of use and did not have a separate section specifically analysing the results for time spent on social media, it did not match our inclusion criteria. It found mixed results for the longitudinal link between social media and depression, no evidence for longitudinal relationships between social media use and anxiety, and two studies showing evidence that high levels of social media use predict higher internalising symptoms or psychological distress (Tang et al., 2021).

In general, the included reviews covered research insufficient for making causal statements about social media's impact on mental health. M. Liu et al. (2022) proposed a dose-response relationship between social media use and depressive symptoms, although they (as most other reviews) cautioned that findings may be confounded by unmeasured variables, reverse causality or measurement error, and therefore are of low quality and cannot be used to make causal statements concerning social media's impacts on mental health. Although effect sizes were generally small, and their clinical relevance debated (e.g. by Ferguson et al. 2025), the consistency of findings across both cross-sectional and longitudinal studies suggests a robust association. However, it should be noted while longitudinal studies can demonstrate temporal order, they do not confirm causality on their own.

To assess their ability to make causal inferences, Cochrane-endorsed risk of bias tools like ROBINS-I can be valuable. An approach similar to that of Purba et al. (2023b) can also be effective, where existing risk of bias tools, such as the Newcastle-Ottawa Scale (Wells et al., 2000), were adapted to incorporate insights from Cochrane frameworks. For instance, Purba et al. (2023b) modified the Newcastle-Ottawa Scale to integrate elements from the Cochrane ROBINS-I tool, with input from GRADE Public Health Group members. This adaptation allowed for a more thorough evaluation, including the adjustment for pre-identified confounding domains, other justifiable confounders, and assessing attrition and missing data. In their review, Purba et al. (2023b) demonstrated that the inclusion of four RCTs improved the certainty of evidence for a related outcome (i.e. unhealthy dietary behaviours) from low to moderate. However, it should be noted that observational evidence automatically starts at low certainty in the GRADE framework, with the potential to be either upgraded or downgraded based on specific factors. In contrast, RCTs generally start at high certainty, though they too can be downgraded if certain issues, like risk of bias or imprecision, are present (Guyatt et al., 2008; Purba, 2023b).

The systematic reviews in our umbrella review did not locate any experimental interventions specifically on social media use and adolescent mental health and wellbeing. While we review experimental studies in this area in our supplementary review below, to our knowledge, no study targeted this specific research question. The most relevant study was an RCT of 220 adolescents and young adults aged 17–25 years (73% 17–19 years) who reduced their social media use to one hour a day for three weeks, and where improvements regarding depression, anxiety, sleep quality and fear of missing out were found. However, the sample was clinical in nature, with all participants experiencing at least two of four specified symptoms of depression and anxiety (Davis & Goldfield, 2025). Additional studies on decreasing or removing social media use and wellbeing or mental health have studied non-adolescent populations (Hunt et al., 2018; Lemahieu et al., 2025; Plackett et al., 2023; Radtke et al., 2022), while those that studied children and adolescents did so implementing broader screen time reduction interventions (Schmidt-Persson et al., 2024). (We review these studies in the introduction of our supplementary review below). We can therefore not rely on such experimental data to raise the certainty of evidence from low for our understanding of the impact of time spent on social media on adolescent mental health. Nonetheless, it does suggest that even single well-designed RCTs in this area could significantly improve the quality of evidence and the evidence foundation for policy decisions. Beyond RCTs, well-designed natural experiments (real world studies) such as the one included in this review by Beneito and Vicente-Chirivella (2022) could serve to fill this research gap.

A notable feature across reviews was the high heterogeneity of findings, particularly for those studying depressive and internalising symptom outcomes. Interestingly, this was not observed for antisocial behaviour. Several reviews proposed that such heterogeneity could reflect unmeasured or poorly measured moderating factors. These may include inconsistencies in the operationalisation of both social media use and mental health outcomes, such as whether self-report or objective data were used to measure the exposure (social media use), or whether mental health outcomes were assessed through clinical interviews or questionnaires (M. Liu et al., 2022). Further it could be because individual impacts from social media are determined by things other than time spent using it (such as the content consumed, or activities displaced for the individual adolescent) and largely unmeasured individual vulnerabilities or inequalities. Differences between cross-sectional, cohort and experimental designs may also contribute (Ferguson et al., 2025), as well as a lack of understanding of subgroups of young people beyond sex and age (e.g. ethnicity or sexual/gender minority identification) that could change the potential impact of social media on mental health.

Review Limitations

This research has multiple strengths. It was conceptualised alongside stakeholder engagement, with policymakers from DSIT involved in defining its scope and content. Our review included thorough consideration of the quality of assessed reviews (using the AMSTAR-2 tool), including an overview of their ability to consider causality (in their use, or otherwise, of the GRADE criteria and Bradford Hill's viewpoints for causality). This is a response to previous literature describing poor quality assessment practice in this field (Purba et al., 2023b). Furthermore, this review was externally peer reviewed by five relevant experts.

However, there are also multiple limitations to consider. Due to time constraints, the review screening was carried out only by the lead author (IF), though the extraction and quality coding was carried out independently by two coders each (IF and BD). An independent third rater then verified quality review (JP). We also chose to conduct a narrative synthesis rather than a meta-analysis. This decision was based on the high degree of heterogeneity among the included studies, particularly in terms of outcome measures and methodological approaches, which rendered meta-analytic techniques less appropriate. While a narrative approach allowed us to capture the nuance and complexity of the literature, it does limit our ability to provide standardised effect size estimates that would facilitate direct comparison across studies.

We deliberately excluded research conducted with clinical populations, as our focus was on understanding mental health as an outcome of social media use within the general adolescent population. While this approach improves the specificity of our conclusions, it limits their generalisability to clinical populations, where the evidence base remains scarce (Fassi et al., 2024). We also excluded studies examining smartphone or social media 'addiction' or problematic use that was not defined using time-based metrics fully reported in the study (e.g. through questionnaires targeting specifically problematic use), due to ongoing debate around the conceptual clarity and scientific validity of this construct.

Our review is further limited by the quality of the available reviews and the scope of the primary studies they included, which were generally of low quality. For example, some authors blend all outcome variables together and do not reveal results specific to anxiety or depression. The limitations and low quality of several of the included studies are unfortunately something that we cannot resolve through an umbrella review methodology.

We did not conduct our own search of the primary study literature, and as a result some relevant studies may have been missed. In addition, given the inherently slow pace of systematic review publication, our synthesis may not fully capture the most recent empirical developments in this rapidly evolving field. We did, however, conduct a secondary narrative literature review focusing on experimental studies (see below). We felt that these would contribute meaningfully to the overall certainty of the evidence. Overall, while the body of research suggests a potential link between social media use and mental health outcomes — especially at higher levels of use — the quality of available data, common methodological weaknesses and assumptions made in many reviews limit the strength of causal conclusions that can currently be drawn in our report.

Implications for Research

This review highlights several key implications for future research aimed at strengthening the evidence base concerning the relationship between social media, smartphone and AI use, and child and adolescent developmental outcomes such as mental health. Prioritising these will help ensure that research keeps pace with rapidly evolving digital technologies and provides robust, actionable evidence to inform policy and practice:

- There is a pressing need for studies that can establish causal relationships between social media use and mental health outcomes in adolescents. This includes the delivery of high-quality RCTs and natural experimental evaluations, the use of objective social media usage data, and targeted research on subgroups defined by characteristics beyond age and sex, such as ethnicity and socio-economic background.
- Current research shows high variability in outcomes related to time spent on social media, particularly regarding depression and anxiety. Collaborative efforts are needed to explore unmeasured or underexplored moderators that may account for this heterogeneity and to better understand why effects differ greatly across studies.
- There is a clear need to move beyond simplistic metrics like time spent on social media. Research should prioritise the development and use of theory-driven, validated measures that capture more nuanced aspects of social media engagement.
- Researchers should provide timely reviews that go beyond duration of social media use to include factors such as the timing of use (e.g. before bedtime, at night or during school hours), the type of content consumed, the design features interacted with, and that target a wider set of developmental outcomes.
- Future research should expand beyond social media to consider the mental health impacts of digital technology use more broadly, including emerging technologies such as AI chat applications, which are increasingly prevalent in adolescents' digital environments.

Implications for Policy and Practice

This review presents several important takeaways for policymakers and practitioners concerned with adolescent mental health and digital technology use:

- We can conclude that time spent on social media may increase mental health problems in adolescents. While there is consistent evidence of a small correlation between increased time spent on social media and worse adolescent mental health outcomes, and this is also shown (at least in subgroups of adolescents) in about half of longitudinal studies, the overall certainty of whether this indicates a causal relationship remains low. This is due to the poor quality of many primary studies and the high variability in findings across research.
- There is a notable lack of high-quality experimental research, particularly RCTs focused on healthy adolescents. Conducting such research could significantly improve the evidence base, especially in determining whether reductions in social media or

smartphone use can lead to measurable mental health benefits. While some evidence from screen time reduction studies in children and adults suggests possible benefits, findings remain mixed, even though there is also no strong evidence to suggest that abstaining from social media causes harm.

- While our umbrella review method of evidence review, synthesising previous systematic syntheses of evidence, is highly robust and transparent, it is inherently retrospective. There is an unavoidable delay between what children and adolescents are currently experiencing online, the completion of primary studies, and their inclusion in high-level syntheses. As a result, current evidence will lag behind emerging trends and technologies.
- Policymakers must weigh not only the strength of available evidence but also the potential consequences of delayed action. In the context of adolescent mental health and social media use, the absence of high-quality evidence should not be misinterpreted as evidence of no harm taking place. It will be important to assess the risks and benefits of waiting for more evidence versus the risks and benefits (including unintended consequences) of policy intervention on the basis of a low-quality evidence base.
- The current lack of high-quality, policy-relevant evidence underscores the urgent need for a cross-government National Research Strategy on Online Harms. This should be accompanied by long-term investment in high-quality, independent research, as well as improved data access and infrastructure. The limited support from social media companies for safety-related research stands in contrast to safety standards in other consumer industries and further justifies the need for public sector leadership in this area.

Conclusion

Taken together, these findings suggest a consistent positive association between time spent on social media and adolescent mental health problems, meaning that those adolescents who use more social media also report more mental health problems. An emerging but still mixed body of longitudinal studies suggests that these associations may also extend over time, with greater social media use at one time point potentially predicting subsequent declines in mental health, offering stronger evidence than purely correlational data. However, the quality of primary studies is generally low, with high risk of bias, and overall findings that are highly heterogeneous. The ultimate certainty of the relationship being causal remains low.

There is a clear need for improved primary studies employing more robust, objective measurement approaches, adequate confounder adjustment (in the case of observational studies), as well as well-designed experimental studies involving diverse populations. Should such studies — especially experimental RCTs, where ethically and practically feasible — yield consistent results, e.g. showing improved mental health outcomes following reductions in adolescent social media use, this would substantially strengthen the evidence base for both research and policymaking.

Supplementary Literature Review: Narrative Synthesis of the Relationship between Content Viewed on Social Media and Social Media/Smartphone Bans on Adolescent Mental Health and Wellbeing

Background

Adolescence, the time between 10 and 19 years of age, is understood as the transitional period between childhood and adulthood. It is characterised by a set of behaviours, including increased risk taking, peer orientation and valuation of social reward (Steinberg, 2010). Adolescence is also a stage of mental health and wellbeing vulnerability (Orben et al., 2022a), where certain psychopathologies are most likely to first emerge (Costello et al., 2011; Solmi et al., 2022). As adolescent social realities shift increasingly towards the digital realm, there is a renewed pressure on scientists and policy makers to better understand how social media and smartphone use affects neurodevelopment and wellbeing.

Our umbrella review above showed that there is a consistent positive and small cross-sectional correlation between time spent on social media and adverse adolescent mental health outcomes, as well as aligned longitudinal evidence. However, the umbrella review is subject to two limitations. First, authors of the seven included reviews routinely criticised the emphasis on measures of 'time spent' on social media, noting that some of the high heterogeneity found in the primary studies synthesised might be due to this measure averaging across the features or content of social media that drive its impact on adolescent developmental outcomes (Fassi et al., 2024; Ferguson et al., 2025; Ivie et al., 2020; Keles et al., 2020; M. Liu et al., 2022). Second, none of the seven included reviews had synthesised experimental or RCT studies which had removed social media or smartphone use in adolescent samples. This absence was identified as a central reason for the low certainty of evidence regarding the causal impact of time spent on social media on adolescent mental health and wellbeing.

Social Media Content

The first limitation has been recognised across the research landscape for multiple years, where it has been argued that rigorous evaluations of social media's impacts require valid and accurate measures of social media use that move beyond measures of time spent but consider both the content viewed and its quality (Meier & Reinecke, 2021; Valkenburg et al., 2022). Furthermore, others have developed theoretical frameworks that outline how effects of social media on socialisation, wellbeing and mental health are probably amplified by its specific features, such as permanence, quantifiability and increased frequency of contact (Nesi et al., 2018).

There is increasing recognition of the importance of the valence of content viewed, and the emotion evoked by social media, rather than just the amount of time spent on it (Lin & Utz, 2015; Schreiner et al., 2021). For example, a cross-sectional survey of 2,000 students found that each 10% increase in negative experiences on social media was significantly associated with a 20% increase in the odds of depressive symptoms (OR = 1.2, 95% CI [1.11, 1.31]). Others have noted a particular salience of visual content on adolescent wellbeing: findings suggest that the desire to achieve a balance between attractiveness and authenticity in self-presentation, and the importance of likes for social approval, may be a source of social media induced stress (Bell, 2019).

A series of convincing mechanisms by which social media content type might affect adolescent wellbeing have emerged across the scientific literature (Choukas-Bradley et al., 2022; Orben et al., 2024). For example, upwards social comparison has been argued to be potentially causal related to passive social media use (i.e. scrolling through a newsfeed) and mental health outcomes, through promoting feelings of envy, rumination and depression (Verduyn et al., 2017). Increased access to information about others' activities and presented realities can also promote feelings of social exclusion, referred to as 'Fear Of Missing Out' (Burnell et al., 2019; Hunt et al., 2018). Theory-based possible mechanisms exist by which social media content type might affect adolescent mental health and wellbeing (Orben et al., 2024), underscoring this as an important and evolving area of research with regards to understanding the complexities of the consequences of social media use.

Individual-level Social Media and Smartphone Interventions

There has also been increased recognition of the second limitation noted in our umbrella review: the absence of experimental evidence examining the impact of social media or smartphone use bans or reductions on the adolescent age group (Odgers & Jensen, 2020). Experimental evidence specifically on adolescents — while the focus of much observational research — has been sparse, potentially due to the complexity of getting this age group involved in intensive studies which involve the removal or reduction of smartphone or social media use.

A study meeting some, but not all, of our inclusion criteria, was a randomised-control trial of 220 adolescents and young adults aged 17–25 years with pre-existing emotional distress who were asked to reduce their social media use to one hour a day for three weeks. While no mean age was given, 73% of the sample was 17–19 years old and therefore meet our review's definition of adolescents. Those in the social media reduction intervention group, relative to controls with no reduction in their social media use, showed decreases in depression, anxiety and fear of missing out, as well as increases in amount of night time sleep during the intervention period (Davis & Goldfield, 2025). A separate publication of the same underlying dataset also found positive impacts of the intervention on appearance and weight esteem relative to controls (Thai et al., 2024). However, the sample participants were selected to all be experiencing at least two of four symptoms of depression and anxiety and therefore classed as a clinical sample, which presents reason for exclusion in our review.

Another experimental study by Walsh et al. (2024) randomly allocated participants to one of four conditions: smartphone use restriction, social media use restriction, water restriction (active control) and a control. Relative to controls, participants who restricted smartphones reported higher scores on several wellbeing indicators. Those assigned to restrict only social media use reported few benefits and instead demonstrated increased negative emotion. However, the participants of this study were beyond our adolescent age range of interest and therefore excluded from synthesis in our review.

Further, a study of 66 female 17–24-year-old undergraduates (mean age = 19.1 years) found that abstaining from social media use for one week improved body satisfaction and self-esteem relative to controls (Smith et al., 2024). This improvement was more pronounced in those women with average to high levels of thin-ideal internalisation. However, the sample participants did not meet age range for inclusion.

Quasi-experimental evidence on the impact of social media on mental health has also emerged. Braghieri et al. (2021) used the staggered introduction of Facebook across US colleges to design a natural experiment on the relationship between Facebook use and student mental health, with artificial 'unexposed' groups created in those colleges the rollout reached at later stages. They found that Facebook use (Facebook expansion) at a college had a negative impact on student mental health, also increasing the likelihood of reported academic impairment due to poor mental health. Potential mechanisms included Facebook's platforming of social comparisons (Braghieri et al., 2021). However, the participants of this study were of college age, and therefore beyond the adolescent age range of interest.

A small number of studies examined the effects of reducing screen time or social media use in children and adolescents. One secondary evaluation of an RCT conducted in Denmark involved 181 children (mean age = 9.5 years), where family leisure screen time — defined broadly — was restricted to three hours per week or less over a two-week period. As part of the intervention, tablets and smartphones belonging to all children and at least one parent were also handed over to the research team. Compared to the control group, the intervention group showed a marked improvement in mental health, particularly strong for a reduction in internalising symptoms, and an increase in prosocial behaviours (Schmidt-Persson et al., 2024). Yet, the intervention extended beyond social media or smartphone abstinence to a family-centred intervention of screen use that included parents. Further, while 408 families initially expressed interest in a 'family-based screen media reduction trial' and were eligible for the intervention, they had to be above the 40th percentile of respondents on total leisure screen time, and only 89 families participated. This suggests that the sample has a risk of being unrepresentative, and aspects of the intervention may not have been suitable for certain families (even though those who participated were largely compliant).

There have been further studies on young adult populations. One study of 111 university students (mean age = 22.7 years) found that limiting screen time to under two hours a day improved wellbeing and sleep quality while decreasing depressive symptoms and stress relative to controls (Pieh et al., 2025). Another study of 143 undergraduates found that limiting social media use to 30 minutes across various social media platforms for three weeks improved loneliness and depressive symptoms relative to the control group (Hunt et al., 2018). Yet, again, none of these studies can be used to make specific claims about adolescents.

Two meta-analyses and one systematic review of social media abstinence interventions have been published recently, yet there isn't anything specific for adolescents. One found a relatively even split in 39% of reviewed primary studies finding improvements to wellbeing after social media abstinence, 30% finding mixed impacts and 30% finding no impacts (Plackett et al., 2023). Another meta-analysis found no relationship between social media abstinence and positive mental health outcomes (Lemahieu et al., 2025). The systematic review by Radtke et al. (2022), concluded that: 'Even though a few more studies revealed positive, rather than negative, consequences from digital detox interventions, most of the studies showed either no effects or mixed findings regarding digital detox efficacy' (Radtke et al., 2022). Yet, neither of the reviews found good evidence of social media abstinence causing harm. As they were not completed on adolescent populations that might experience unique impacts from social media and smartphone use due to their developmental stage, their results again need to be interpreted with caution for this age group (Orben & Blakemore, 2023).

More systematic evidence reviews on child and adolescent populations, as well as comparisons between different types of intervention (screen time vs social media; reduction vs abstinence) are urgently needed. While this cannot be addressed by this supplementary review directly, we aim to additionally identify other critical studies beyond those narratively reviewed above on the specific research question of social media or smartphone bans and adolescent mental health or wellbeing outcomes.

School-level Social Media and Smartphone Interventions

There is also a growing body of research exploring the impact of bans within a school context. Much of this research does not target our primary outcome of mental health directly, so we also extend this synthesis in part to discuss both primary (i.e. wellbeing and mental health) and relevant secondary (i.e. bullying, academic attainment and physical health behaviours) outcomes, which are not considered elsewhere in this review. This synthesis is not comprehensive, and for a more in-depth discussion, see the report by Rahali et al. (2024) and a recent reviews by Campbell et al. (2024) and Böttger and Zierer (2024).

Primary Outcomes

To our knowledge there exist only three studies exploring the relationship between school-wide smartphone bans and wellbeing: two are not peer reviewed (one is a master's thesis, and one is a preprint of an economics paper) and all three generally report inconsistent findings. Guldvik and Kvinnsland (2018) utilised natural variation in school-wide smartphone policy by analysing 493 teenagers (of 1,250 contacted) attending Norwegian middle school (13–16 years old) who responded to a survey requesting information about their historical and present smartphone policy. When comparing schools' before and after policies that prevented the use of phones during the school day, there was no significant difference in the self-reported social wellbeing of students. Similarly, Abrahamsson (2024) reported no effect on social wellbeing in their Norwegian sample of middle schools (n = 529, from a total of 1,187, age 13–16) before and after the implementation of smartphone bans. Of note, in this study, 'ban' refers to any policy whereby smartphone use is restricted (i.e. ranging from 'do not bring to school' to 'silent mode during lectures'). Abrahamsson (2024) also found no overall effect of smartphone bans on students' likelihood of receiving treatment or the intensity of treatment for psychological symptoms and disorders, while subgroup analysis by sex revealed that girls experienced a 29% reduction in visits to mental health practitioners two to four years post-ban (p = 0.011–0.008), with no corresponding change in visits to general practitioners. Further subgroup analysis on socio-economic status revealed that this effect was most significant for girls with low-educated fathers (p = 0.019–0.003).

Most recently, the SMART Schools study (Goodyear et al., 2025) evaluated secondary school phone-use restriction policies on mental health and wellbeing related outcomes involving a nationally representative sample in England. Cross-sectional and observational in design, and with the corresponding limits to make causal conclusions, it compared a primary outcome of mental wellbeing (assessed via the Warwick-Edinburgh Mental Well-Being scale; WEMWBS) and included outcomes related to poor mental health (anxiety and depression) in the body of secondary outcomes. In their sample, 20 schools had restrictive smartphone policies, and 10 schools had permissive policies. In adolescents aged 12–15 years, whilst there was a significant decrease in screen time on smartphones and social media for students attending schools with restrictive policies, there was no significant difference in the mental wellbeing of students in schools with restrictive policies compared to those with permissive policies (adjusted MD = -0.48, 95% CI [-2.05, 1.06], p = 0.62). No statistically significant interactions with school policy were observed for mental wellbeing across sex, year group, ethnicity and deprivation (measured via Income Deprivation Affecting Children Index). However, increased time spent on phones and social media was individually significantly associated with worsened mental health and wellbeing outcomes, as well as physical activity, sleep, attainment and disruptive behaviour outcomes.

Secondary outcomes

Both studies by Guldvik and Kvinnsland (2018) and Abrahamsson (2024) explored the relationship between smartphone bans and mental health indirectly through the observation of changes in bullying behaviour following the introduction of smartphone bans. Firstly, Guldvik and Kvinnsland (2018) demonstrated that, for both male and female students, there was a significant post-treatment decrease in the reported school-wide bullying when a ban was implemented for three years or more. For male students, this effect was also significant in the immediate treatment year following the ban. This suggests bans are most impactful on the cohort of students who had a ban continuously through middle school (or lower secondary school, age 13–16). In Abrahamsson (2024), there was no significant relationship between smartphone bans and student-reported bullying incidence at a school-wide level, with a decrease of 0.25–0.35 standard deviations (p = 0.067–0.094) in bullying two to four years following the introduction of bans. When considering subgroups, analyses revealed that female students exposed to a full-time three-year smartphone ban experienced a decline in reporting bullying incidents by 0.42 standard deviations (p = 0.039) compared to unaffected girls. These findings must be interpreted with caution, as there is no correction for multiple testing, and at no other time point is the post-treatment effect statistically significant.

It is important to consider that the intentions regarding the introduction of smartphone bans in schools is oftentimes driven by factors beyond wellbeing. There is a group of studies, including those previously discussed, that all examine whether restrictive phone policies are associated with improvements in academic performance (Abrahamsson, 2024; Beland & Murphy, 2016; Goodyear et al., 2025; Guldvik & Kvinnsland, 2018; Kessel et al., 2020). To summarise, the evidence is unclear whether smartphone bans lead to significant improvements in attainment at the population level. However, some studies report that findings appear to be moderated by particular subgroups, with greater benefits observed among lower-achieving students (Beland & Murphy, 2016) and those from lower socio-economic backgrounds (Abrahamsson, 2024). These effects have not replicated across all contexts, and studies that have considered nationally-representative samples of schools have failed to reproduce significant effects (Goodyear et al., 2025; Guldvik & Kvinnsland, 2018; Kessel et al., 2020). Ultimately, the findings from this literature are inconsistent and nuanced, and require careful consideration that is beyond the scope of this review. For a more detailed discussion, please see the aforementioned reviews by Rahali et al. (2024) and Campbell et al. (2024).

Beyond academic attainment, there has been some recent exploration of the effects of school-wide phone bans on physical activity levels. In a quasi-experimental intervention study, Pawlowski et al. (2021) implemented a strict four-week smartphone ban (phones handed into school at the start of the day) with pupils aged 10–14, between August–October 2020. Physical activity and screen engagement was assessed via pre-and post-intervention measures. A phone ban was associated with a decrease in vigorous physical activity, but an increase in moderate intensity physical activity and the frequency of physical activity engagement during recess periods (i.e. breaks and lunch). There was a greater increase in moderate physical activity levels for girls compared to boys, but there were no differences observed in age.

Smartphone ban type and duration of implementation

Schools vary in the types of school smartphone 'bans' that are implemented, ranging from those classified as stricter (phones inaccessible to pupils; not permitted on school premises; stored in another location; reception, lockers or pouches) to lenient (phones accessible, but turned off or on silent mode in bags). The most common types of smartphone 'ban' implemented were more lenient and required pupils to have phones turned off and stored in bags (or placed on silent mode during class) (Abrahamsson, 2024; Goodyear et al., 2025). In the SMART Schools Study, comparisons between the impacts of more lenient and strict policie showed no evidence of a difference in outcomes for mental wellbeing, anxiety or depression (Goodyear et al., 2025). Findings were similar for mental health and bullying in the recent Norwegian study, however, a stricter phone policy did positively impact on attainment (Abrahamsson, 2024). In the earlier Norwegian study (Guldvik & Kvinnsland, 2018), there were no differences in outcomes observed for wellbeing and attainment, however, stricter policies did impact on bullying. The majority of restrictive phone policies in the UK from the SMART Schools study were implemented in the last 1–2 years (Goodyear et al., 2025). Data from Norway indicates that the length of time a pupil is exposed to a policy may impact on outcomes (Abrahamsson, 2024). Overall, the findings from studies are mixed, and variations in policy categorisations, types and duration of implementation across studies limit the ability to draw robust conclusions, but evidence from Norway implies that impacts on attainment and bullying tend to be more influenced by stricter phone policies and longer-term exposure.

The Current Review

This supplementary narrative literature review therefore aimed to address the two key limitations identified in the initial umbrella review: (1) the lack of experimental evidence examining the impact of social media or smartphone use bans or reductions specifically on adolescents, and (2) the focus on 'time spent' as the main measure of social media use. To do so, we narratively reviewed evidence on the association between the content viewed on social media platforms and adolescent mental health and wellbeing, as well as the effects of social media or smartphone bans on these same outcomes. Specifically, we additionally review the quality and nature of primary studies and systematic reviews addressing the three following themes:

Social media content and adolescent developmental outcomes:
Objective 1a. The association between content viewed on social media platforms (including messaging applications) and adolescent mental health.
Objective 1b. The association between content viewed on social media platforms (including messaging applications) and adolescent wellbeing.

Social media bans and adolescent developmental outcomes:
Objective 2a. The association between social media bans and adolescent mental health.

Objective 2b. The association between social media bans and adolescent wellbeing.

Smartphone bans and adolescent developmental outcomes:
Objective 3a. The association between smartphone bans and adolescent mental health.
Objective 3b. The association between smartphone bans and adolescent wellbeing.

Important: Please note, that while pre-specified, this search was not systematic, and we synthesised our findings narratively. This review is therefore broader, less in-depth and has a higher risk of bias. It should only be regarded as supplementary evidence to the umbrella review above rather than a standalone research output.

Methods

We registered our search strategy before the review commenced, as agreed with DSIT. We searched Google Scholar with a pre-specified search strategy and extracted the first 60 studies presented for each objective. Each of those studies were then screened for inclusion. We consulted experts to supplement this with studies that had not been identified in our initial search.

Search Methods for Identification of Primary Studies and Systematic Reviews

We followed the PRISMA reporting guidance (Page et al., 2021b), as well as the PRIOR reporting guidance (Gates et al., 2022). This study was registered with PROSPERO: https://www.crd.york.ac.uk/PROSPERO/view/CRD42025641338 (PROSPERO ID:CRD42025641338) (see Appendix 1.1).

Inclusion and Exclusion Criteria

Participants

Inclusion
We included studies investigating adolescents aged 10–19 years. Where reviews explored a broader age range, they were included if the mean age of participants fell between 10 and 19 years.

Exclusion
We excluded studies where the mean age in the population of interest was younger than 10 or older than 19. We further defined 'fell between 10–19 years' as between 10.00 and 19.00 years after registration.

Exposure

Inclusion

- Social media defined as 'internet-based, disentrained, and persistent channels of masspersonal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content' (Carr & Hayes, 2015).
- Smartphones defined as portable cellular devices with internet access and capacity to host applications.
- AI chat applications defined as any chatbot that 'makes the use of digital technology to create systems capable of performing tasks commonly thought to require intelligence' (Department for Science, Innovation and Technology, 2019).

Exclusion

- Studies investigating internet/computer/media activities other than social media, AI chat application use or smartphone use.

- Studies investigating social media, AI chat applications or smartphones as a recruitment method.
- Studies investigating social media dating platforms.
- Studies investigating social media or smartphone reduction. This criterion was not registered and was applied after the search was completed.

Outcome

Inclusion

The outcomes of interest were mental health and wellbeing. All measurements of outcomes were considered for inclusion, including standardised questionnaires, self-report, categorical diagnoses, reports from parents, guardians and peers, and physiological measures.

Exclusion

Studies that focused exclusively on clinical populations with pre-existing diagnosed mental health disorders unrelated to social media were excluded, to ensure that outcomes are directly linked to the effects of social media. When reviews examined one or more primary outcomes, they were considered for inclusion if relevant data could be extracted.

Study Type

Inclusion

Systematic reviews and meta-analyses, and primary research studies.

Exclusion

Editorials, commentaries, conference abstracts and non-peer reviewed papers.

Additional specification after PROSPERO registration

After our initial search, we found it necessary to further refine our inclusion criteria. We decided to additionally include umbrella reviews, as this was initially unclear in the pre-registered inclusion criteria. We included eating behaviour and body image/appearance judgement as mental health outcomes if they were measured using a scale or sub-scale taken from a clinical measure of eating disorders. We did not include studies of cyberbullying or victimisation if they were not specific to social media or smartphone use. We did not include studies based on measures related broadly to wellbeing such as radicalisation or sexual behaviours. Social media/smartphone bans were defined as the complete abstinence from social media or smartphones during specific times, settings or overall.

Selection of Primary Studies and Systematic Reviews

Searches were carried out in Google Scholar. The first 60 hits for each of the three objectives were screened, resulting in a total of 180 articles reviewed. Results were imported to Zotero for deduplication (Corporation for Digital Scholarship, 2023) and screened with the use of Covidence software (Covidence, 2025). Following the screening, additional records were identified through screening of reference lists and expert correspondence.

Data Extraction

Data were extracted in Microsoft Excel by the lead author (IF) and BD separately. Any disagreements between IF and BD were resolved by AO. The data extraction template can be found in Appendix 1.4.

Risk of Bias Assessment of Primary Studies

Risk of bias assessment was conducted independently at outcome level by IF and MR, using an adapted version of the Newcastle-Ottawa Scale (Purba et al., 2023b; Wells et al., 2000) (see Appendix 1.11). Separate versions of the scale were used for cohort and cross-sectional studies. The scales were adapted by Purba et al. (2023b) to incorporate insights from the Cochrane ROBINS-I RoB tool with assistance from GRADE Public Health Group Members. This included assessing adjustment for pre-identified critical confounding domains, other justifiable confounders, attrition and missing data. A primary strength of this approach is its ability to assess the quality of studies, incorporating elements which underpin a study's ability to make causal inferences (Purba et al., 2023b). Any disagreements in ratings on risk of bias between the two reviewers were resolved by a third reviewer, LG.

Additionally, we considered whether authors utilised the Bradford Hill viewpoints for causality (Hill, 1965). These are a set of principles used to assess evidence of a causal relationship between cause and effect in epidemiology (Guyatt et al., 2008; Hill, 1965).

Quality Assessment of Systematic Reviews

The quality of included systematic reviews and meta-analyses were assessed using the AMSTAR-2 criteria (see Appendix 1.10).

Additionally, we considered whether authors utilised GRADE criteria (Schwingshackl et al., 2021). This provides a systematic approach to evaluating certainty of evidence in systematic reviews and meta-analyses.

Data Synthesis

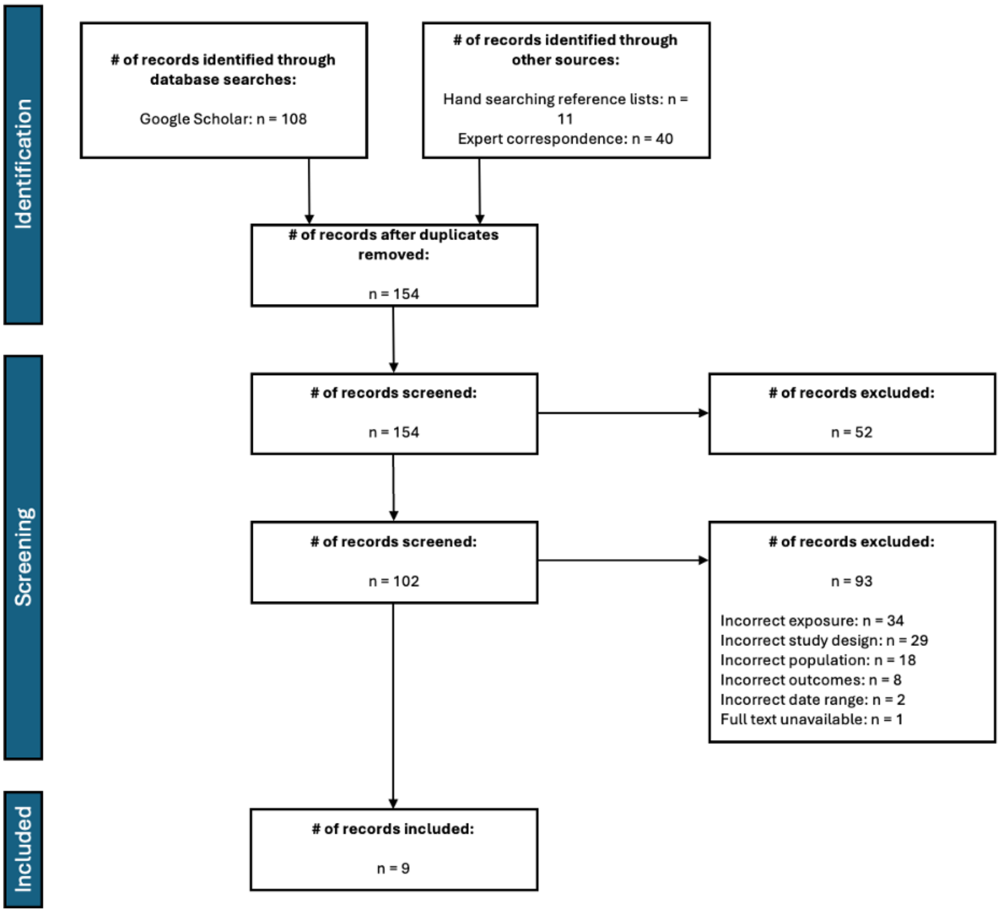
The synthesis of each objective focused largely on documenting the direction of harm or benefit observed in each primary study, evaluating the evidence's ability to support causal conclusions, considering the methodological aspects of data and addressing the impact of interventions. For systematic reviews and meta-analyses identified, textual summaries were reported.

Results

Figure 4 summarises the review selection process, carried out according to PRISMA guidelines (Page et al., 2021b).

Our internet database search yielded 108 titles. Following deduplication, the lead reviewer (IF) screened 154 items by title and abstract. Of these, 52 were excluded and 102 progressed to full text screening. On full text screening, 93 were excluded due to reasons including incorrect exposure, incorrect study design, incorrect population, incorrect outcomes or incorrect date range. One full text was unavailable, with unsuccessful attempts to reach the author. Nine records were ultimately included in the narrative synthesis.

Figure 4. PRISMA flow diagram of the screening process.



Description of included studies and systematic reviews

All included records were primary studies (n = 7) or systematic reviews (n = 2) published after May 2007, there were no meta-analyses (Appendix 1.13).

Six primary studies and two systematic reviews addressed Objective 1. Specifically, we found three primary studies and one systematic review addressing Objective 1a (social media content and its relation to mental health), two primary studies and no systematic reviews addressing Objective 1b (social media content and its relation to wellbeing) and one primary study and one systematic review addressing both Objective 1a and 1b. We found no studies addressing Objective 2, and one primary study addressing Objective 3b.

Regarding Objective 1 (the relationship between exposure to content on social media and adolescent mental health and wellbeing), the primary studies included between 103 and 10,904 participants. They were carried out in countries including the United Kingdom (n = 1) (Kelly et al., 2018), the United States (n = 3) (Hoffman et al., 2023; Hummel & Smith, 2015; Meier & Gray, 2014), the Netherlands (n = 1) (Valkenburg et al., 2017) and Belgium (n = 1) (Frison & Eggermont, 2016).

The primary study examining Objective 3 (the relationship between smartphone bans and adolescent mental health and wellbeing) was carried out in Spain (Beneito & Vicente-

Chirivella, 2022). However, this study did not report on the number of participants.

Findings

We aimed to identify patterns in the type of content found to influence adolescent mental health or wellbeing, the mechanisms via which such an effect might occur, and the moderating factors of this effect. We also aimed to identify the characteristics of social media and smartphone bans, and whether they were consistently associated with specific mental health and wellbeing outcomes in the population of interest. The systematic reviews included here explored findings across 659,567 participants, whilst the primary studies included explored findings across 13,731 participants.

For each broad objective we first report the systematic reviews and then the primary studies.

Objective 1a: Exposure to social media content and mental health

Systematic reviews

Holland and Tiggemann (2016) systematically reviewed the literature on the relationship between specific Facebook actions (including Facebook feedback seeking, Facebook comments, the amount of social grooming behaviours on Facebook, underweight Facebook profile pictures, exposure to appearance related content) and disordered eating outcomes, which we classified as a mental health outcome, as well as broader body image beliefs and behaviour, which were not included in this review. Narratively synthesising the results of 20 primary studies (of which five were longitudinal and fifteen cross-sectional) across 5,981 participants, the authors found that there was a link between use of social media and disordered eating outcomes, especially with regards to photo-based exposures (uploading or viewing) and negative feedback seeking. They also found that recent studies have moved away from focusing on overall social media use instead favouring more granular operationalisations of social media use. Only one of six studies investigating gender differences found a significant difference between males and females (Thompson & Lougheed, 2012), specifically showing that significantly more female Facebook users agreed with the statement that Facebook causes body dissatisfaction. The review therefore concluded that the impact of social media on disordered eating might not be broadly gendered.

Primary studies

Three studies, covering 12,628 participants, explored Objective 1a. Two studies investigated the relationship between negative content exposure on social media and depressive symptoms (Frison et al., 2016; Kelly et al., 2018). Frison et al. (2016) investigated the short-term longitudinal and reciprocal relationships between peer victimisation/negative experiences on Facebook and adolescent depressive symptoms in Belgian 12–19-year-olds (measured using the Centre for Epidemiological Studies Depression Scale for Children). The authors did not find that peer victimisation/negative experiences on Facebook predicted more depressive symptoms six months later, but that depressive symptoms predicted more peer victimisation/negative experiences on Facebook six months later (Frison et al., 2016).

They also found that negative Facebook experiences at Time 1 increased adolescents' depressive symptoms at Time 2 specifically among those with low levels of perceived peer support ($\beta = 0.12$, $p < 0.05$), but not among those with medium or high levels ($\beta = -0.01$, $p = 0.75$). This effect was reciprocal: adolescent depressive symptoms at Time 1 predicted increased negative Facebook experiences at Time 2 among those with low perceived peer support (β = 0.11, p < 0.05), but not among those with the highest levels of perceived friend support (β = -0.3, p = 0.67)(Frison et al., 2016). However, a path-by-path (closer) analysis revealed that this effect was not consistent across different groups over time, such that the initial moderating effect was weak.

Using data from the UK Millennium Cohort Study, Kelly et al. (2018) investigated the relationship between online harassment experiences and depressive symptoms, as measured by the validated Mood and Feelings Questionnaire. Social media use and depressive symptoms were positively associated with online harassment across genders. Yet girls, compared to boys, were more likely to be involved in online harassment both as victim and perpetrator. Online harassment was also found to be a mediating factor linking social media use to depressive symptoms across genders.

Meier and Grey (2014) found time spent on Facebook did not predict body-image disturbance in young girls. However, time spent engaged in photo-related activity on Facebook was specifically associated with more weight dissatisfaction, thin ideal internalisation and a drive for thinness. This suggests that there is something particularly salient about curated visual content which promotes social comparison, thereby impacting mental health outcomes related to eating disorders.

Objective 1b: Exposure to social media content and wellbeing

Systematic reviews

We identified one umbrella review (a review of reviews) on social media use and adolescent mental health and wellbeing. Sala et al. (2024) investigated the literature published between 2012 and 2023, synthesising the findings from 24 primary studies across 654,676 participants. Consistent with other reviews, the authors noted a predominance of cross-sectional primary literature, with the minority (only 4%) being experimental or quasi-experimental. All reviews included considered subclinical wellbeing outcomes (such as internalising or externalising outcomes), with 20% measuring problematic behaviours and a minority of 12.5% measuring clinical outcomes such as psychiatric diagnoses. The review identified that the relationship between social media use and adolescent outcomes is influenced by individual demographic and psychological characteristics, individual use of social media and social media content and design.

When reviewing the influence of social media feedback, Sala et al. (2024) concluded that receiving feedback on social media can affect wellbeing positively or negatively, depending on the type (positive, negative and ostracism, i.e. being ignored or excluded online) (Webster et al., 2021). Negative feedback or ostracism can damage wellbeing, and being ignored or excluded on social media can undermine sense of belonging and trigger fear of missing out, increasing emotional distress (Shankleman et al., 2021; Webster et al., 2021). While positive feedback can enhance self-worth, self-image and life satisfaction, particularly when it is given by close friends (Course-Choi & Hammond, 2021; Shankleman et al., 2021; Webster et al., 2021), the pursuit of it can also lead to selective self-presentation, reduced authenticity and hypervigilance, which may in turn harm self-esteem and lead to social comparison and rumination (Bottaro & Faraci, 2022; Shankleman et al., 2021).

When reviewing the influence of content recommended or encountered on social media, Sala et al. (2024) also highlight both positive and negative impacts. For example, inspirational and educational content can enable better learning and engagement with social and political issues, such as climate activism (Popat & Tarrant, 2023; Zhou & Cheng, 2022). Social media also offers spaces to discuss mental health, reduce stigma and create peer support networks, which can be important for young people such as those recovering from eating disorders (Chung et al., 2021). However, social media also exposes users to harmful content, including unreliable health advice, violent or sexual material and distressing news (Bozzola et al., 2022; Popat & Tarrant, 2023), negatively impacting mood and behaviour (Shankleman et al., 2021). Of particular concern is the ease of access to pro-eating disorder and self-harm content, which can normalise dangerous behaviours and lead to desensitisation (Bozzola et al., 2022; Memon et al., 2018; Moss et al., 2023).

Primary studies

Three studies explored Objective 1b, exploring the effects of social media content across 2,539 participants (Hoffman et al., 2023; Frison et al., 2016; Valkenburg et al., 2024). Frison et al. (2016) investigated the short-term longitudinal and reciprocal relationships between peer victimisation/negative experiences on Facebook and adolescent life satisfaction in Belgian 12–19-year-olds. In contrast to their results above, which found that peer victimisation/negative experiences on Facebook did not predict depressive symptoms six months later, the authors found peer victimisation/negative experiences did predict a decrease in life satisfaction six months later. A decrease in life satisfaction, however, did not predict more peer victimisation/negative experiences on Facebook six months later (Frison et al., 2016). Frison et al. (2016) also found that young adolescents (12–13 years) experience significantly less Facebook harassment experiences at Time 1 ($M = 1.38$, $SD = 0.54$) compared to middle adolescents (14–16 years; $M = 1.47$, $SD = 0.51$).

Of the reviewed primary studies, only one investigated the effects of viewing positive content on social media (Valkenburg et al., 2017). It examined the cross-sectional and longitudinal relationships between social media use and self-esteem (assessed via the validated social acceptance subscale of the self-perception profile for adolescents; Harter, 2012) and specifically investigated whether the valence of feedback received on social media explained this relationship. The valence of feedback received explained the concurrent relationship between social media use and social self-esteem, but not the longitudinal relationship. In the concurrent models, there was a significant indirect effect of positive feedback from friends on social self-esteem (wave 1: $\beta = 0.10$, $p < 0.001$, 95% CI [0.07, 0.13], wave 2: $\beta = 0.07$, $p < 0.001$, 95% CI [0.40, 0.10], wave 3: $\beta = 0.09$, $p < 0.001$, 95% CI [0.06, 0.13]). The indirect effect from social media use to self-esteem through positive feedback was also significant in all three data waves (wave 1: $\beta = 0.03$, $p < 0.023$, 95% CI [0.01, 0.06], wave 2: $\beta = 0.02$, $p < 0.049$, 95% CI [0.00, 0.04], wave 3: $\beta = 0.04$, $p < 0.002$, 95% CI [0.01, 0.06]) (Valkenburg et al., 2017).

In an exploration of a specific type of content exposure during the COVID-19 pandemic, Hoffman et al. (2023) investigated the relationship between viewing COVID-19 related information on social media and the psychosocial wellbeing of adolescents, whilst considering the importance of trust in this material as a potential moderator. In a mixed gender sample from the United States, the researchers revealed a zero-positive (beneficial) relationship between COVID-19 related content exposure on social media and wellbeing. Interestingly, when trust was added as a moderator, for those with higher levels of trust in COVID-19 information found on social media, the relationship between information encountered on social media and wellbeing was positive (beneficial). However, for those with low levels of trust, this relationship was negative (harmful). This study highlights trust as an important potential moderator between social media exposure and outcomes. However, its relevance remains limited due to its specific focus on the COVID-19 pandemic.

Objective 2: Social media bans and mental health and wellbeing outcomes

This review did not identify any relevant primary studies or systematic reviews on the effects of social media bans on adolescent mental health and wellbeing outcomes. Recent literature on the impacts of social media abstinence has identified several studies relevant to adults, but little literature relevant to the adolescent population (Lemahieu et al., 2025). This points to an increased need for evaluation of social-media policies in this space.

Objective 3: Smartphone bans and mental health and wellbeing outcomes

Objective 3a: Smartphone bans and mental health outcomes

No primary studies or systematic reviews were found exploring the relationship between smartphone bans and mental health outcomes.

Objective 3b: Smartphone bans and wellbeing outcomes

Only one primary study exploring the relationship between smartphone bans and adolescent wellbeing outcomes was found (Beneito & Vicente-Chirivella, 2022). Due to its methodology, it was not possible to extract the number of participants involved in this study.

Beneito and Vicente-Chirivella (2022) exploit the across-region variation introduced by two of the autonomous governments in Spain establishing mobile phone bans in schools after 2015. This study aimed to utilise this quasi-natural experiment to perform a comparative-case analysis to investigate the impact of this policy on educational attainment and bullying incidence. In Galicia, there was a non-significant effect of the policy for bullying outcomes in those under 12 years (likely due to the fact that this population does not have access to a mobile phone), and significant effects of the intervention leading to a reduction in bullying outcomes in those between 12–14 years ($\beta = -0.650$, $p < 0.01$) and those aged 13–17 years ($\beta = -0.796$, $p < 0.01$) (Beneito and Vicente-Chirivella, 2022). Similarly, in Castilla de La Mancha, there was a non-significant effect of the policy on children under 12 years, but a significant effect in those aged 12–14 years ($\beta = -1.100$, $p < 0.01$) and aged 15–17 years ($\beta = -0.359$, $p < 0.05$) (Beneito & Vicente-Chirivella, 2022). This underscores the potential efficacy of smartphone bans in improving wellbeing outcomes in this age group, as well as highlighting a renewed need for RCT or natural experiment evaluation studies of such interventions in UK populations.

Summary of the Quality of Evidence

Primary studies

The quality of included primary studies was assessed using an adapted version of the Newcastle-Ottawa Scale, with separate scales used for cross-sectional and cohort studies (Appendix 1.11). Specifically, the Newcastle-Ottawa scale was adapted to incorporate insights from the Cochrane ROBINS-I RoB tool, with assistance from GRADE Public Health Group members during development (Purba et al., 2023b; Wells et al., 2000). This included assessing adjustment for pre-identified critical confounding domains, other justifiable confounders, attrition and missing data, thereby facilitating an assessment of a study’s ability to make causal inferences.

All three studies pertaining only to Objective 1a, the relationship between exposure to social media content and mental health, were rated as low risk of bias (Hummel & Smith, 2015; Kelly et al., 2018; Meier & Gray, 2014).

The study that was related to both Objective 1a and 1b, the relationship between exposure to social media content and wellbeing, was rated moderate risk of bias (Frison et al., 2016). The two studies that examined just Objective 1b were rated moderate (Hoffman et al., 2023) and high risk of bias (Valkenburg et al., 2017).

The study exploring the relationship between smartphone bans and mental health was rated as low risk of bias (Beneito & Vicente-Chirivella, 2022), with the quasi-natural experiment design ensuring sample representativeness.

Systematic Reviews and Meta-analyses

The quality of included reviews was assessed using the AMSTAR-2 tool (Shea et al., 2017), with both reviews found to be of critically low quality (Holland & Tiggemann, 2016; Sala et al., 2024).

Discussion

Summary of Findings

In this synthesis, we considered the results of seven primary studies and two systematic reviews investigating the effects of social media and smartphone use on adolescent mental health and wellbeing. We found only one additional study on the impact of smartphone bans on the wellbeing of adolescents.

Impacts of content consumed

Our review identified two systematic reviews that reported that the impact of adolescent social media use on mental health (Holland & Tiggemann, 2016) and wellbeing (Sala et al., 2024) differed depending on the type of content consumed. Sala et al. (2024) found that social media feedback and content can significantly influence adolescents' wellbeing. Positive feedback and inspiring content may boost self-esteem, support mental health, and encourage social engagement, while negative feedback, exclusion and exposure to harmful or distressing material can lead to anxiety, social comparison and the normalisation of risky behaviours. The impact is especially pronounced in vulnerable users, such as those with low self-esteem or mental health difficulties (Sala et al., 2024). The second review focused specifically on disordered eating outcomes, finding that exposure to visual content and negative feedback were specifically associated with disordered eating behaviours and decreased body image (Holland & Tiggermann, 2016). Such findings underscore that the impacts of social media use may rely in part on the content consumed.

In our primary studies, viewing certain types of content on social media was associated with several maladaptive mental health and wellbeing outcomes. However those impacts were not clear cut, with various inconsistent and mixed associations (Frison et al., 2016; Valkenburg et al., 2017). In a longitudinal study investigating the concurrent and longitudinal relationships between adolescents' use of social media and their social esteem, Valkenburg et al. (2017) found significant positive concurrent correlations between adolescents' social media use and their social self-esteem in all three waves of data collection. Moreover, receiving positive feedback from friends and acquaintances enhanced social self-esteem in the short term. Initial social self-esteem was also correlated with later social media use, suggesting that adolescents with higher self-esteem are more likely to engage with social media over time. However, the longitudinal results were not consistent with these concurrent findings, such that social media use was not linked to self-esteem over time, indicating that the effects of social media use are inconsistent with regards to both time and the individual. An additional primary study specifically from the COVID-19 pandemic also classed the effects of some social media content as beneficial: Hoffman et al. (2023) found that exposure to COVID-19 information on social media was positively associated with emotional, psychological and social wellbeing. This effect was moderated by trust in COVID-19 content viewed online, where having high trust in social media information was associated with a positive effect on wellbeing, and low trust in social media led to a null effect.

There was substantial heterogeneity noted in the outcomes measured across studies. Subgroup analyses did not reveal any consistent effect of age or gender on adolescent mental health and wellbeing. Further, there was heterogeneity in the primary study quality assessed, with the best quality evidence found for the studies relating content of social media to mental health, while the study on smartphone bans was of moderate quality. Both systematic reviews were classed as critically low quality.

Smartphone and social media bans

Despite growing public and academic concern over adolescents' smartphone and social media use, there remains a lack of experimental evidence directly examining the effects of bans or reductions on individuals in this age group. As previously noted in our umbrella review, the adolescent population (while the focus of considerable observational research) has been largely absent from intensive experimental studies. This gap may be due in part to the practical and ethical challenges of conducting restrictive interventions with adolescents, who may find it difficult to comply with protocols that require significant reductions in device or platform use.

A growing body of research has explored the effects of school-level smartphone and social media interventions, although the evidence remains limited and variable, as reviewed in our narrative introduction. Our additional review only found one study on the impact of smartphone bans on the wellbeing of adolescents, highlighting a broader lack of intervention-based research in this area. Using a natural experiment with data from two states in Spain, Beneito and Vicente-Chirivella (2022) found that school smartphone bans significantly reduced bullying among adolescents aged 12–17 years, though effects were non statistically significant for children under 12. These findings suggest the potential benefits of such policies and emphasise the need for more rigorous studies, such as RCTs and additional natural experiment evaluations, to better understand the impact of smartphones and social media on youth. The limited number of studies found is likely a result of the methodological challenges associated with conducting RCTs with children and adolescents — particularly their greater time and resource demands.

Review Limitations

As mentioned above, the studies included in the narrative literature review were identified through a search of Google Scholar. For each objective and outcome, the first 60 search results were screened, resulting in a total of 180 records reviewed. It is important to note that, due to time constraints, the selection was not systematic; instead, records were prioritised based on relevance as determined by Google Scholar's internal algorithm. This means that the distribution of studies across each objective and outcome is not necessarily reflective of the volume of relevant literature in the field. This is especially important given that there was only one study identified considering the relationship between smartphone bans and adolescent mental health and wellbeing, and none considering the relationship between social media bans and adolescent mental health and wellbeing. Consequently, the results of this review focus largely on the impact of content exposure on mental health and wellbeing (Objective 1).

Conclusion

This supplementary narrative review has built upon the previous umbrella review findings by addressing two key gaps in the existing literature: the overreliance on time-based measures of social media use and the absence of experimental or quasi-experimental research evaluating the impact of removing or restricting social media or smartphone access among adolescents. In synthesising the findings from seven primary studies and two systematic reviews, we found that the relationship between adolescent digital engagement and mental health is highly contingent on the quality, content and context of online interactions and content consumed, and not merely the duration of use.

The evidence from content-focused studies indicates that the valence and type of content viewed may significantly shape outcomes. Positive, affirming content may bolster self-esteem and encourage positive outcomes, whereas exposure to negative feedback, exclusionary interactions or appearance-based and photographic comparisons may be detrimental to psychological wellbeing and mental health. Importantly, the effects were not uniform: they varied depending on individual vulnerabilities such as existing mental health conditions or low baseline self-esteem. There is evidence that certain types of harmful content (e.g. visual content or content relating to disordered eating) may cause harm, especially for certain populations.

This review highlights a significant gap in experimental research on social media and smartphone restrictions among adolescents. While there are some initial evaluations of school smartphone policies, existing intervention-based research on individual social media reduction largely focused on adults or older adolescents, often in university settings, with one additional study of adolescents with pre-existing mental health symptoms. These limitations constrain the generalisability of current findings and underscore the urgent need for more rigorous, adolescent-specific trials and natural experiment evaluations.

Overall, the evidence reviewed supports a necessary shift in research priorities — from simplistic measures such as 'time spent' to more nuanced, context-sensitive analyses of social media use and smartphone access. Future research should pay closer attention to the types of content adolescents encounter, the structural features of digital platforms, and the diverse ways these experiences affect different subgroups within the adolescent population.

Appendix 1.1 — PROSPERO protocol registration

Ioanna Fokas, Lukas Gunschera, Zhuo Yao Yap, Amrit Kaur Purba, Amy Orben. *The relationship between social media, smartphone use, AI-chat applications and developmental outcomes in children and young people: An Umbrella Review*. PROSPERO 2024 Available from: https://www.crd.york.ac.uk/PROSPERO/view/CRD42025641338

fAppendix 1.2 — Systematic review checklists

PRIOR checklist, Gates et al. (2022)

Table 4. Completed PRIOR checklist of this umbrella review

Section Topic	Item No.	Item	Location (page no.)
Title	1	Umbrella Review of the Relationship Between Time Spent on Social Media, Smartphones, AI Chat Applications, and Adolescent Mental Health and Well-Being	p. 87 Appendix 1 title page
Abstract	2	Provide a comprehensive and accurate summary of the purpose, methods, and results of the overview of reviews.	p. 86 Appendix 1 Overview
Introduction			
Rationale	3	Describe the rationale for conducting the overview of reviews in the context of existing knowledge.	p. 88 Appendix 1 Background
Objectives	4	Provide an explicit statement of the objective(s) or question(s) addressed by the overview of reviews.	p. 88 Appendix 1 Background
Methods			
Eligibility criteria	5a	Specify the inclusion and exclusion criteria for the overview of reviews. If supplemental primary studies were included, this should be stated, with a rationale	p. 89 Appendix 1 Methods — Inclusion and exclusion criteria
	5b	Specify the definition of 'systematic review' as used in the inclusion criteria for the overview of reviews.	p. 89 Appendix 1 Methods — Search methods for identification of reviews and eligibility criteria
Information Sources	6	Specify all databases, registers, websites, organisations, reference lists, and other sources searched or consulted to identify systematic reviews and supplemental primary studies (if included). Specify the date when each source was last searched or consulted.	p. 89 Appendix 1 Methods — Search methods for identification of reviews and eligibility criteria
Search Strategy	7	Present the full search strategies for all databases, registers and websites, such that they could be reproduced. Describe any search filters and limits applied.	p. 135 Appendix 1.3
Selection Process	8a	Describe the methods used to decide whether a systematic review or supplemental primary study (if included) met the inclusion criteria of the overview of reviews.	p. 89 Appendix 1 Methods — Search methods for identification of reviews and eligibility criteria
	8b	Describe how overlap in the populations, interventions, comparators, and/or outcomes of systematic reviews was identified and managed during study selection.	p. 92 Appendix 1 Methods — Primary Study Overlap Assessment
Data collection process	9a	Describe the methods used to collect data from reports.	p. 91 Appendix 1 Methods — Data Extraction
	9b	If applicable, describe the methods used to identify and manage primary study overlap at the level of the comparison and outcome during data collection. For each outcome, specify the method used to illustrate and/or quantify the degree of primary study overlap across systematic reviews.	p. 92 Appendix 1 Methods — Primary Study Overlap Assessment
	9c	If applicable, specify the methods used to manage discrepant data across systematic reviews during data collection.	N/A

Data items	10	List and define all variables and outcomes for which data were sought. Describe any assumptions made and/or measures taken to identify and clarify missing or unclear information.	p. 146 Appendix 1.4 — Data Extraction Table
Risk of bias assessment	11a	Describe the methods used to assess risk of bias or methodological quality of the included systematic reviews.	p. 92 Appendix 1 Methods — Risk of Bias Assessment
	11b	Describe the methods used to collect data on (from the systematic reviews) and/or assess the risk of bias of the primary studies included in the systematic reviews. Provide a justification for instances where flawed, incomplete, or missing assessments are identified but not re-assessed.	N/A
	11c	Describe the methods used to assess the risk of bias of supplemental primary studies (if included).	N/A
Synthesis methods	12a	Describe the methods used to summarise or synthesise results and provide a rationale for the choice(s).	p. 93 Appendix 1 Methods — Data Synthesis
	12b	Describe any methods used to explore possible causes of heterogeneity among results.	p. 93 Appendix 1 Methods — Data Synthesis
	12c	Describe any sensitivity analyses conducted to assess the robustness of the synthesised results	p. 93 Appendix 1 Methods — Data Synthesis
Reporting bias assessment	13	Describe the methods used to collect data on (from the systematic reviews) and/or assess the risk of bias due to missing results in a summary or synthesis (arising from reporting biases at the levels of the systematic reviews, primary studies, and supplemental primary studies, if included).	p. 92 Appendix 1 Methods — Reporting Bias Assessment
Certainty assessment	14	Describe the methods used to collect data on (from the systematic reviews) and/or assess certainty (or confidence) in the body of evidence for an outcome.	p. 92 Appendix 1 Methods — Certainty Assessment
Results			
Systematic review and supplemental primary study selection	15a	Describe the results of the search and selection process, including the number of records screened, assessed for eligibility, and included in the overview of reviews, ideally with a flow diagram.	p. 93 Appendix 1 Results — Review Selection
	15b	Provide a list of studies that might appear to meet the inclusion criteria, but were excluded, with the main reason for exclusion.	p. 165 Appendix 1.7 — Umbrella Review Exclusions
Characteristics of systematic reviews and supplementary primary studies	16	Cite each included systematic review and supplemental primary study (if included) and present its characteristics.	p. 95 Appendix 1 Results — Characteristics of reviews
Primary study overlap	17	Describe the extent of primary study overlap across the included systematic reviews	p. 94 Appendix 1 Results — Primary study overlap
Risk of bias in systematic reviews, primary studies, and supplemental primary studies	18a	Present assessments of risk of bias or methodological quality for each included systematic review.	p. 97 Appendix 1 Results — Risk of bias of reviews and primary studies
	18b	Present assessments (collected from systematic reviews or assessed anew) of the risk of bias of the primary studies included in the systematic reviews.	N/A
	18c	Present assessments of the risk of bias of supplemental primary studies (if included)	N/A
Summary or synthesis of results	19a	For all outcomes, summarise the evidence from the systematic reviews and supplemental primary studies (if included). If meta-analyses were done, present for each the summary estimate and its precision and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	p. 98 Appendix 1 Results — Synthesis of results

	19b	If meta-analyses were done, present results of all investigations of possible causes of heterogeneity.	N/A
	19c	If meta-analyses were done, present results of all sensitivity analyses conducted to assess the robustness of synthesised results.	N/A
Reporting biases	20	Present assessments (collected from systematic reviews and/or assessed anew) of the risk of bias due to missing primary studies, analyses, or results in a summary or synthesis (arising from reporting biases at the levels of the systematic reviews, primary studies, and supplemental primary studies, if included) for each summary or synthesis assessed.	p. 100 Appendix 1 Results — Reporting bias
Certainty of evidence	21	Present assessments (collected or assessed anew) of certainty (or confidence) in the body of evidence for each outcome.	p. 100 Appendix 1 Results — Evidence certainty
Discussion			
Discussion	22a	Summarise the main findings, including any discrepancies in findings across the included systematic reviews and supplemental primary studies (if included).	p. 102 Appendix 1 Discussion — Summary of findings
	22b	Provide a general interpretation of the results in the context of other evidence.	p. 102 Appendix 1 Discussion
	22c	Discuss any limitations of the evidence from systematic reviews, their primary studies, and supplemental primary studies (if included) included in the overview of reviews. Discuss any limitations of the overview of reviews methods used.	p. 102 Appendix 1 Discussion
	22d	Discuss implications for practice, policy, and future research (both systematic reviews and primary research). Consider the relevance of the findings to the end users of the overview of reviews, e.g, healthcare providers, policymakers, patients, among others.	p. 106 Appendix 1 Implications for Research
Other information			
Registration and protocol	23a	Provide registration information for the overview of reviews, including register name and registration number, or state that the overview of reviews was not registered.	p. 115 Appendix 1 Data Availability Statement
	23b	Indicate where the overview of reviews protocol can be accessed, or state that a protocol was not prepared.	p. 115 Appendix 1 Data Availability Statement
	23c	Describe and explain any amendments to information provided at registration or in the protocol. Indicate the stage of the overview of reviews at which amendments were made.	p. 115 Appendix 1 Data Availability Statement
Support	24	Describe sources of financial or non-financial support for the overview of reviews, and the role of the funders or sponsors in the overview of reviews.	p. 82 Appendix 1 Acknowledgements
Competing interests	25	Declare any competing interests of the overview of reviews' authors.	p. 82 Appendix 1 Acknowledgements
Author information	26	Provide contact information for the corresponding author. Describe the contributions of individual authors and identify the guarantor of the overview of reviews.	p. 82 Appendix 1 Acknowledgements
Availability of data and other materials	27	Report which of the following are available, where they can be found, and under which conditions they may be accessed: template data collection forms; data collected from included systematic reviews and supplemental primary studies; analytic code; any other materials used in the overview of reviews.	p. 83 Appendix 1 Data Availability Statement

Table 5. Completed PRISMA checklist of this umbrella review.

Section and Topic	Item #	Checklist item	Location (page no.)
TITLE			
Title	1	Identify the report as a systematic review.	p. 87
ABSTRACT			
Abstract	2	**See the PRISMA 2020 for Abstracts checklist.**	We did not include a scientific abstract due to the policy nature of this report, we will include one if taken to publication.
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	p. 87
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	p. 88
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	p. 89
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	p. 89
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	pp. 135–144
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	p. 89
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	p. 91
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	p. 90
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	pp. 89–91
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	p. 92

Section and Topic	Item #	Checklist item	Location (page no.)
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	N/A (Narrative synthesis)
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	p. 93
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	N/A (Narrative synthesis)
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	N/A (Narrative synthesis)
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	p. 93
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A (Narrative synthesis)
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A (Narrative synthesis)
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	p. 92
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	p. 92
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	p. 94
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	pp. 165–170
Study characteristics	17	Cite each included study and present its characteristics.	pp. 161–164
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	p. 173
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	N/A (Narrative

Section and Topic	Item #	Checklist item	Location (page no.)
			synthesis)
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	p. 95
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. **If comparing groups, describe the direction of the effect.**	N/A (Narrative synthesis)
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A (Umbrella Review), however we report the included reviews heterogeneity analyses in: p. 98 Results: Synthesis of results: heterogeneity
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A (Umbrella Review), however we report the included reviews sensitivity analysis in: p. 99 Results: Synthesis of results: moderators
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	p. 100
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	p. 100
DISCUSSION			

Section and Topic	Item #	Checklist item	Location (page no.)
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	p. 102
	23b	Discuss any limitations of the evidence included in the review.	pp. 84–85
	23c	Discuss any limitations of the review processes used.	p. 105
	23d	Discuss implications of the results for practice, policy, and future research.	pp. 106–107
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	p. 83
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	p. 83
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	p. 83
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	p. 82
Competing interests	26	Declare any competing interests of review authors.	p. 82
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	p. 83

From: Page et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. This work is licensed under CC BY 4.0. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/

Appendix 1.3 — Search Strategies for Systematic Synthesis

Table 6. MEDLINE search strategy.

String number	String
1	(“social media” OR “online communit*” OR “social app*” OR “social networking app*” OR “social networking site*” OR “online communicat*” OR “online messag*” OR “online platform” OR “facebook” OR “youtube” OR “whatsapp” OR “messenger” OR “snapchat” OR “wechat” OR “instagram” OR “qq” OR “tumblr” OR “tiktok” OR “twitter” OR “reddit” OR “linkedin” OR “X” OR “web2.0” OR “telegram” OR “social media” [mh] OR “social networking” [mh])
2	(“android” OR “apple” OR “samsung” OR “smartphone use” OR “smartphone usage” OR “cell phone use” OR “cell phone usage” OR “cellphone” OR “mobile device use” OR “mobile device usage” OR “screen time” OR “device use” OR “online interaction” OR “engagement” OR “smartphone behaviour” OR “smartphone behavior”)
3	(“AI” OR “artificial intelligence” OR “chatbot” OR “application” OR “assistant” OR “technology” OR “chat” OR “interaction” OR “chatgpt” OR “siri” OR “alexa” OR “virtual assistant” OR “conversational AI” OR “chatbot” or “artificial intelligence”[mh] OR “chatbot”[mh])
4	(“adolescen*” OR “teen*” OR “youth” OR “young people” OR “young person” OR “juvenile” OR “high school student” OR “middle school student” OR “secondary school” OR “student” OR “undergraduate” OR “adolescent behavior” [mh] OR “adolescent” [mh] OR “adolescent health” [mh] OR “adolescent development” [mh])
5	(“mental health” OR “mental health problem” OR “mental health disorder” OR “mental health risk” OR “emotional problem” OR “emotional disorder” OR “emotional risk” OR “psychosocial problem” OR “psychosocial disorder” OR “psychosocial risk” OR “disorder” OR “stress*” OR “distress” OR “emotional health” OR “psychopathology” OR “internalising” OR “internalisation” OR “eating disorder” OR “anorexia nervosa” OR “anorexia” OR “disordered eating” OR “bulimia” OR “bulimia nervosa” OR “restriction” OR “orthorexia” OR “binge eating” OR “suicidal ideation” OR “suicid*” OR “suicide attempt” OR “self harm” OR “self injur*” OR “eating disorders” [mh] OR “anorexia nervosa” [mh] OR “bulimia nervosa” [mh] OR “depression” [mh] OR “anxiety” [mh] OR “agoraphobia” [mh] OR “obsessive compulsive disorder”[mh] OR “mood disorders”[mh] OR “phobic disorders” [mh] OR “bipolar and related disorders”[mh] OR “depressive disorders”[mh] PR “dysthymic disorder”[mj] OR “premenstrual dysphoric disorder”[mh] OR “seasonal affective disorder”[mh])

6	(“wellbeing” OR “quality of life” OR “life satisfaction” OR “satisfaction” OR “emotional health” OR “social wellbeing” OR “contentment” OR “resilience” OR “protection” OR “support” OR “social connectedness” OR “social engagement” OR “self-esteem” OR “addiction” OR “comparison” OR “loneliness” OR “social isolation” OR “social support” OR “community participation” OR “integration” OR “networks” OR “interpersonal relationship*” OR “social isolation”[mh] OR “social support”[mh])

Legend: Search strategy. Date of search — 1 January 2025. Interface - Pub. Database and coverage — Medical Literature Analysis and Retrieval System Online (MEDLINE). Limits applied 05/2007–01/2025.

Table 7. MEDLINE search strategy outcomes.

Objective Number	String Order	Result Number
1	(STRING 1) AND (STRING 4) AND ((STRING 5) OR (STRING 6))	445
2	(STRING 2) AND (STRING 4) AND ((STRING 5) OR (STRING 6))	503
3	(STRING 3) AND (STRING 4) AND ((STRING 5) OR (STRING 6))	941

Legend: Search strategy and number of results for each objective for Pubmed MEDLINE database.

Table 8. CDSR search strategy.

String Number	String
1	(“social media” OR “online communication” OR “social app” OR “social networking app*” OR “social networking site*” OR “online messaging” “online platform” OR “facebook” OR “youtube” OR “whatsapp” OR “messenger” OR “snapchat” OR “wechat” OR “instagram” OR “qq” OR “tumblr” OR “qzone” OR “tiktok” OR “twitter” OR “reddit” OR “linkedin” OR “x” OR “web 2.0” OR “telegram” OR MeSH descriptor: [Social Media] explode all trees OR MeSH descriptor: [Social Networking] explode all trees)
2	(“android” OR “apple” OR “samsung” OR “smartphone use” OR “mobile phone use” OR “cellphone use” OR “smartphone usage” OR “mobile phone usage” OR “cellphone usage” OR “device usage” OR “engagement” OR “online interaction” OR “screentime” OR “handheld devices” MeSH descriptor: [cell phone] explode all trees OR MeSH descriptor: [smart phone] explode all trees)
3	(“AI” OR “artificial intelligence” OR “chatbot” OR “virtual assistant” OR “technology” OR “chat” OR “machine learning” OR “deep learning” OR “alexa” OR “siri” OR “automated chat” OR “smart assistant” OR “chat interface” OR MeSH descriptor: [Machine Learning] explode all trees OR MeSH descriptor: [Artificial Intelligence] explode all trees)
4	(“adolescent” OR “teen” OR “teenager” OR “youth” OR “young people” OR “young person” OR “young adult” OR “juvenile” OR “high school student” OR “secondary school student” OR “middle school student” OR “highschooler” OR “middle schooler” OR “undergraduate” OR MeSH descriptor: [Adolescent Behavior] explode all trees OR MeSH descriptor: [Adolescent] explode all trees OR MeSH descriptor: [Adolescent Health] explode all trees OR MeSH descriptor: [Adolescent Psychology] explode all trees OR MeSH descriptor: [Adolescent Development] explode all trees)
5	(“mental health” OR “mental health problem” OR “mental health disorder” OR “mental health risk” OR “emotional health” OR “emotional problem” OR “emotional risk” OR “emotional disorder” OR “psychosocial health” OR “psychosocial problem” OR “psychosocial risk” OR “emotional behaviour” OR “emotional behavior” OR “depression” OR “stress” OR “anxiety” OR “major depressive disorder” OR “psychopathology” OR “internalisation” OR “internalising problem” OR “eating disorder” OR “anorexia nervosa” OR “anorexia” OR “disordered eating” OR “bulimia” OR “bulimia nervosa” OR “restriction” OR “orthorexia” OR “binge eating” OR “suicidal ideation” OR “suicide” OR “suicide attempt” OR “self-harm” OR “self injury” OR MeSH descriptor: [Eating Disorders] explode all trees OR MeSH descriptor: [Anorexia Nervosa] explode all trees MeSH descriptor: [Bulimia Nervosa] explode all trees

	MeSH descriptor: [Binge Eating Disorder] explode all trees OR MeSH descriptor: [Suicide] explode all trees OR MeSH descriptor: [Self-Injurious Behavior] explode all trees OR MeSH descriptor: [Suicide, Attempted] explode all trees OR MeSH descriptor: [Depression] explode all trees OR MeSH descriptor: [Anxiety] explode all trees OR MeSH descriptor: [Anxiety Disorders] explode all trees OR MeSH descriptor: [Agoraphobia] explode all trees OR MeSH descriptor: [Anxiety, Separation] explode all trees OR MeSH descriptor: [Obsessive-Compulsive Disorder] explode all trees OR MeSH descriptor: [Panic Disorder] explode all trees OR MeSH descriptor: [Phobic Disorders] explode all trees OR MeSH descriptor: [Bipolar and Related Disorders] explode all trees OR MeSH descriptor: [Mood Disorders] explode all trees OR MeSH descriptor: [Depressive Disorder] explode all trees OR MeSH descriptor: [Dysthymic Disorder] explode all trees OR MeSH descriptor: [Premenstrual Dysphoric Disorder] explode all trees OR MeSH descriptor: [Seasonal Affective Disorder] explode all trees)
6	(“wellbeing” OR “quality of life” OR “life satisfaction” OR “satisfaction” OR “emotional health” OR “social wellbeing” OR “contentment” OR “resilience” OR “protection” OR “support” OR “social connectedness” OR “social engagement” OR “self-esteem” OR “addiction” OR “comparison” OR “loneliness” OR “social isolation” OR “social support” OR “community participation” OR “integration” OR “interpersonal relationship”* OR MeSH descriptor: [Social Isolation] explode all trees OR MeSH descriptor: [Social Support] explode all trees)

Legend: Search strategy. Date of search — 1 January 2025. Interface - Cochrane Library. Database and coverage — CDSR = Cochrane Database of Systematic Reviews. Limits applied 05/2007–01/2025.

Table 9. CDSR search strategy outcomes.

Objective Number	String Order	Result Number
1	(STRING 1) AND (STRING 4) AND ((STRING 5) AND (STRING 6))	29
2	(STRING 2) AND (STRING 4) AND ((STRING 5) AND (STRING 6))	31
3	(STRING 3) AND (STRING 4) AND ((STRING 5) AND (STRING 6))	50

Legend: Search strategy and number of results for each objective for Cochrane Database of Systematic Reviews.

Table 10: PROSPERO search strategy.

Objective Number	**String**
1	(“social media” OR “facebook” OR “twitter” OR “instagram” OR “reddit” OR “snapchat”) AND (“adolescent” OR “young” OR “teen” OR “youth”) AND (“mental health” OR “disorder” OR “psychosocial” OR “psychopathology” OR “eating disorder” OR “depression” OR “anxiety” OR “internalizing” OR “habit” OR “wellbeing” OR “satisfaction” OR “support” OR “health”)
2	(“smartphone” OR “apple” OR “samsung” OR “android” OR “cell” OR “mobile”) AND (“adolescent” OR “young” OR “teen” OR “youth”) AND (“mental health” OR “disorder” OR “psychosocial” OR “psychopathology” OR “eating disorder” OR “depression” OR “anxiety” OR “internalizing” OR “habit” OR “wellbeing” OR “satisfaction” OR “support” OR “health”)
3	**(“**artificial intelligence” OR “ai” OR “chatbot” OR “alexa” OR “siri” OR “chat-gpt” OR “virtual assistant”) AND (“adolescent” OR “young” OR “teen” OR “youth”) AND (“mental health” OR “disorder” OR “psychosocial” OR “psychopathology” OR “eating disorder” OR “depression” OR “anxiety” OR “internalizing” OR “internalising” OR “habit” OR “wellbeing” OR “satisfaction” OR “support” OR “health”)

Legend: Search strategy. Date of search 1 January 2025. Interface - Prospero. Database and coverage - Prospero Library. Limits applied 05/2007–01/2025.

Table 11. PROSPERO search strategy outcomes.

Objective Number	String Order	Result Number
1	STRING 1	1027
2	STRING 2	1525
3	STRING 3	410

Legend: Search strategy and number of results for each objective for Prospero database.

Table 12. Google Scholar search strategy.

Objective	String
1	1a: (“social media” OR “social network” OR “online community” OR “messaging” OR “messaging-apps”) AND (“content”) AND (“adolescent” OR “young person” OR “youth” OR “teenager” or “teen”) AND (“mental health” OR “disorder” OR “problem” OR “anxiety” OR “depression” OR “internali”* OR “eating disorder” OR “psychopathology”) AND (“uk” OR “united kingdom”) 1b: (“social media” OR “social network” OR “online community” OR “messaging” OR “messaging-apps”) AND (“ban” OR “restriction” OR “blocking” OR “exclusion”) AND (“adolescent” OR “young person” OR “youth” OR “teenager” or “teen”) AND (“wellbeing” OR “life satisfaction” OR “happiness” OR “satisfaction” OR “connection” OR “loneliness”) AND (“uk” OR “united kingdom”)
2	2a: (“smartphone” OR “mobile” OR “Apple” OR “Android” OR “Samsung” OR “cellphone” OR “mobile device” OR “cellular device”) AND (“ban” OR “restriction” OR “blocking” OR “exclusion”) AND (“adolescent” OR “young person” OR “youth” OR “teenager” or “teen”) AND (“mental health” OR “disorder” OR “problem” OR “anxiety” OR “depression” OR “internali”* OR “eating disorder” OR “psychopathology”) AND (“uk” OR “united kingdom”) 2b: (“smartphone” OR “mobile” OR “Apple” OR “Android” OR “Samsung” OR “cellphone” OR “mobile device” OR “cellular device”) AND (“ban” OR “restriction” OR “blocking” OR “exclusion”) AND (“adolescent” OR “young person” OR “youth” OR “teenager” or “teen”) AND (“wellbeing” OR “life satisfaction” OR “happiness” OR “satisfaction” OR “connection” OR “loneliness”) AND (“uk” OR “united kingdom”)
3	3a: (“AI chat applications” OR “chatbots” OR “artificial intelligence” OR “conversational AI” OR “chatgpt” OR “siri” OR “alexa”) AND (“adolescent” OR “young person” OR “youth” OR “teenager” or “teen”) AND (“mental health” OR “disorder” OR “problem” OR “anxiety” OR “depression” OR “internali”* OR “eating disorder” OR “psychopathology”) AND (“uk” OR “united kingdom”) 3b: (“AI chat applications” OR “chatbots” OR “artificial intelligence” OR “conversational AI” OR “chatgpt” OR “siri” OR “alexa”) AND (“adolescent” OR “young person” OR “youth” OR “teenager” or “teen”) AND (“wellbeing” OR “life satisfaction” OR “happiness” OR “satisfaction” OR “connection” OR “loneliness”) AND (“uk” OR “united kingdom”)

Legend: Search strategy. Date of search — 1 January 2025. Interface - Google. Database and coverage - Google Scholar. Limits applied 05/2007–01/2025

Table 13. Google Scholar search strategy outcomes.

Objective Number	String Order	Result Number
1	STRING 1a + STRING 1b	60
2	STRING 2a + STRING 2b	60
3	STRING 3a + STRING 3b	60

Legend: Search strategy and number of results for each objective for Google Scholar search engine.

Appendix 1.4 — Data Extraction Table

Table 14. Key for data extraction.

Field	Brief description	Guidance	Permissible entries	Notes column
Characteristics of the systematic review				
date	Date of data extraction by lead reviewer.			
source	Where was the study found?	If this is a relevant publication screened in covidence	Cov	
		If this is a relevant publication found via manual searching of reference lists of included studies	M	
		If this is a relevant publication identified via expert correspondence	E	
		If this is a relevant publication found via reference list of systematic review	SR	
study ID	Internal reference number	Source = Covidence	#Cov allocated number	
		Source = Systematic Review	#SR	
		Source = Reference List of included studies	#M	

		Source = Expert Correspondence	#E	
first author	Who is the first author?	Last name, first name		
corresponding author	Insert email of corresponding author.			
publication	Where was the review published?	e.g. journal publication.	Journal name.	
year	Year of publication.			
title	Title of review.			
aim	Aim of review.	Brief free text description of the study's aim.		
objective	Which research objective does the review address?	If multiple, add separate rows for each objective and ensure you apply the scheme consistently throughout. Study ID would be 1A_1 for objective 1, 1A_2 for objective 2.		
search range	What were the years covered in the literature search?	e.g. 2000–2002		
country	Where was the review conducted?	Including location and study context.	e.g. UK, five Midland Secondary Schools.	
setting	Was review setting a high, medium or low-income country?	Use the World Bank Country Income Classification for this.	High income	
			Middle income	
			Low income	
number of effect sizes	How many effect sizes were reported?			

number of primary studies	How many primary studies were included in the review?	Insert number.		
type primary studies	What type of primary studies are included in the review?	If Randomised Control Trial (RCT)	#number-RCT	
		If cohort	#number-C	
		If cross-sectional	#number-CS	
number participants	What was the total number of participants in the review?			
age participants	What was the age range of participants in the review?	Additionally report mean age where possible.		
sex participants		If male	M	
		If female	F	
		If both	M+F	
proportion participants	What is the proportion of male to female participants?	Write as percent.	%M	
			%F	
ethnicity participants	Ethnic breakdown of review participants			
setting	Socioeconomic circumstance of participants.	Record the scale used and the distribution amongst study participants in the analytical sample.		
response rate	What proportion of sampled participants completed the study?	%M, %F		

control variables	Which variables were controlled in the study?			
exposure definition	Categorise under three exposures.	e.g. both question and response options.		
exposure measure	How was the exposure operationalised and measured?		Binary	
			Continuous	
			Categorical	
			Ordinal	
exposure collection	How was the data concerning the exposure collected?	e.g. self-report unvalidated survey.		
exposure date	When did data collection occur for this exposure?			
exposure time	What time period was the exposure measuring?	Is there any information about the duration of the exposure or is it any exposure across the lifespan?	e.g. ever, current	
outcome definition	Categorise by outcome: mental health, wellbeing.		Physical health	
			Lifestyle and health behaviours	
			Educational attainment	
outcome measure	How was the data collected?	Record measurement tool.	e.g. Patient Health Questionnaire	If necessary, note down any oddities that are worth remembering; e.g. study x might have implemented measure

				y in a strange way, removed an item, or created a transformed score.
outcome collection	How was the outcome operationalised?		Binary	
			Continuous	
			Categorical	
			Ordinal	
outcome date	What date was data collected for the outcome?			
outcome time	What time-period was the outcome measuring?		e.g. ever, current.	
study method	Analysis method used in reviews (narrative or meta); analysis method for studies.	For primary studies, the analysis method is also indicative of the study's ability to assess causality — add in confounders.		
sensitivity test	Were any sensitivity tests carried out?			
study effect metric	Which effect metric did the study use?			
study analysis method	How was the effect size calculated?	Brief free text description		
homogeneity of variance	Did the study record a Fisher statistic?		e.g. Record statistic	

p value of effect size	What is the p value associated with the effect size?			
study effect size	Record if the review is quantitative.			
study results	What were the key results of the review?	Brief free text recording of the review results.		
subgroup analysis				
gender/sex findings	What were the results of any specific analyses pertaining to gender/sex?	Brief free text recording of analysis results.		
age findings		What were the results of any specific analyses pertaining to age?	Brief free text recording of analysis results.	
socioeconomic circumstance findings		What were the results of any specific analyses pertaining to socioeconomic circumstance?	Brief free text recording of analysis results.	
user/market generated content		What were the results of any specific analyses pertaining to the impacts of user and market generated content, respectively?	Brief free text recording of analysis results.	
other		What were the results of any other subgroup analyses?	Brief free text recording of analysis results.	
quality of findings				

quality assessment tool/***risk of bias tool***	Name of risk of bias tool used and notes on method.	e.g. Newcastle-Ottawa Scale. If an adapted version is used, please state what changes have been made to the original tool.		
quality assessment results/***risk of bias results***	Quality assessment/ Risk of Bias results for each question and overall.			
GRADE/certainty of evidence	Has the certainty of evidence been assessed using GRADE? yes/no.			
GRADE/certainty of evidence results	If applicable, GRADE/certainty of evidence for each question and overall.	e.g. moderate, low, very low.		
Hill’s Criteria for Causation considered	yes/no.			
Hill’s Criteria for Causation results	Results if applicable.	e.g. plausibility, coherence.		
ROB-2 use — RCTs	yes/no			
AMSTAR-2 result/***Newcastle-Ottawa Scale Results***				
publication bias	Notes if applicable.			
conflicts of interest	Any possible conflicts of interest?		Yes	
			No	
			Not reported	
funding source			If yes record the name of funding bodies	

			No	
			Not reported	
harmful/beneficial/inconsistent	Was the effect of the exposure on the participants harmful, beneficial or inconsistent?	harmful beneficial inconsistent		
notes	Additional notes on any aspect of study design, analysis or quality of evidence.	i.e. notes on need to contact study authors for information and their responses once received. In some instances, email will need to be found, or Research Gate communication to take place; a long process so give authors 1.5 weeks.		

Legend: GRADE = Grading of Recommendations, Assessment and Evaluation Tool, ROB-2 = Risk of Bias Tool 2, AMSTAR-2 = A Measurement Tool to Assess Systematic Reviews. Table showing reviewer instructions for data extraction categories. ****Italicised Bold*** entries are for narrative strategy primary research studies only.

Appendix 1.5 — Systematic review primary study overlap visualisation

Table 15. Total Corrected Covered Area across reviews.

	M. Liu et al., 2022	**Cunningham et al., 2021**	**Fassi et al., 2024**	**Keles et al., 2020**	**Ivie et al., 2020**	**Purba et al., 2023b**	**Ferguson et al., 2025**
Al-Qudah & Baloum, 2018			X				
Azhari et al., 2022							X
Barthorpe et al., 2020			X				X
Beeres et al., 2021							X
Babic et al., 2017							X
Banjanin et al., 2015	X		X	X	X		
Banyai at el., 2017							
Boers et al., 2019	X		X				
Bonaksen et al., 2022			X				
Blomfeld et al., 2014					X		
Barry et al., 2017		X			X		X
Brooke & Longstreet, 2015		X					
Burke et al., 2021			X				
Brunborg et al., 2019	X		X		X	X	
Brunborg et al., 2017					X		
Cayubit et al., 2022			X				
Calandri et al., 2021	X		X				
Chen, 2009						X	
Chau, 2022						X	
Creasy et al., 2013							X
Corey et al., 2014			X				

Costa et al., 2020	X						
Coyne et al., 2013						X	
Coyne et al., 2023			X				
Chdntsova et al., 2023			X				
Coyne et al., 2019	X		X			X	X
Davison et al., 2022							X
Dumas et al., 2023			X				
Datu et al., 2012			X				
Downey et al., 2020							X
Dredge et al., 2020	X		X				
Ellis et al., 2020	X		X				
Fardouly et al., 2018		X	X				
Fardouly et al., 2020	X		X				X
Ferguson et al., 2021			X				X
Froyland, 2020						X	
Frison & Eggermont, 2016			X				
Frison & Eggermont, 2020			X				
Frison & Eggermont, 2017							X
Frison et al., 2019			X				
Fiztgerakd et al., 2021			X				
Frison et al., 2016	X				X		
Hanna et al., 2017			X				
Hartas et al., 2021							X
Heffer et al., 2019			X				
Hamilton et al., 2021			X				X
Hökby et al., 2016							X

Hoare et al., 2017			X				X
Heffer et al., 2019							X
Holmgren & Coyne, 2017			X				
Houghton et al., 2018			X				
Huang et al., 2023			X				
Hanprathet et al., 2015							
Jelenchick et al., 2013			X				
Jensen et al., 2019							X
Karaman et al., 2019			X				
Kandola et al., 2021			X				X
Kleppang et al., 2021			X				
Kilary et al., 2014		X					
Kreski et al., 2021							X
Kelly, 2023			X				
Kelly et al., 2018	X						X
Li, 2017							X
Leventhal et al., 2021							X
Lujiten et al., 2022			X				
Lemola et al., 2014	X						
Maheux et al., 2022			X				
Ma et al., 2021	X						
Mundy et al., 2021			X				X
Moitra & Madan, 2022			X				
McAllister et al., 2021	X		X				X
Oberst et al., 2017					X		
O’Dea and Campbell, 2011				X			

Morin-Major et al., 2015	X	X			X		
Nera and Barber, 2014		X		X			
Nesi et al., 2022			X				
Nesi et al., 2021			X				X
Necmi Ucar et al., 2018			X				
Noel et al., 2022			X				
Niu et al., 2016					X		
Orben et al., 2019							X
Orben & Przybylski, 2019a							X
Orben & Przybylski, 2019b							X
Ohannesian et al., 2021			X				
Orben, Przybylski & Blakemore, 2022							X
Polittea et al., 2023			X				
Padilla-Walker et al., 2019	X		X				
Pantic et al., 2012	X		X		X		
Przybylski & Weinstein, 2017							X
Riehm et al., 2019			X				X
Rodgers et al., 2020			X				
Rogers et al., 2017		X					
Roberston et al., 2022							X
Rutter et al, 2021			X				
Sela et al., 2020	X						
Sampasa Kanyinga & Lewis, 2015			X	X			
Schlesinger, 2022							X
Shoshani et al., 2021	X						

Svensson et al., 2022							X
Shoshani et al., 2021			X				
Shaw et al., 2015			X				
Simonic et al., 2014			X				
Steele et al., 2023			X				
Story, 2021	X						X
Tador et al., 2015			X				
Tamura et al., 2017	X		X				
Tao et al., 2021	X		X				
Thorisdottir et al., 2019	X		X		X		
Tsitsika et al., 2014			X	X			
Twenge et al., 2018a							X
Twenge et al., 2018b							X
Twenge et al., 2019			X				
Twenge & Campbell, 2019							X
Twenge & Farley, 2020			X				X
Twenge et al., 2021	X				X		X
Turk et al., 2021			X				
Yan et al., 2017				X			
Vannucci, 2019			X			X	
Van Rooji et al., 2017		X					
Vernon, Modecki & Barber, 2017				X			
Viner et al., 2019							X
Ward, 2018							X
Winstone et al., 2022							X

Wang et al., 2018							
Xie et al., 2018							
Woods et al., 2016	X		X		X		
Yan et al., 2017			X				
Zielenski et al., 2021	X						X

Legend: Total list of unique studies with visualisations of inclusion in each paper. For full references to studies cited, see bibliographies of included reviews.

Table 16. Pairwise Corrected Covered Area.

	M. Liu et al. (2022)	**Ferguson et al. (2024)**	**Keles et al. (2020)**	**Fassi et al. (2024)**	**Cunningham et al. (2021)**	**Purba et al. (2023b)**	**Ivie et al. (2020)**
Ferguson et al. (2024)	0.10769231						
Keles et al. (2020)	0.03225806	0					
Fassi et al. (2024)	0.21052632	0.10891089	0.04347826				
Cunningham et al. (2021)	0.03225806	0.01960784	0	0			
Purba et al. (2023b)	0.06666667	0.1960784	0	0	0		
Ivie et al. (2020)	0.1875	0.03571429	0.05882353	0.06849315	0.125	0	

Legend: Calculated Covered Area calculations between each pair of papers. 🟥 = Very high (>15%), 🟧 = High (11–15%), 🟨 = Moderate (6–10%), 🟩 = Slight (0–5%), ☐ = None (0%).

Appendix 1.6 — Characteristics of Included Reviews, Systematic Synthesis

Table 17. Characteristics of Included Reviews.

Citation	Outcome	Title	Aim	Time period	No. of primary studies	Exposure	Outcome	Funding
Objective 1a: Social Media and Mental Health								
Cunningham et al. (2021)	MH	Social media and depression symptoms: a meta-analysis	To quantitatively summarise and compare the concurrent relations between depression symptoms and time spent using social networks, intensity of social network use, and problematic social network use.	Up to 2019 (no specified start date)	6 studies	Time spent on social media (also examined other measures not synthesised here)	Depressive symptoms	NR
Fassi et al. (2024)	MH	Social media use and internalising symptoms in clinical and community adolescent samples: A systematic review and meta-analysis	Synthesise, quantify and compare evidence on the association between social media use and internalising symptoms in adolescent clinical and community samples.	2007–2023	65 studies	Time spent on social media (also examined other measures not synthesised here)	Internalising symptoms	MRC, Wellcome, Stellenbosch University, Jacobs Foundation, National Institute for Health and Care Applied Research Centre,

								Place2Be, Emmanuel College, University of Cambridge, UK Research and Innovation
Ivie et al. (2020)	MH	A meta-analysis of the association between adolescent social media use and depressive symptoms	Quantify relationship between adolescent social media use and mental health outcome using meta-analytic techniques.	Up to 2020 (no specified start date)	12 studies	Time spent on social media	Continuous measures of depressive symptoms	NR
Keles et al. (2020)	MH	A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents	Explore the influence of social media use on depression, anxiety and psychological distress in adolescents.	Up to 2018 (no specified start date)	6 studies	Time spent on social media (also examined other measures not synthesised here)	Depression, anxiety or psychological distress (measured using validated instruments: K-6 scale; BDI; depressed mood scale; Youth Self Report problem	NR

							checklist; General Health Questionnaire-28; CESD; CESD (Chinese edition); DSMV checklist)	
M. Liu et al. (2022)	MH	Time spent on social media and risk of depression in adolescence: a dose-response meta-analysis	Review the evidence on the relationship between time spent on social media and depression.	Up to 2022 (no specified start date)	26 studies	Time spent on social media	Depression scores on standardised questionnaires (CESD; SMFQ; BDI; PHQ9; CDI; BSI; HADS; OSCD)	Research Foundation of Education Bureau of Hunan Province
Purba et al. (2023b)	WB	Social media use and health risk behaviours in young people: a systematic review and meta-analysis	Examine the association between social media use and health risk behaviours in adolescents (defined as those 10–19 years).	1997–2022	6 studies	Time spent on social media (also examined other measures)	Antisocial behaviour (also reported in the review: use of alcohol, drugs, tobacco, electronic nicotine delivery systems, unhealthy dietary behaviour, inadequate physical activity, gambling and sexual risk, and multiple risk behaviours)	MRC, Chief Scientist Office, NHS Scotland, Senior Clinical Fellowship, Wellcome Trust

Both Objective 1a: Social Media and Mental Health and Objective 1b: Social Media and Wellbeing								
Ferguson et al. (2025)	MH/WB	There is no evidence that time spent on social media is correlated with adolescent mental health problems: findings from a meta-analysis	• Establish the effect size between social media use and mental health/wellbeing in adolescence. • Establish the prevalence of best practice in studies in the existing literature, and their impact on observed effect sizes.	2012–2022	46 studies	Time spent on social media	Search terms included internalising symptoms, clinical diagnoses and wellbeing	NR
Objective 1b: Social Media and Wellbeing								
No reviews found								
Objective 2: Smartphones and Mental Health/Wellbeing								
No reviews found								
Objective 3: AI Chat Applications and Mental Health/Wellbeing								
No reviews found								

Legend: Abbreviations: MH = Mental Health, WB = Wellbeing, ** NR = Not Reported

Appendix 1.7 — Study Exclusions

Systematic Synthesis Exclusions

Several systematic reviews were considered for inclusion, but ultimately were deemed to have not met PICO criteria. The decisions underpinning these exclusions are summarised below. References of these studies are not included in the bibliography but are available from the author team on request.

Review	Review Title	Reason for Exclusion
Best et al. (2014)	Online communication, social media, and adolescent wellbeing: a systematic narrative review	Wrong exposure
Blanchard et al. (2023)	Associations between social media, adolescent mental health and diet: a systematic review	Wrong exposure
Conte et al. (2024)	Scrolling through adolescence: a systematic review of the impact of TikTok on adolescent mental health.	Wrong exposure
Damodar et al. (2022)	Trending: a systematic review of social media use's influence on adolescent anxiety and depression	Wrong exposure
Haverson et al. (2025)	Digital technology use and wellbeing in young children: a systematic review and meta-analysis	Wrong population
Hassrick et al. (2021)	Benefits and risks: a systematic review of information communication technology use by autistic people	Wrong population
Stiglic & Viner (2019)	Effects of screentime on the health and well-being of children and adolescents: a systematic review of reviews	Wrong exposure
Wang (2020)	Smartphone overuse and visual impairment in children and young adults: a systematic review and meta-analysis	Wrong outcome

Umbrella Review Exclusions

Given the PICO inclusion criteria detailed in the PROSPERO pre-registration and methods section of this review,* the decision was made not to include umbrella reviews in this synthesis. However, we checked the four relevant umbrella reviews that appeared from our search strategy to ensure that we had not missed any relevant systematic reviews for inclusion. Included studies are highlighted in bold. Whilst a 2020 meta-review by Meier and Reinecke was noted, it was excluded from consideration due to its exploration of social media use and the umbrella of computer-mediated communication, which included media beyond the scope of this review, such as email correspondence (Meier & Reinecke, 2022).

*Systematic reviews and meta-analyses will be considered for inclusion.

Valkenburg et al., 2022

Table 18. Systematic reviews in Valkenburg et al., 2022, with reason for exclusion.

Review	Review Title	Reason for Exclusion
Meta-analyses		
Huang (2021)	Correlations of online social network size with well-being and distress: a meta-analysis	Wrong population — Mean age across the included sample was 24.47 years of age, with a range between 14–60.
Ivie et al. (2020)	**A meta-analysis of the association between adolescent social media use and depressive symptoms**	**Included**
Liu et al. (2019)	Digital communication media use and psychological well-being: a meta-analysis	Retracted — article retracted from peer-reviewed publication, with retraction statement found here: https://doi.org/10.1093/jcmc/zmad003 .
Vahedi and Zannella (2021)	The association between self-reported depressive symptoms and the use of social networking sites: a meta-analysis	Wrong population — undergraduate sample and therefore the majority of the sample is over the age of 19. They coded for adult/non-adult but only included as moderators.
Yin et al. (2019)	Cultural background and measurement of usage moderate the association between social networking sites usage and mental health: a meta-analysis	Wrong population and exposure — Included samples from general populations, including those under 10 (i.e. not limited to the adolescent population): age was coded as adolescents (18 years old or below), adults (19–70) and mixed age-group. They included age as a moderator and reported results separately; however this is for a broad range of social media use. While they report a moderating analysis for different types of social media use, this is not then moderated by age.
Yoon et al. (2019)	Is social network site usage related to depression? A meta-analysis of Facebook-depression relations	Wrong population — carried out analyses on a sample including the general adult population.
Systematic Reviews		
Alonzo et al. (2021)	Interplay between social media use, sleep quality and mental health in youth: a systematic review	Wrong population — 16–25 years (mean = 20.5 years).
Cataldo et al. (2021)	Social Media usage and development of psychiatric disorders in childhood and adolescence: a review	Wrong exposure — no measure of time spent on social media.
Course-Choi and Hammond (2021)	Social media use and adolescent well-being: a narrative review of longitudinal studies	Wrong exposure — investigated broad exposure of frequency of social media use. Only 3 of the 14 included papers reported on time spent, with no separate analysis of time spent.
Keles et al. (2020)	**A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents**	**Included**
Neophytou et al. (2019)	Effects of excessive screen time on neurodevelopment, learning, memory, mental health and neurodegeneration: a scoping review	Wrong study design — scoping review.
Schønning et al. (2020)	Social media use and mental health and wellbeing among adolescents — a scoping review.	Wrong study design — scoping review.

Vidal et al. (2020)	Social media use and depression in adolescents: a scoping review	Wrong study design — scoping review.
Webster et al. (2020)	Association between social networks and subjective wellbeing in adolescents: a systematic review	Wrong exposure — did not explore time spent on social media.
Narrative Reviews		
Abi-Jaoude et al. (2020)	Smartphones, social media use, and youth mental health	Wrong study design — narrative review.
Dienlin and Johannes (2020)	The impact of digital technology use on adolescent wellbeing	Wrong study design — narrative review.
McLean et al. (2019)	How do ‘selfies’ impact adolescents’ well-being and body confidence? A narrative review	Wrong study design — narrative review.
Odgers & Jensen (2020)	Adolescent mental health in the digital age: facts, fears and future directions	Wrong study design — narrative review.
Odgers & Jensen (2020)	Adolescent development and growing divides in the digital age	Wrong study design — narrative review.
Odgers et al. (2020)	Screen time, social media use and adolescent development	Wrong study design — narrative review.
Orben (2020)	Teenagers, screens and social media: a narrative review of reviews and key studies	Wrong study design — narrative review.
Smith et al. (2021)	Belonging and loneliness in cyberspace: impact of social media on adolescents’ wellbeing	Wrong study design — narrative review.
Twenge (2019)	More time on technology, less happiness? Associations between digital-media use and psychological wellbeing	Wrong study design — narrative review.

Sala et al., 2024

Table 19. Systematic reviews in Sala et al., 2024, with reason for exclusion.

Review	Review Name	Reason for Exclusion
Ivie et al. (2020)	**A meta-analysis of the association between adolescent social media use and depressive symptoms**	**Included**
Keles et al. (2020)	**A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents**	**Included**
Chung et al. (2021)	Adolescent peer influence one eating behaviours via social media: scoping review	Wrong study design — scoping review.
Moss et al. (2023)	Assessing the impact of Instagram use and deliberate self-harm in adolescents: a scoping review	Wrong study design — scoping review.
Webster et al. (2021)	Association between social networks and subjective well-being in adolescents: a systematic review	Wrong exposure — did not explore time spent on social media.
Popat and Tarrant (2023)	Exploring adolescents’ perspectives on social media and mental health and wellbeing: a qualitative literature review	Wrong study design — qualitative literature review.

Sarmiento et al. (2020)	How does social media use relate to adolescents' internalising symptoms? Conclusions from a systematic narrative review	Wrong exposure — only six of the included 68 reviews focused on time spent on social media, and this was not analysed or reported separately.
Hamm et al. (2015)	Prevalence and effect of cyberbullying on children and young people	Wrong study design — scoping review.
Varona et al. (2022)	Problematic use or addiction? A scoping review on conceptual and operational definitions of negative social networking site use in adolescents	Wrong study design — scoping review.
Zhou & Cheng (2022)	Relationship between online social support and adolescent mental health: a systematic review and meta-analysis	Wrong exposure — does not measure the effects of time spent on social media.
Senekal et al. (2023)	Social media and adolescent psychosocial development: a systematic review	Wrong exposure — no focus on time spent on social media.
McCrae et al. (2017)	Social media and depressive symptoms in childhood and adolescence: a systematic review	Wrong exposure — does not report on time spent on social media.
Cataldo et al. (2021)	Social media usage and development of psychiatric disorders in childhood and adolescence: a review	Wrong exposure — refers to 'problematic' social media use, which was listed under exclusion criteria due to the lack of a consensus in the field.
Course-Choi and Hammond (2021)	Social media use and adolescent well-being: a narrative review of longitudinal studies	Wrong exposure — investigated broad exposure of frequency of social media use. Only three of the 14 included papers reported on time spent, with no separate analysis of time spent.
Vidal et al. (2020)	Social media use and depression in adolescents: a scoping review	Wrong study design — scoping review.
Schønning et al. (2020)	Social media use and mental health and wellbeing among adolescents — a scoping review	Wrong study design — scoping review.
Vannucci et al. (2020)	Social media use and mental health and wellbeing among adolescents — a scoping review	Wrong study design — scoping review.
Sedgwick et al. (2019)	Social media, internet use and suicide attempts in adolescents	Wrong exposure — does not explore time spent on social media.
Nolan et al. (2017)	Social networking site use by adolescent mothers: can social support and social capital be enhanced by online social networks? A structured review of the literature	Wrong exposure — does not focus on time spent on social media.
Memon et al. (2018)	The role of online social networking on deliberate self-harm and suicidality in adolescents: a systematised review of the literature	Wrong exposure — only two of the included nine studies reported on time spent on social media, and this was not reported under a separate narrative section.
Bozzola et al. (2022)	The use of social media in children and adolescents: a scoping review on the potential risks	Wrong study type — scoping review.
Bottaro & Faraci (2022)	The use of social networking sites and its impact on adolescents' emotional wellbeing: a scoping review	Wrong study type — scoping review.
M. Liu et al. (2022)	**Time spent on social media and risk of depression in adolescents: a dose-response meta-analysis**	**Included**

Shankleman et al. (2021)	Adolescent social media use and wellbeing: a systematic review and thematic meta-synthesis	Wrong exposure — does not explore time spent on social media.

Dickson et al., 2018

Table 20. Systematic reviews in Dickson et al., 2018 (Appendix 3.5, social media use, and Appendix 3.9, smartphone use), with reason for exclusion.

Social Media Use

Paper Citation	**Paper Title**	**Reason for Exclusion**
Allen et al. (2014)	Social media and social connectedness in adolescents: the positives and potential pitfalls	Wrong study type - Not a systematic review (summative synthesis with no formal search strategy).
Baker & Algorta (2016)	The relationship between online social networking and depression: a systematic review of quantitative studies	Wrong exposure - not measuring time spent on social media.
Christofferson (2016)	How are social networking sites effecting teen's [sic.] social and emotional development: a systemic review	Not peer reviewed and published — Master's thesis.
Clifton et al. (2013)	New perspectives on the contribution of digital technology and social media use to improve the mental wellbeing of children and young people: a state-of-the-art review	Wrong exposure — covering digital technology as a whole, not focusing specifically on time spent on social media.
Curtis et al. (2018)	Meta analysis of the association of alcohol-related social media use with alcohol consumption and alcohol-related problems in adolescent and young adults	Wrong exposure — focus on alcohol related content as opposed to time spent on social media.
Dobrean & Pasarelu 2016	Impact of social media on social anxiety: a systematic review	Wrong exposure and population — did not focus on time spent on social media, and did not have specific adolescent analysis.
Dyson et al. (2016)	A systematic review of social media use to discuss and view deliberate self-harm acts	Wrong exposure — focus on social media content type, rather than time spent on social media.
Erfani & Abedin. (2018)	Impacts of the use of social network sites on users' psychological well-being: a systematic review	Wrong exposure and population — operationalised social media use as 'intensity of use', 'frequency of use' and 'network size' and then reported on these summatively rather than reporting on each individual exposure; and did not examine adolescents separately.
Frost et al. (2017)	A systematic review of the mental health outcomes associated with Facebook use	Wrong exposure and population — included studies which reported on diverse conceptualisations of Facebook: 'number of Facebook friends, number of logins to Facebook, attitudes towards Facebook use, or the indicators of an addiction construct compromising a combination of behavioural and attitudinal variables'; and did not examine adolescents separately.
Marino et al. (2018)	The associations between problematic Facebook use, psychological distress and well-being among adolescents and young adults: a systematic review and meta-analysis	Wrong exposure — investigates 'problematic' social media use.

McCrae et al. (2017)	Social media and depressive symptoms in childhood and adolescence: a systematic review	Wrong exposure — does not report on time spent on social media.
Nolan et al. (2017)	Social networking site use by adolescent mothers: can social support and social capital be enhanced by online networks? A structured review of the literature	Wrong exposure — does not report on time spent on social media.
Mubarak & Mubarak (2015)	Online self-disclosure and wellbeing of adolescents: a systematic literature review	Wrong exposure — focused on the extent of online self-disclosure, rather than time spent on social media.
Rice et al. (2016)	Social media and digital technology use among indigenous young people in Australia: a literature review	Wrong exposure — did not focus on time spent on social media.
Seabrook et al. (2016)	Social networking sites, depression and anxiety	Wrong exposure and population — investigated frequency of use and included the general population in samples of included studies.
Twomey & O'Reilly (2017)	Associations of self-presentation on Facebook with mental health and personality variables: a systematic review	Wrong exposure and population — general population; did not focus on time spent on social media.

Smartphone Use

Paper Citation	**Paper Title**	**Reason for Exclusion**
Elhai et al. (2017)	Problematic smartphone use: a conceptual overview and systematic review of relations with anxiety and depression psychopathology	Wrong exposure and population — investigates problematic smartphone use and general population.
Vahedi et al. (2018)	The association between smartphone use, stress and anxiety: a meta-analytic review	Wrong population — mean age over 18.

Arias-de la Torre, 2020

Table 21. Systematic reviews in Arias-de la Torre, 2020, with reason for exclusion.

Paper Citation	**Paper Name**	**Reason for Exclusion**
Best et al. (2014)	Online communication, social media and adolescent wellbeing: a systematic narrative review	Wrong exposure — did not measure time spent on social media.
Wu et al. (2016)	A systematic review of recent research on adolescent social connectedness and mental health with internet technology use	Wrong exposure — 'internet technology' use includes television, telephones and computers.
Seabrook et al. (2016)	Social networking sites, depression and anxiety: a systematic review	Wrong exposure and population — investigated frequency of use and included the general population in samples of included studies.
McCrae et al. (2017)	Social media and depressive symptoms in childhood and adolescence: a systematic review	Wrong exposure — does not report on time spent on social media.
Marino et al. (2018)	The associations between problematic Facebook use, psychological distress and wellbeing among adolescents and young adults	Wrong exposure — investigates 'problematic' social media use.
Keles et al. (2020)	**A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents**	**Included**

Yoon et al. (2019)	Is social network site usage related to depression? A meta-analysis of Facebook-depression relations	Wrong population — carried out analyses on a sample including the general adult population.

Appendix 1.8 — AMSTAR-2 Key

Table 22. AMSTAR-2 results by domain.

	Liu et al. 2022	**Ferguson et al. 2024**	**Keles et al. 2020**	**Fassi et al. 2024**	**Purba et al. 2023**	**Ivie et al. 2020**	**Cunningham et al. 2021**
Did the research questions and inclusion criteria for the review include the components of PICO?	🟩	🟩	🟩	🟩	🟩	🟩	🟩
Did the report of the review contain an explicit statement that the review methods were established prior to the conduct of the review, and did the report justify any significant deviations from the protocol?	🟩	🟩	🟨	🟩	🟩	🟥	🟩
Did the review authors explain their selection of the study designs for inclusion in the review?	🟥	🟩	🟥	🟩	🟩	🟥	🟥
Did the review authors use a comprehensive literature search strategy?	🟨	🟨	🟨	🟨	🟩	🟨	🟨
Did the authors perform study selection in duplicate?	🟩	🟩	🟩	🟩	🟩	🟩	🟩
Did the review authors perform data extraction in duplicate?	🟩	🟩	🟩	🟩	🟩	🟩	🟩
Did the review authors provide a list of excluded studies and justify the exclusions?	🟥	🟥	🟥	🟥	🟩	🟥	🟥
Did the review authors describe the included studies in adequate detail?	🟩	🟨	🟨	🟨	🟨	🟨	🟩
Did the review authors use a satisfactory technique for assessing the risk of bias in individual studies included in the review?	🟩	🟩	🟩	🟨	🟩	🟨	🟥
Did the review authors report on the sources of funding for the studies included in the review?	🟥	🟥	🟥	🟩	🟩	🟥	🟥
If meta-analysis was performed, did the review authors use appropriate methods for statistical combination of results?	🟩	🟩	N/A	🟩	🟩	🟩	🟩
If meta-analysis was performed, did the review authors assess the potential impact of RoB in individual studies on the results of the meta-analysis or other evidence synthesis?	🟥	🟥	N/A	🟩	🟩	🟥	🟥
Did the review authors account for RoB in individual studies when interpreting/discussing the results of the review?	🟥	🟥	🟩	🟩	🟩	🟥	🟥
Did the authors provide a satisfactory explanation for, and discussion of, any	🟩	🟩	🟥	🟩	🟩	🟩	🟩

heterogeneity observed in the results of the review?	🟩	🟩	🟥	🟩	🟩	🟩	🟩
If they performed quantitative synthesis, did the review authors carry out an adequate investigation of publication bias (small study bias) and discuss its likely impact on the results of the review?	🟩	🟩	N/A	🟩	🟩	🟩	🟩
Did the review authors report any potential sources of conflict of interest, including any funding they received for conducting the review?	🟩	🟩	🟩	🟩	🟩	🟩	🟥

🟩 = Yes, 🟨 = Partial Yes, 🟥 = No.

Appendix 1.9 — Quality Assessment Tables for Systematic Reviews

Under the AMSTAR-2 framework, reviews are rated as high (no or one non-critical weakness), moderate (multiple non-critical weaknesses), low (one critical flaw), or critically low (more than one critical flaw), reflecting decreasing levels of methodological reliability and confidence in the findings.

Table 23. Methodological quality of reviews as assessed by AMSTAR-2 Criteria.

Review Citation	AMSTAR-2 Results
OBJECTIVE 1	
Objective 1a	
Cunningham et al. (2021)	Critically Low
Fassi et al. (2024)	Critically Low
Ivie et al. (2020)	Critically Low
Keles et al. (2020)	Critically Low
M. Liu et al. (2022)	Critically Low
Purba et al. (2023b)	High
Objective 1a and 1b	
Ferguson et al. (2025)	Critically Low
OBJECTIVE 2	
No studies found	
OBJECTIVE 3	
No studies found	

Legend: AMSTAR 2 = A Measurement Tool to Assess Systematic Reviews. Reviews rated ‘critically low’, ‘low’, ‘moderate’ or ‘high’ according to the number of critical domains not met. A higher score indicates better methodological quality.

Appendix 1.10 — AMSTAR-2 tool

Table 24. AMSTAR-2 tool details.

1. Did the research questions and inclusion criteria for the review include the components of PICO?

For Yes:

☐ Population

☐ Intervention

☐ Comparator group

☐ Outcome

---

2. Did the report of the review contain an explicit statement that the review methods were established prior to the conduct of the review and did the report justify any significant deviations from the protocol?

For Partial Yes:	*For Yes:*	
The authors state that they had a written protocol or guide that included ALL the following:	As for partial yes, plus the protocol should be registered and should also have specified:	
☐ review question(s)	☐ a meta-analysis/synthesis plan, if appropriate, and	☐ Yes ☐ Partial Yes ☐ No
☐ a search strategy	☐ a plan for investigating causes of heterogeneity	
☐ inclusion/exclusion criteria	☐ a plan for investigating causes of heterogeneity	
☐ a risk of bias assessment		

---

3. Did the review authors explain their selection of the study designs for inclusion in the review?

For Yes, the review should satisfy ONE of the following:

- ☐ Explanation for including only RCTs
- ☐ OR Explanation for including only NRSI
- ☐ OR Explanation for including both RCTs and NRSI

☐ Yes
☐ No

---

4. Did the review authors use a comprehensive literature search strategy?

For Partial Yes (all the following):	*For Yes,* should also have (all the following):	
☐ searched at least 2 databases (relevant to research question)	☐ searched the reference lists/bibliographies of included studies	☐ Yes ☐ Partial ☐ Yes ☐ No
☐ provided key word and/or search strategy	☐ searched trial/study registries	
☐ justified publication restrictions (e.g. language)	☐ included/consulted content experts in the field	
	☐ where relevant, searched for grey literature	
	☐ conducted search within 24 months of completion of the review	

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5. Did the review authors perform study selection in duplicate?

For Yes, either ONE of the following:

☐ at least two reviewers independently agreed on selection of eligible studies and achieved consensus on which studies to include OR ☐ two reviewers selected a sample of eligible studies and achieved good agreement (at least 80 percent), with the remainder selected by one reviewer.	☐ Yes ☐ No

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6. Did the review authors perform data extraction in duplicate?

For Yes, either ONE of the following:

☐ at least two reviewers achieved consensus on which data to extract from included studies OR ☐ two reviewers extracted data from a sample of eligible studies and achieved good agreement (at least 80 percent), with the remainder extracted by one reviewer.	☐ Yes ☐ No

---

7. Did the review authors provide a list of excluded studies and justify the exclusions?

For Partial Yes:	*For Yes,* must also have:	
☐ provided a list of all potentially relevant studies that were read in full-text form but excluded from the review	☐ justified the exclusion from the review of each potentially relevant study	☐ Yes ☐ Partial Yes ☐ No

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8. Did the review authors describe the included studies in adequate detail?

For Partial Yes (ALL the following):	*For Yes*, should also have ALL the following:

☐ described populations	☐ described population in detail	☐ Yes ☐ Partial Yes ☐ No
☐ described interventions	☐ described intervention in detail (including doses where relevant)	
☐ described comparators	☐ described comparator in detail (including doses where relevant)	
☐ described outcomes	☐ described study's setting	
☐ described research designs	☐ timeframe for follow-up	

9. Did the review authors use a satisfactory technique for assessing the risk of bias (RoB) in individual studies that were included in the review?

RCTs

For Partial Yes, must have assessed RoB from:	*For Yes,* must also have assessed RoB from:	
☐ unconcealed allocation, and	☐ allocation sequence that was not truly random, and	☐ Yes ☐ Partial Yes ☐ No ☐ Includes only NRSI
☐ lack of blinding of patients and assessors when assessing outcomes (unnecessary for objective outcomes such as all-cause mortality)	☐ selection of the reported result from among multiple measurements or analyses of a specified outcome	

NRSI

For Partial Yes, must have assessed RoB:	*For Yes,* must also have assessed RoB:	
☐ from confounding, and	☐ methods used to ascertain exposures and outcomes, and	☐ Yes ☐ Partial Yes

☐ from selection bias	☐ selection of the reported result from among multiple measurements or analyses of a specified outcome	☐ No ☐ Includes only RCTs

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10. Did the review authors report on the sources of funding for the studies included in the review?

For Yes: ☐ Must have reported on the sources of funding for individual studies included in the review. Note: Reporting that the reviewers looked for this information but it was not reported by study authors also qualifies	☐ Yes ☐ No

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11. If meta-analysis was performed did the review authors use appropriate methods for statistical combination of results?

RCTs *For Yes:* ☐ The authors justified combining the data in a meta-analysis AND they used an appropriate weighted technique to combine study results and adjusted for heterogeneity if present. AND investigated the causes of any heterogeneity	☐ Yes ☐ No ☐ No meta-analysis conducted

For NRSI
For Yes (ALL the following):

☐ The authors justified combining the data in a meta-analysis ☐ They used an appropriate weighted technique to combine study results, adjusting for heterogeneity if present ☐ They statistically combined effect estimates from NRSI that were adjusted for confounding, rather than combining raw data, or justified combining raw data when adjusted effect estimates were not available ☐ They reported separate summary estimates for RCTs and NRSI separately when both were included in the review	☐ Yes ☐ No ☐ No meta-analysis conducted

---

12. If meta-analysis was performed, did the review authors assess the potential impact of RoB in individual studies on the results of the meta-analysis or other evidence synthesis?

For Yes:

☐ Included only low risk of bias RCTs OR ☐ If the pooled estimate was based on RCTs and/or NRSI at variable RoB, the authors performed analyses to investigate possible impact of RoB on summary estimates of effect.	☐ Yes ☐ No ☐ No meta-analysis conducted

---

13. Did the review authors account for RoB in individual studies when interpreting/ discussing the results of the review?

For Yes:

☐ Included only low risk of bias RCTs	☐ Yes ☐ No

OR

☐ If RCTs with moderate or high RoB, or NRSI were included the review provided a discussion of the likely impact of RoB on the results

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14. Did the review authors provide a satisfactory explanation for, and discussion of, any heterogeneity observed in the results of the review?

For Yes:

☐ There was no significant heterogeneity in the results	☐ Yes ☐ No

OR

☐ If heterogeneity was present the authors performed an investigation of sources of any heterogeneity in the results and discussed the impact of this on the results of the review

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15. If they performed quantitative synthesis did the review authors carry out an adequate investigation of publication bias (small study bias) and discuss its likely impact on the results of the review?

For Yes:

☐ Performed graphical or statistical tests for publication bias and discussed the likelihood and magnitude of impact of publication bias	☐ Yes ☐ No ☐ No meta-analysis conducted

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16. Did the review authors report any potential sources of conflict of interest, including any funding they received for conducting the review?

For Yes: ☐ The authors reported no competing interests OR ☐ The authors described their funding sources and how they managed potential conflicts of interest	☐ Yes ☐ No

Appendix 1.11 — Newcastle-Ottawa Scale

For cross-sectional and cohort primary studies, an adapted version of the Newcastle-Ottawa Scale for assessing risk of bias (RoB) was used. This appendix presents the algorithms used for assessing domain-level and overall RoB. RoB was first calculated at domain level, and then an overall RoB grade was assigned to each study through consideration of the reported RoB grades across all domains.

Adapted Newcastle-Ottawa Scale (NOS): cross-sectional studies

Used when assessing cross-sectional studies.

Domain A - Selection

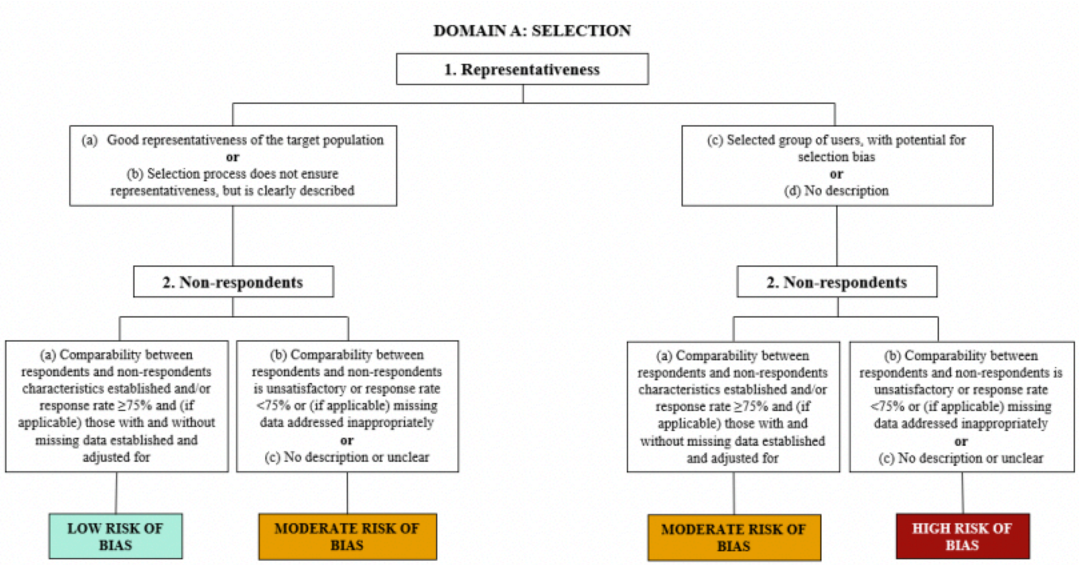
Selection — representativeness of original sample:

a) Good representativeness of the target population (e.g. all subjects, random sampling)
b) Selection process does not ensure representativeness, but is clearly described (e.g. non-probability sampling)
c) Selected group of users, with the potential for selection bias
d) No description

Selection — non-respondents

a) Comparability between respondents and non-respondents; characteristics established and/or response rate ≥75% of original sample and (if applicable) those with and without missing data are established and adjusted for
b) Comparability between respondents and non-respondents is unsatisfactory or response rate <75% or (if applicable) missing data addressed inappropriately
c) No description or unclear

Figure 5. Algorithm to assess the Selection domain of the adapted NOS for cross-sectional studies.



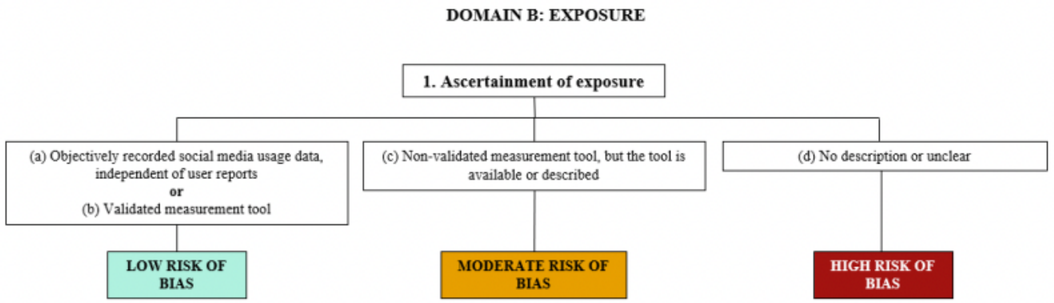
Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Selection. From Purba et al. (2023b).

Domain B — Exposure

Exposure — Ascertainment of exposure

a) Objectively recorded social media usage data, independent of user reports
b) Validated measurement tool
c) Non-validated measurement tool, but the tool is available or described
d) No description or unclear

Figure 6. Algorithm to assess the Exposure domain of the adapted NOS for cross-sectional studies

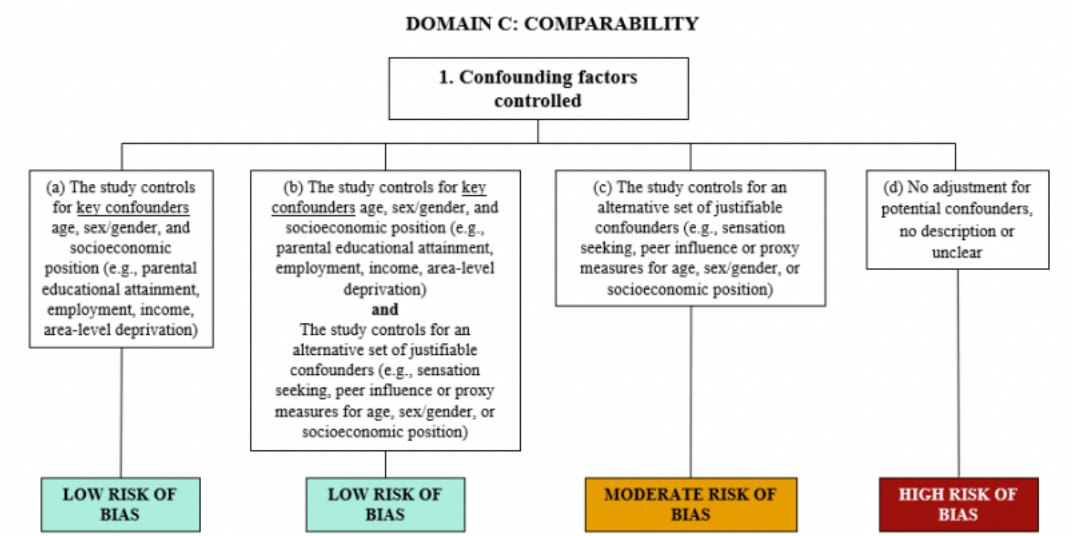


Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Exposure. From Purba et al. (2023b).

Domain C — Comparability
Comparability — Based on analysis of interest. Confounding factors are controlled

- a) The study controls for key confounders age, sex/gender and socioeconomic circumstance (e.g. parental educational attainment, employment, income, area-level deprivation)
- b) The study controls for key confounders age, sex/gender and socioeconomic circumstance (e.g. parental educational attainment, employment, income, area-level deprivation) and the study controls for an alternative set of justifiable confounders (e.g. sensation seeking, peer influence or proxy measures for age, sex/gender or socioeconomic circumstance)
- c) The study controls for an alternative set of justifiable confounders (e.g. sensation seeking, peer influence or proxy measures for age, sex/gender or socioeconomic circumstance)
- d) No adjustment for potential confounders, no description, or unclear

Figure 7. Algorithm to assess the Comparability domain of the adapted NOS for cross-sectional studies



Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Comparability. From Purba et al. (2023b).

Domain D — Outcome

a) Outcome — Assessment of outcome
b) Independent clinical assessment or validated measurement tool
c) Medical/administrative records
d) Self-report
e) No description, or other inadequate

Adapted Newcastle-Ottawa Scale (NOS): cohort studies

Used when assessing cohort studies

Domain A — Selection

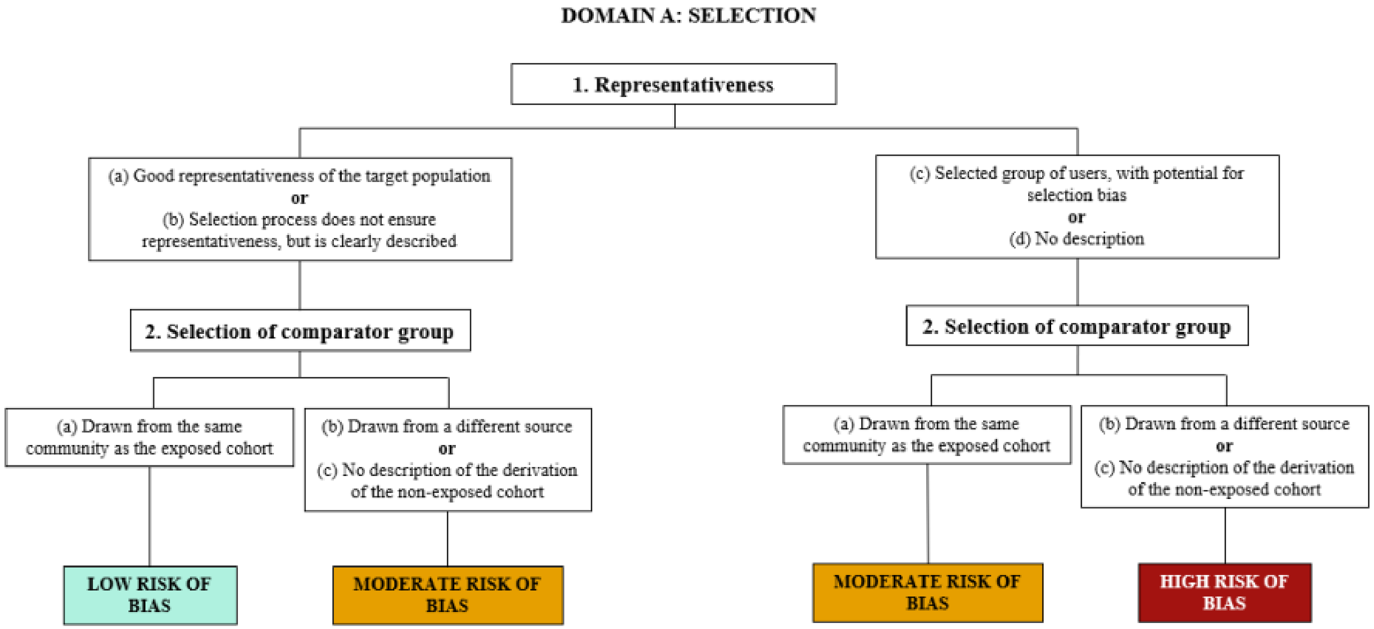
Selection — representativeness of original sample:

a) Good representativeness of the target population (e.g. all subjects, random sampling)
b) Selection process does not ensure representativeness, but is clearly described (e.g. non-probability sampling)
c) Selected group of users, with the potential for selection bias
d) No description

Selection — Selection of the comparator group

a) Drawn from the same community as the exposed cohort
b) Drawn from a different source
c) No description or derivation of the non-exposed cohort

Figure 8. Algorithm to assess the Selection domain of the adapted NOS for cohort studies

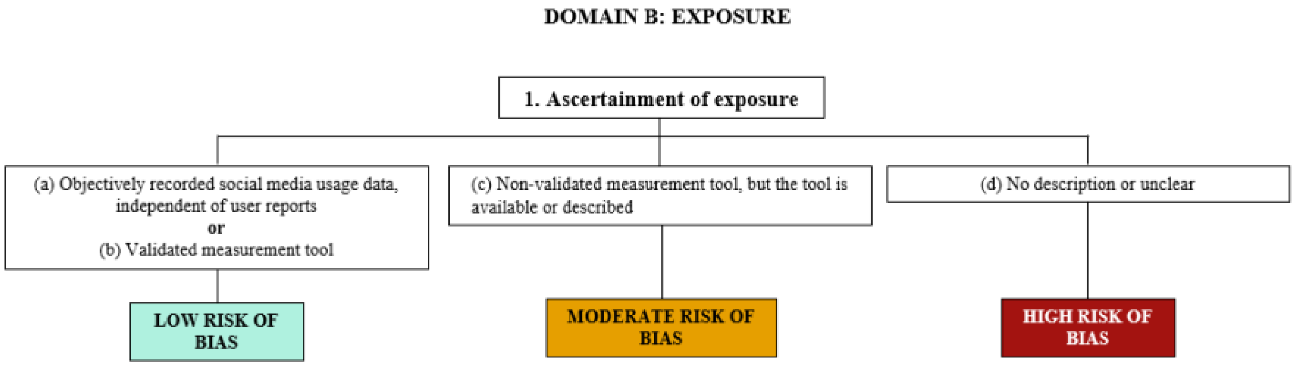


Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Selection. From Purba et al. (2023b).

Domain B — Exposure
Exposure — Ascertainment of exposure

a) Objectively recorded social media usage data, independent of user reports
b) Validated measurement tool
c) Non-validated measurement tool, but the tool is available or described
d) No description or unclear

Figure 9. Algorithm to assess the <u>Exposure</u> domain of the adapted NOS for cohort studies



Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Exposure. From Purba et al. (2023b).

Domain C — Comparability

Comparability — Based on analysis of interest. Confounding factors are controlled

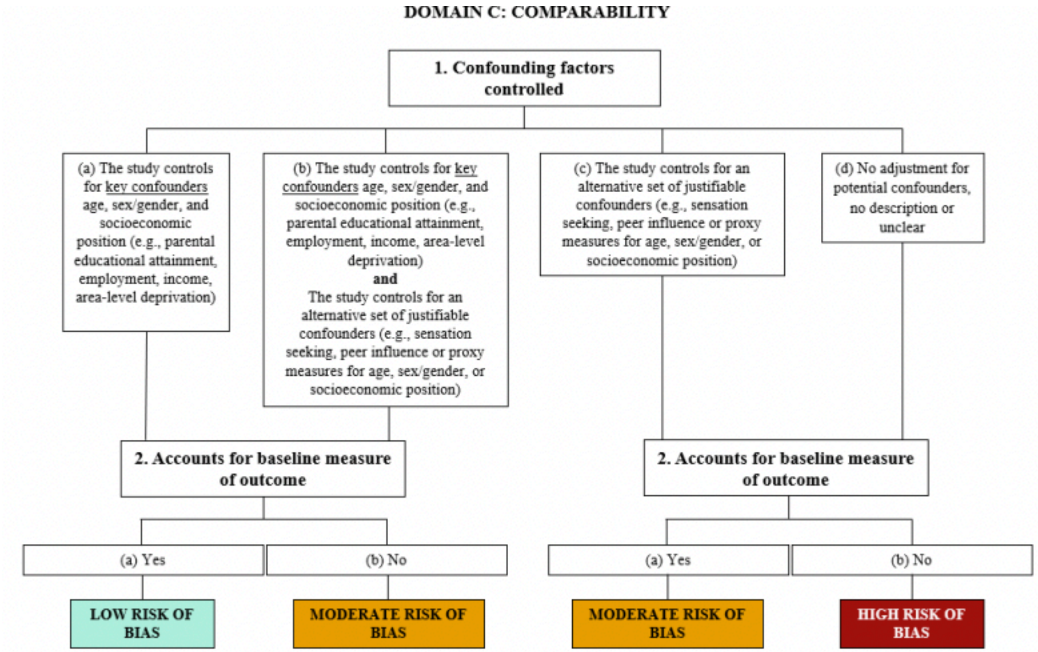
a) The study controls for key confounders age, sex/gender and socioeconomic circumstance (e.g. parental educational attainment, employment, income, area-level deprivation)
b) The study controls for key confounders age, sex/gender and socioeconomic circumstance (e.g. parental educational attainment, employment, income, area-level deprivation) and the study controls for an alternative set of justifiable confounders (e.g. sensation seeking, peer influence or proxy measures for age, sex/gender or socioeconomic circumstance)
c) The study controls for an alternative set of justifiable confounders (e.g. sensation seeking, peer influence or proxy measures for age, sex/gender or socioeconomic circumstance)
d) No adjustment for potential confounders, no description, or unclear

Comparability — Accounts for baseline measure of outcome

a) Yes

b) No

Figure 10. Algorithm to assess the Comparability domain of the adapted NOS for cohort studies.



Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Comparability. From Purba et al. (2023b).

Domain D — Outcome

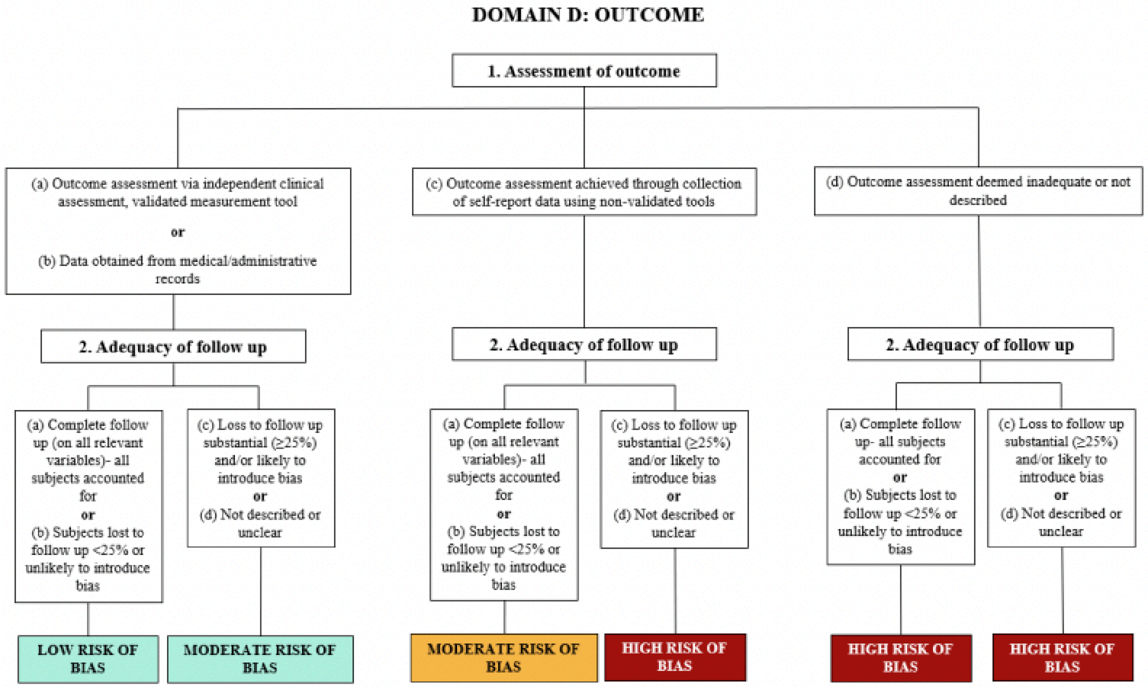
Outcome — Assessment of outcome

a) Independent clinical assessment or validated measurement tool
b) Medical/administrative records
c) Self-report

   d) No description, or other inadequate

Outcome — Adequacy of follow up
   a) Complete follow up (on all relevant variables) — all subjects accounted for
   b) Subjects lost to follow up or due to missing data <25%, unlikely to introduce bias, or accounted for using weights, imputation etc.
   c) Loss to follow up substantial (≥25%) and/or likely to introduce bias
   d) Not described or unclear

Figure 11. Algorithm to assess the Outcome domain of the adapted NOS for cohort scales



Legend: Diagram showing the sequential steps of the algorithm to assess RoB in Outcome. From Purba et al. (2023b).

Assessment of outcome for domain-level and overall RoB

Each domain was allocated with a low, moderate or high RoB grade as illustrated in Table 25. Once all domains were graded, Table 26 was used to allocate an overall RoB judgement for each included primary study.

Table 25. Domain level RoB grades.

Domain	Risk of bias (RoB) judgement		
Selection	Low risk of bias	Moderate risk of bias	High risk of bias
Exposure	Low risk of bias	Moderate risk of bias	High risk of bias
Comparability	Low risk of bias	Moderate risk of bias	High risk of bias
Outcome	Low risk of bias	Moderate risk of bias	High risk of bias

Table 26. Algorithm to clarify overall RoB grade.

Overall risk of bias judgement	Criteria
Low risk of bias	Study is not judged to be at high risk of bias for any domain **and** is judged to be at low risk of bias for either the Exposure or Comparability domain.
Moderate risk of bias	Study does not meet criteria for either High Risk of bias or Low risk of bias.
High risk of bias	Study is judged to be at high risk of bias in at least one domain.

Appendix 1.12 — Quality Assessment Tables for Narrative Synthesis

Table 27. Risk of Bias assessments for primary studies using the Newcastle-Ottawa Scale.

Study citation	Newcastle-Ottawa Scale Results
OBJECTIVE 1	
Objective 1a	
Meier & Gray (2014)	Low risk of bias
Hummel & Smith (2015)	Low risk of bias
Kelly et al. (2018)	Low risk of bias
Objective 1a and 1b	
Frison et al. (2016)	Moderate risk of bias
Objective 1b	
Hoffman et al. (2023)	Moderate risk of bias
Valkenburg et al. (2017)	High risk of bias
OBJECTIVE 2	
No studies found	
OBJECTIVE 3	
Objective 3a	
No studies found	
Objective 3b	
Beneito & Vicente-Chirivella (2022)	Low risk of bias

Legend: Risk of bias of included studies, assessed via the Newcastle-Ottawa Scale. Reviews are rated on risk of bias according to key criteria, receiving ratings of ‘low risk of bias’, ‘moderate risk of bias’, or ‘high risk of bias’. A higher risk of bias represents a worse rating.

Under the AMSTAR-2 framework, reviews are rated as high (no or one non-critical weakness), moderate (multiple non-critical weaknesses), low (one critical flaw), or critically low (more than one critical flaw), reflecting decreasing levels of methodological reliability and confidence in the findings.

Table 28. Quality of included systematic reviews and meta-analyses using AMSTAR-2 criteria.

Review Citation	AMSTAR-2 Results
OBJECTIVE 1	
Objective 1a	
Holland & Tiggemann (2016)	Critically low
Objective 1a and 1b	
Sala et al. (2024)	Critically low
OBJECTIVE 2	
No studies found	
OBJECTIVE 3	
No studies found	

Legend: AMSTAR-2 = A Measurement Tool to Assess Systematic Reviews. Reviews rated ‘critically low’, ‘low’, ‘moderate’ or ‘high’ according to the number of critical domains not met. A higher score indicates better methodological quality.

Appendix 1.13 — Characteristics of Included Studies, Narrative Literature Review

Table 29. Characteristics of included studies — primary studies.

Citation	Title	Study design	N	Mean age	Aim	Exposure	Outcome	Funding
Objective 1a: Social media content and mental health								
Hummel & Smith (2015)	Ask and you shall receive: desire and receipt of feedback via Facebook predicts disordered eating concerns.	Longitudinal	185	18.7	• To examine whether certain types of Facebook content (i.e. status updates, comments) relate to eating concerns and attitudes.	Facebook use (feedback seeking and status updates)	• Disordered eating behaviour, measured using the Eating Disorder Examination Questionnaire–4	NR
Kelly et al. (2018)	Social media use and adolescent mental health: findings from the UK millennium cohort study	Cross-sectional (with confounders assessed at previous waves)	10,904	14.3	• To assess whether social media use is associated with adolescents' depressive symptoms. • To investigate multiple potential explanatory pathways via online	Online harassment experience	• Depressive symptoms, measured using the validated mood and feelings questionnaire	ESRC

					harassment, sleep, self-esteem and body-image.			
Meier & Gray (2014)	Facebook photo activity associated with body disturbance in adolescent girls	Cross-sectional	103	15.4	• To update the media effects literature by exploring how Facebook use may influence adolescent girls' body image, particularly with regards to appearance focused content	Facebook use (total FB, specific FB feature use) and total appearance exposure score (use of FB photo applications relative to total FB use)	• Weight satisfaction using the eight item ordinal weight satisfaction subscale of the Binge Eating Scale • Drive for Thinness, measured using the validated seven-item. Drive for Thinness subscale of the Eating Disorder Inventory, which is rated ordinally	NR
Both Objective 1a: Social media content and mental health and Objective 1b: Social media content and wellbeing								
Frison et al. (2016)	The short-term longitudinal and reciprocal relations	Longitudinal	1621	14.8	• To examine the short-term longitudinal and reciprocal relationships	Negative experiences on Facebook	• Depressive symptoms, ten-item version of the Center for Epidemiological	Flemish Fund for Scientific Research

	between peer victimisation on Facebook and adolescents' wellbeing				between peer victimization on Facebook (i.e. negative Facebook experiences from the victims' perspective) and adolescents' psychosocial wellbeing (i.e. depressive symptoms and life satisfaction).		Studies Depression Scale for Children (CES-D) • Life satisfaction (five items) • Friend support, measured via the validated ordinal Multidimensional Scale of Perceived Social Support.	
Objective 1b: Social media content and wellbeing								
Hoffman et al. (2023)	The importance of trust in the relation between COVID-19 information from social media and wellbeing among adolescents and young adults	Cross-sectional	168	17.4	• To investigate the relationship between COVID-19 focused information on social media platforms and the emotional, psychological and social wellbeing of adolescents. • To consider the role of trust as a	Exposure to COVID-19 information on Facebook, Twitter, Instagram.	• Emotional, psychological and social wellbeing, measured with the validated Mental Health Continuum Short Form	National Science Foundation, Wellcome Trust, Economic and Social Research Council

					potential moderator of this relationship.			
Valkenburg et al. (2017)	The concurrent and longitudinal relationships between adolescents' use of social network sites and their social self-esteem.	Longitudinal	852 (wave 1), 783 (wave 2), 750 (wave 3)	12.5 (wave 1), 13.5 (wave 2), 14.4 (wave 3)	• To investigate the concurrent and longitudinal relationships between adolescents' use of social network sites (SNSs) and their social self-esteem. • To investigate whether the valence of the feedback that adolescents receive on SNSs can explain these relationships.	Four items about amount of positive feedback on messages or photos received from close friends or acquaintances on Facebook	• Social self-esteem measured using the Social Acceptance Subscale of the self-perception profile for adolescents.	European Research Council
Objective 2a: Social media bans and mental health								
No studies found								
Objective 2b: Social media bans and wellbeing								
No studies found								
Objective 3a: Smartphone bans and mental health								
No studies found								

Objective 3b: Smartphone bans and wellbeing								
Beneito & Vicente-Chirivella (2022)	Banning mobile phones in schools: evidence from regional-level policies in Spain	Longitudinal	NR	6–17 years	• In 2015, the autonomous governments of two Spanish regions banned phones in schools, causing across-region variation in a quasi-natural experiment • To perform a comparative-case analysis and investigate its impact on PISA scores and bullying.	Smartphone ban	• Prevalence of bullying per 10,000 children • Also reported Average Programme for International Student Assessment (PISA) scores in maths and science per region, but this is out of scope	Generalitat Valenciana, European Regional Defence Fund, ERDF: A way of making Europe

Legend: *NR = Not Reported

Table 30. Characteristics of included studies — Systematic Reviews, Umbrella Reviews and Meta-analyses.

Citation	Title	Aim	Time frame	No. of primary studies	Exposure	Outcome	Funding
Objective 1a: Social media content and mental health							
Holland & Tiggemann (2016)	A systematic review of the impact of the use of social networking sites on body image and disordered eating outcomes	• An emerging literature has investigated the influence of SNSs on body image and disordered eating. The present paper aims to systematically review the available research in this area.	NR	20	Specific Facebook activities (exposure to attractive vs unattractive users, Facebook feedback seeking, Facebook status and comment coding, amount of social grooming behaviours on Facebook, underweight Facebook profile picture vs overweight Facebook profile picture, appearance related exposure, viewing Facebook pictures	• Disordered eating, using the validated, ordinal, Eating Disorder Examination Questionnaire. • Also measures body dissatisfaction, internalisation of beauty ideals and self-objectification using the validated, ordinal, Sociocultural Attitudes Towards Appearance Questionnaire, appearance comparison using	NR

						the validated, ordinal, Appearance Comparison Scale, self-surveillance using the validated Objectified Body Consciousness Scale	
Both Objective 1a: Social media content and mental health and Objective 1b: Social media content and wellbeing							
Sala et al. (2024)	Social Media Use and adolescents' mental health and well-being: an umbrella review	• To analyse and present the risks and opportunities for adolescents' mental health and wellbeing associated with Social Media Use • To analyse the main risk mitigation proposals presented in systematic, scoping and narrative literature reviews and meta-analyses.	2012–2023	24	Social Media Exposure (visualised content, peer feedback)	• Mental health outcomes (internalising, depression, anxiety, suicidality, rating disorder, non-suicidal self-injury); the majority of the studies relied on self-reported estimations of social media use and mental health outcomes; other studies	NR

						called for objective data collection and the importance of validated instruments for measurement of mental health outcomes, but these are not named.	
Objective 2a: Social media bans and mental health							
No studies found							
Objective 2b: Social media bans and wellbeing							
No studies found							
Objective 3a: Smartphone bans and mental health							
No studies found							
Objective 3b: Smartphone bans and wellbeing							
No studies found							

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Appendix 2: Research Activity Overview Summary

March 2025

Executive Summary

This report provides a map of research activities investigating the intersection between child and adolescent developmental outcomes and social media, smartphone and AI chat application use. The developmental outcomes of interest are mental health, wellbeing, physical health, lifestyle/habits and educational attainment. It synthesises ongoing, planned and funded research in this space, aiming to highlight gaps and inform future funding priorities.

Key findings are:

1. Most of the funding is directed towards studies on adolescents, with significantly less investment in research on children and infants. This imbalance likely reflects historical trends, as children have traditionally engaged with social media, smartphones and AI less than adolescents. Furthermore, research involving children presents greater logistical and ethical challenges. However, given the increasing digital engagement of younger age groups, there is a growing need for targeted funding in this area.
2. A large part of research is focused on mental health and wellbeing, with relatively little attention given to other outcomes such as physical health, lifestyle behaviours and educational attainment. This might be appropriate due to significant concerns about mental health and wellbeing in adolescent and child populations, but needs to be acknowledged.
3. There are few investments in RCTs or evaluation of natural experiments, with more funding instead focused on improving measurement and observational data analysis.
4. The United States (US) has made greater investments in studying the impact of AI use, including chat apps, on children and adolescents, while there is a paucity of this research in the United Kingdom (UK).
5. The US further hosts several dedicated digital media and technology research centres. These centres bring together experts to conduct large-scale, agile and specialised research, an infrastructure that is largely lacking or small scale in the UK. Expanding such research capacity in the UK could strengthen the nation’s ability to assess and respond to the evolving challenges of digital media in adolescent development.

Methods

This report includes information compiled from surveying leading researchers and funding organisations relevant to the research area of social media, smartphones and AI, and their impact on child and adolescent outcomes. Our team reviewed the research and funding landscape to pinpoint key informants in both ecosystems. Following detailed input from our Research Consortium, we expanded our initial search to additional funding bodies and independent researchers recommended by the wider team. We also used an iterative sampling methodology, using team websites and targeted internet searches to expand our reach.

Individuals and known major funders were initially contacted via email by Dr Amy Orben and asked to fill out a form via the Microsoft Forms platform, which included questions about:

- Study name
- Outcome explored
- Study setting
- Study date
- Study methods
- Current study status
- Principal investigators
- Collaborating institutions
- Brief study description
- Study funder and amount

Contacts were given a week to fill in this form. Non-respondents were followed up with via email by the Project Manager and Research Assistant of the Project Delivery Team and given an additional week to respond. A list of contacts can be found in Appendix 2.1. Our detailed survey can be found in Appendix 2.2.

Following this process, a list of studies provided was collected (Appendix 2.3).

UK Research

Current

Current research in the UK largely explores the relationship between social media use and adolescent mental health and wellbeing outcomes. Research funded by UK Research and Innovation (UKRI), the Economic and Social Research Council (ESRC), the National Institute of Health (NIH), the Medical Research Council (MRC), the Wellcome Trust and philanthropic organisations (e.g. the Huo Family Foundation, the Rosetree Trust, the Prudence Trust) covers a range of research objectives which can be grouped into three broad categories: 1) measurement-focused research, 2) risk and resilience observational research, 3) policy-focused research and 4) intervention-focused research.

Measurement-focused research aims to develop valid self-report methods for investigating the uses and impacts of social media. Examples include a mixed methods study being carried out by Dr Margarita Panayiotou at the University of Bath which aims to test an event-contingent Ecological Momentary Assessment (EMA) application as a self-report measure of social media experience. Another example of measurement-based research is the DIORA study (Dynamic Interplay of Online Risk and Resilience in Adolescence) led by Professor Edmund Sonuga-Barke (Kings College London) and Professor Sonia Livingstone (London School of Economics) who are developing and validating a new measure, the DAFI (Digital Activities and Feelings Inventory) which records a range of digital activities and associated subjective experiences. This work forms part of the UKRI-MRC funded Digital Youth Programme led by Professor Chris Hollis and Professor Ellen Townsend at the University of Nottingham.

Risk and resilience research aims to identify modifiable protective factors (moderators) for known online harms (e.g. cyberbullying). As part of the UKRI-MRC Digital Youth Programme, Dr Praveetha Patalay and Professor Yvonne Kelly at University College London are using a data driven approach in the Millenium Cohort and Australian National Cohort to identify moderators to adverse mental health impacts of cyberbullying in adolescents as a basis for intervention targets.

Policy-focused research is being carried out to develop evidence-based policy within the sector. With regards to social media, an example is a project run between the University of Exeter, the University of Birmingham and the University of Cambridge, aiming to develop recommendations to be used by policy and practice stakeholders to promote algorithmic literacy in young people. Awareness of how social media algorithms work to promote content that the user identifies with, as well as to maximise scrolling and consumption, might prompt adolescents to think critically about their social media/smartphone use and its impacts on their wellbeing. Concerning smartphones, the STARTING School Study, led by the University of Birmingham, aims to conduct research on the effects of digital media in schools to inform policy initiatives. The researchers are focusing on the transition between primary and secondary school at the start of adolescence, exploring both risk and resilience factors in smartphone use for wellbeing currently.

Finally, intervention-focused research uses digital media as a vehicle for therapeutic interventions for mental health problems and social isolation. These remain largely out of the scope of the Research Activity Overview Summary due to their focus on smartphones/social media as a vehicle for interventions. However, some studies also focused on interventions such as smartphone bans or 'detoxes'. Victoria Goodyear's NIHR funded work 'SMART Schools: Smartphones, Social Media and Adolescent Mental Wellbeing' is one such example (Goodyear et al., 2025). Another intervention-focused approach is the testing of device management apps that add delays, introduce 'friction' or block/limit use of specific social media platforms and apps. To date these promising approaches have not been formally tested in the UK.

This report identified only one ongoing study in the UK that follows an experimental study design (involving direct manipulation of one or more variables). Twelve of the ongoing studies (33%) were observational (the researcher did not manipulate variables, but focused on finding associations), four (12.5%) were qualitative (collecting and presenting non-numeric data): five of these included cohort studies (observational studies where a cohort of people is followed over time), and one a scoping review (a systematic review focused on summarising evidence without assessing its quality). Eight studies (25%) utilised mixed methods (combining both qualitative and quantitative approaches).

The study designs that dominate the field have important implications for the ability to establish causality in the relationship between social media/smartphone use and adolescent developmental outcomes. Few, if any, studies were identified that investigated mechanisms of digital engagement, harms and potential mitigating interventions from a theory-driven perspective. The emphasis on observational and qualitative research in the field facilitates research that establishes associations, rather than confirming causal relationships. While observational data can be used for causal inference if appropriate epidemiological methodology is used, few of the research teams funded have this expertise.

We also found little evidence for projects addressing the intersection between social media, smartphone and AI chat app use and 1) physical health and 2) educational attainment, with the SMART Schools project at the University of Birmingham constituting a notable exception. Funded by the National Institute for Health and Care Research (NIHR) and run by the University of Birmingham and the NHS Women and Children's Foundation Trust, this study aimed to determine the impact of school time restrictions of smartphone use on mental wellbeing (primary outcome), as well as sleep, physical activity, classroom behaviour and attainment, and addictive use. It therefore explored five outcomes of interest: mental health, wellbeing, educational attainment, lifestyle habits and physical health (Goodyear et al., 2025). The results of this study, which was ongoing at the time of writing, were published in early 2025.

Finally, there is no UK-based current research exploring effects of AI chat applications on adolescent or child populations' developmental outcomes of interest. Further, there is limited work on the impact of digital technology use on young children, with only one project identified for this age group led by Manchester Metropolitan University which concluded in 2024.

Planned Research

Looking ahead to 2028, the UK is also home to a considerable body of planned individual research studies. Such projects build on emerging initiatives and capabilities such as data donation and multi-timeframe measurement bursts to capture rich data on daily life in relation to digital media.

There is an increasing interest to study the impact of individual differences on the link between social media and wellbeing beyond demographics. A PhD studentship funded through the MRC Doctoral Training Partnership between the University of Bath and the University of Bristol stated plans to use longitudinal and experimental designs to assess the impact of different cognitive styles on social media use and wellbeing, objectively tracking social media activity through participant data donation. Planned research led by Dr Amy Orben at the University of Cambridge also aims to take a mechanistic approach to the understanding of whether cognitive and brain development during adolescence predisposes young people of a certain age to being impacted more by social media. This research will include a systematic manipulation of social media use in a longitudinal study, thereby serving to bridge the current research gap in experimental evidence and develop an intervention that allows adolescents to experiment with changing their own social media use to improve their mental health.

Furthermore, Dr Amrit Kaur Purba at the University of Cambridge is leading a study that adopts a causal epidemiological Target Trial framework approach to determine the optimal age for adolescents to begin using social media, based on its impact on mental health and life satisfaction. Dr Purba is also currently under review for funding for a five-year research initiative aimed at exploring the potential causal relationship between exposure to alcohol, drug use and anti-social behaviour content on social media, and adolescents' engagement in offline alcohol and drug use and anti-social behaviours. The study will draw on objective social media data donation — in collaboration with the Born in Bradford Cohort and Smart Data Donation Service — and employ the Target Trial framework to inform tailored and context-sensitive policy recommendations.

Planned research about smartphone use in general is sparse but largely aims to locate and support groups who are especially implicated in its effects or are at risk. An Engineering and Physical Sciences Research Council (EPSRC) funded project run between the University of Bath and the University of Bristol plans to work with neurodivergent individuals, and patients with Parkinson's and Dementia and their carers, to design technology which enables social connectedness. Representing those who might be more vulnerable to the harms of smartphone use, a project run by the University of Birmingham aims to co-produce school-based social media policies and practices related to smartphone use that are translatable into practice.

While there is no funding planned or provided beyond individual research studies and smaller-scale research programmes in this space, some planned or pre-existing research centres partially or fully include the study of social media or smartphones on wellbeing. The proposed Leverhulme Research Centre for the Science of Wellbeing, led by Professor Paul Dolan, which is currently undergoing review for funding, aims to integrate perspectives and methods from across the social sciences and humanities (including economics, psychology, philosophy, geography, sociology, anthropology, media and communications and computer science) to create new approaches to generating and implementing the evidence base on wellbeing in general. If fully funded by the Leverhulme Foundation, its research efforts will run from 2025–2035 and there will be some limited work (about one full-time postdoctoral position) focusing on the digital world. *We note retrospectively that funding was not approved for this centre.* The NIHR MindTech HealthTech Research Centre (2024–2029), led by Professor Chris Hollis, aims to catalyse the development of new HealthTech for areas of unmet need and high disease burden. While this is slightly different to the study of digital technology effects, it can help develop robust methodological approaches (e.g. health economics, human factors, UX (user experience) etc.) and research translation across patients, the public, the healthcare system and the economy. Evaluating new digital tools that allow young people to control their digital activities and social media experience, as well as impact of engagement with AI chatbots, is an area of growing interest to MindTech.

The Digital Futures for Children Centre, led by Professor Sonia Livingstone at the London School for Economics, stands out as a UK-based research centre focusing on the impacts of digital technology on youth. Run in collaboration with the philanthropic NGO, 5Rights, this centre facilitates research advancing the understanding of the benefits and challenges presented by digital technology for children. It aims to conduct critical and practical research on topics such as online safety and digital literacy, to provide evidence-backed advocacy and foster dialogues between academics and policymakers. Critically, it aims to amplify children’s voices, ensuring active youth participation with the research that represents them. These efforts underscore growing recognition of the importance of interdisciplinarity research in addressing societal problems, laying the groundwork for the UK to be a global leader in this regard.

As with current ongoing research, we note a paucity of planned research focusing on educational attainment and physical health outcomes. Almost all planned research is observational in nature, underscoring the relative lack of opportunities to make causal inference. No major projects exploring AI chatbot use by children and young people were identified by our search in the UK.

Major Funders

Major government backed funders in the UK landscape include the UKRI: MRC and ESRC, and NIHR. Philanthropic organisations funding work in the social media/smartphone research space include the Huo Family Foundation (who will be increasing their funding in this space as of next year), and the Rosetree Trust. Both these types of organisations offer a mixture of study-specific funding schemes and funding for smaller academic programmes within the field of interest. Grant sizes range from £23,000–£ 4,000,000. A comprehensive overview of ongoing and planned projects, with the respective funding details, can be seen in Appendix 2.3.

US Research

Current Research

Our review found many projects in the US tackling a range of research questions in social and digital media and adolescent and child outcomes.

One major point of difference between the US and the UK is that the former is home to several larger centres and academic programmes which are built and funded specifically to sit at the intersection between digital media and youth development and wellbeing. While in the UK the closest is the Digital Futures for Children research centre at London School of Economics and Political Science (LSE), the US has at least four, which are often substantially larger — and more in planning.

These are often funded by philanthropies, or by universities to attract philanthropic investment, showing the larger scope and success of this funding stream in the US. Examples include the Winston National Center on Technology Use, Brain and Psychological Development, funded by the Winston Family Fund and led by Professor Mitch Prinstein and Professor Eva Telzer. The centre not only has several research studies underway but is also working on capacity building by training future researchers, through programmes including PhDs and assistant professors. The centre has funding for education, outreach, research and participant (adolescent) engagement dedicated to the effects of social and digital media.

Similarly, the Centre for Digital Thriving, funded by the philanthropic Susan Crown Exchange in partnership with a private company, Pivotal Ventures, is led by Dr Emily Weinstein and Dr Carrie James at the Harvard Graduate School of Education. It is focused on platforming research that explores how digital technology is shaping our society and young people. It is part of a larger initiative, Project Zero, which carries out research in fields where there is little (‘zero’) current knowledge. They have completed work on school-based social media interventions.

Dr Megan Moreno, at the University of Wisconsin, leads the Technology and Adolescent Mental Wellness programme, which strives to identify the ways in which technology can support adolescent mental wellness. Finally, Thriving in a Digital Environment (TYDE) is a pan-university research initiative supported by the University of Virginia, and co-led by Dr Nancy Deutsch and Professor Bethany Teachman. It aims to distinguish between harmful and adaptive technology use, also supporting research collaborations that will enhance public understanding of the relationship between youth mental health and digital technology. This continued effort to bring together specialists in the field fosters a collaborative research environment that drives advanced work, that is scalable and has the potential to make notable impact in the policy landscape.

Planned Research

Reflecting the general trends seen in UK-based research, research efforts in the US also prioritise investigating mental health and wellbeing outcomes as opposed to the lifestyle, educational attainment or physical health. There is, however, a broader collection of research in social media, smartphone and AI applications — with increasing investment in the latter.

With regards to social media, a project funded by the National Institute of Mental Health (NIMH) aims to experimentally test whether social media restriction modifies social media engagement and mental health, therefore generating causal evidence with regards to the relationship between social media and wellbeing. Run by Candice Odgers at Duke University, this study involves a large representative sample of 2,500 11–15-year-olds, who will be followed over four years. A subset of 750 adolescents will be followed intensely via Ecological Momentary Assessment (EMA — repeated and high-fidelity sampling of a participant's daily life) to experimentally test whether social media restriction modifies social media engagement and impacts mental health symptoms in the moment, across days, and over years. A project at the University of Washington aims to explore the effect of parental smartphone use on parent-child interaction quality and child development, adding to the body of evidence that has identified potential windows of developmental sensitivity in the effects of digital media on children and young people. These projects reflect a general commitment to evidence-based interventions and policies, as in the UK.

A marked difference can be seen between the UK and US with regards to attempts to understand the relationship between AI and adolescent development. This report identified no current or planned projects at the intersection of AI and adolescent development in the UK. In the US, research initiatives at the University of Illinois and Harvard University are being planned to examine how parents, teachers and young people engage in AI, identifying targetable factors which moderate its effects. Researchers are providing policy guidelines regarding youth safety in the AI context, amplifying and protecting young voices in this space. An $8,000,000 funding package run by the Templeton Foundation, another philanthropy, is funding at least three ongoing projects on the intersection between AI and youth development in education and beyond, with four further projects funded in the digital media space.

Major Funders and Changing Contexts

The US supports a research landscape with more centres and larger programme investments due to key national funders such as the National Institutes of Health (including the National Institute of Mental Health, and the National Institute of Child Health and Human Development) being supplemented by support from philanthropic organisations. Examples include the Templeton Foundation, the Susan Crown Exchange and the Winston Family Fund. Grant sizes range from $700,000–$3.4M.

We note that following recent changes within the US administration we are seeing large scale changes enacted to the scientific funding landscape, with funding being reduced as research priorities change. The National Institute of Health faces a proposed 44% decrease in funding (Wadman, 2025). Our report was compiled before such changes, and our conclusions on the US funding landscape should therefore be interpreted with caution.

International Research

Current Research

As in the UK and US, research across Europe and internationally is primarily focused on the adolescent and child developmental outcomes of mental health and wellbeing, with a relative gap in evidence related to physical health and educational attainment outcomes of smartphones and social media. There is also limited investment in research concerning AI chatbot use.

There are some large-scale international collaborations that aim to explore the general impact of phones or social media. A 3-year, ongoing project funded by the NSF, Templeton World Charity Foundation, AXA Postdoctoral Fellowship and NYU Alliance Seed Grant aims to create a global field experiment, using behavioural data from the UK, US and 23 other countries to test the causal influence of social media on polarisation, inter-group attitudes and wellbeing. The project will only sample participants over the age of 18 years and is currently collecting data from 10,000 individuals. Participants will be given an incentive to reduce their social media screen time for approximately two weeks, allowing the researchers to examine the causal effects of reduced social media usage on the outcomes of interest. The researchers will also explore whether the effects of the social media reduction intervention are moderated by several country-level variables (e.g. the strength of a country's democracy). Aside from aiming for causal inference, this project exemplifies the international collaboration that is often required between both academic and funding institutions to ensure that studies are large-scale and well supported, and future findings have broad relevance.

However, criticism of such studies is already emerging, given that a two-week long abstinence period likely does not counteract the long-term impact of screens and therefore would not provide answers pertaining to the underlying question of how technology impacts young people. Further, it is important to examine how participants are recruited for these studies, to mitigate selection bias. For example, those who feel that they would like to reduce their phone use will probably be more likely to sign up to studies exploring screen reduction, as they might be experiencing more negative impacts.

There are also smaller-scale research collaborations between specific countries. For example, a UK-US collaboration funded by Research England aims to evaluate the risks and opportunities of social media for athletes' wellbeing, identifying and evaluating appropriate guidance and actions for support. More could be done to coordinate these efforts, especially in light of research opportunities elsewhere (such as the natural experiment of the social media restrictions coming into force in Australia in late 2025).

Across the international landscape there are also several finer-grained research efforts: researchers are working to identify the 'winners' and 'losers' with regards to the influences of social media and smartphone use. Project AWeSome, funded by the Dutch Research Council over multiple years and individual project grants, aims to investigate the relationship between adolescents' social media use and their wellbeing. The researchers currently plan to pay particular attention to the factors that differentiate those who might find social media beneficial and those who might find it deleterious. This topic will be explored through a large-scale experience sampling study (AWeSome I), as well as a 100-day diary study (AWeSome II) which has just been completed.

Similar in nature to the US-based efforts for the establishment of dedicated research centres, Australia has seen the foundation of the *ARC Centre for the Digital Child*. Funded in 2020 by the Australian Research Council for seven years, this centre received an initial government grant of $35 million, with an additional $33 million from external industry and University partners, this centre aims to shape a positive digital future for children in Australia. In platforming research that helps families to navigate the digital world, the centre helps provide evidence-based insights to shape good policy and practice. It focuses on three main areas: namely, the use of digital technology for 1) healthy digital lives, 2) educational environments and 3) safe digital spaces. The Centre of Excellence programme is one of the most competitive in the National Competitive Grants Programme administered by the Australian Research Council.

Both in the UK and beyond, research is also being focused on the use of smartphones as a vehicle for the delivery of psychological interventions, or the collection of data relevant to wellbeing outcomes. Project PHONOTYPE, funded by the Wellcome Trust in collaboration with the University of New South Wales, is investigating whether digital data from smartphones are useful for identifying young people with amotivation symptoms. However, we consider this type of research largely out of scope for our review, as it focuses on smartphones or social media as delivery vehicles and not their specific outcomes. Yet it is important to note that there is not a clear boundary in many types of digital mental health research.

Planned Research

Planned research in the international space includes several collaborations, many of which are policy-facing. PROMISE: Promoting Well-Being in Preteens, Adolescents, and Young Adults, Toward Improved Social Media Policies, is a planned project with investigators from the University of Vienna, the University of Tartu, University Erlangen-Nuremberg, the University of Cambridge and the University of Navarra. Researchers from Communication, Psychology and Media Studies will test and evaluate policy approaches that address the mental health crisis in children and young people. The project will include a systematic literature synthesis, qualitative exploration, field experiments and computational analysis. In differentiating between preteens, adolescents and young adults, this project will also aim to specify effective policies tailored to each population. This project will include a young people advisory board and co-creation workshop to incorporate the voices of young people to shape outcomes and improve digital experiences. Funded by Austrian Science Fund (FWF — Austria), the Estonian Research Council (ETAG — Estonia), German Research Foundation (DFG — Germany), Economic and Social Research Council (ESRC — United Kingdom) and the Spanish State Research Agency (AEI — Spain), this project exemplifies the importance of trans-national funding efforts for solving truly global problems, despite the additional administrative burden.

Planned research in Switzerland aims to understand the effects of our digital media use on cognitive development, education, health and wellbeing. The researchers will concentrate specifically on the impact on executive functions, given their central role in behaviour regulation and learning. They expect that executive function will both mediate and moderate the relationship between media usage and impacts on health and education. A planned — but currently unfunded — study led by Dr Amy Orben in collaboration with the Black Dog Institute, the University of New South Wales, the Social Policy Research Centre and the Matilda Centre at Sydney University, aims to evaluate the consequences of the 2025 social media 'ban' passed by the Australian Federal Government on youth mental health. If funded (which will be difficult due to the short time frame), this study will be a three-wave longitudinal cohort study, exploring the impact of social media restrictions on online experience, wellbeing, lifestyle behaviours and parents and families of those under 16. An evaluation is also planned by the Australian eSafety Commissioner, in collaboration with the University of Stanford.

As in the case of UK data, this report highlights a lack of research, ongoing or planned, at the intersection of AI use and adolescent developmental outcomes, identifying this as a future priority for funding efforts. Only one planned project on the impacts of AI was identified. Spearheaded by the ARC Centre for the Digital Child in Australia, the Generative AI and Children: Promise, Perils and Pedagogies project aims to capture and triangulate three scales of response to the first year of Generative AI following ChatGPT's release. These scales will be captured via a broader white paper: Generative AI outputs in experimental settings and children's own initial responses to these technologies.

Limitations

Our review revealed a higher number of UK-based funded projects. We assume that this is a consequence of the fact that we received communications from a higher number of UK-based researchers, when compared to their US-based or international counterparts. We therefore expect to be underreporting current and planned research in the US and internationally. With regards to the lack of research in the AI sphere, we have not sampled studies which look at AI utility and safety generally, given that our review focused on 1) the adolescent population, and 2) developmental outcomes such as wellbeing. It is important to note that such research likely does exist and was not captured in our sampling strategy.

Appendix 2.1: List of Individuals and Organisations Contacted

Following input from the Consortium, we identified and reached out to additional funding bodies and independent researchers to expand our understanding of available resources and expertise. This appendix includes the details of all those recommended by the Consortium, as well as their response status, which provides insight into potential funding opportunities and key experts who could inform and support future research efforts in this space. Names were deleted due to data security, but can be provided on request.

Table 31. Key Funders.

Funder	Response
5Rights Foundation	No
American Psychological Association	No
Arts and Humanities Research Council (AHRC)	Yes
British Psychological Society (BPS)	No
Chief Scientist Office (CSO)	No
Children and Screens	No
Children's Media Foundation	Yes — not funding
Economic and Social Research Council (ESRC)	Yes
Engineering and Physical Sciences Research Council (EPSRC)	No
Huo Family Foundation	Yes

Innovate UK	Yes — not funding
John Templeton Foundation	Yes
Medical Research Council (MRC)	Yes
Medical Research Foundation (MRF)	No
MQ Mental Health	Yes — not funding
National Institute for Health and Care Research (NIHR)/National Institute of Mental Health (NIMH)	No
Nesta	Yes — not funding
Nuffield Foundation	Yes
Ofcom	Yes
Rosetree Trust	Yes — not funding
Smart Data Research UK (SDR-UK)	Yes
The International Panel on the Information Environment (IPIE)	No
UNICEF Office of Research	No
Wellcome Trust	No

Table 32. Independent Researchers.

UK Institutions

Institution	Response
Bath Spa University	Yes
Imperial College London	Yes
University College London	No
University of Bristol	No
University of Glasgow	No

US Institutions

Institution	Response
Harvard University	Yes
Harvard T. H. Chan School of Public Health	Yes
New York University	Yes
Northeastern University	Yes
Stanford University	Yes
University of California, Irvine	Yes
University of Michigan	Yes
University of North Carolina, Chapel Hill	Yes

University of Virginia	No
University of Wisconsin-Madison	Yes

Other institutions

Institution	**Response**
FAU Erlangen-Nürnberg, Germany	Yes
University of Amsterdam, Netherlands	Yes
University of Geneva, Switzerland	Yes
University of New South Wales, Australia	Yes
University of Vienna, Austria	Yes
Western Sydney University, Australia	Yes

Appendix 2.2: Research Form Sent to Consortium and Funders

The below form was sent to the Consortium, and recommended funders and independent researchers. It was sent, and data collected, with Microsoft Forms. Subsequently, the answers were exported into Microsoft Excel.

Section 1:

1. Project title

2. Project status

- ☐ **Current**
- ☐ **Funded but not yet started**
- ☐ **Planned**

3. Research areas

- ☐ **Mental Health**
- ☐ **Wellbeing**
- ☐ **Physical Health**
- ☐ **Educational Attainment**
- ☐ **Lifestyle and Health Behaviours**

4. Geographical scope

- ☐ **UK**
- ☐ **USA**
- ☐ **Other ....**

5. Population studied
Please tick all that apply:

- ☐ **Children (0–9)**
- ☐ **Adolescents (10–19)**
- ☐ **Adults (20+)**
- ☐ **LGBTQIA**
- ☐ **Individuals with severe mental illness**
- ☐ **Other ....**

6. Principal investigator

7. Collaborating institutions

8. Start date

9. End date (if applicable)

10. Current project phase (if applicable)

- ☐ **Literature Review**

- ☐ **Data Collection**
- ☐ **Data Analysis**
- ☐ **Writing/Dissemination**
- ☐ **Other ....**

Section 2: Research Objectives and Methodology

11. Brief summary of objectives (1–2 sentences)

12. Study type (e.g. observational, qualitative, experimental)

13. Sample size (optional)

Section 3: Funding Details

14. Has funding been secured?

- ☐ **Yes**
- ☐ **No**

15. Funding body

16. Total funding amount (approx.)

17. Additional comments

Appendix 2.3: Tabular Summaries by Country

We produced a table with key information of each study reported by Consortium members, academic experts, and major funding organisations. There are three tables, split geographically. In each table representing the UK, US and International community respectively, research is organised depending on whether it pertains to social media use, smartphone use or AI chat applications.

NOTE: The data in this table is sensitive and could not be shared publicly. The tables are available from the corresponding author at reasonable request.

Appendix 3: Social Media Research: Limitations and Opportunities Report

February 2025

Overview

The impact of smartphone and social media use on child and adolescent health is a complex and widely debated area of research. Current scientific evidence is marked by inconsistent findings often produced too slowly to keep up with the pace of technological progress. Both researchers and policymakers therefore face significant obstacles in anticipating, understanding and mitigating the potential negative effects of digital technologies on individuals and society.

There is an urgent need to improve the evidence base investigating the impact of smartphones and social media on children and young people to enable evidence-based policy. Yet a range of challenges and limitations have been holding back evidence generation. This report summarises these challenges and explores potential opportunities for improvement and advancement. Building on information provided from a diverse range of experts, it considers solutions to a range of key limitations. Six chapters discuss the challenges to: a) generating causal evidence, b) developing high-quality smartphone and social media measures, c) designing effective intervention research, d) creating and using optimal datasets, e) ensuring work is ethical and responsible, and f) adapting the evidence in response to accelerating technological change.

By examining current approaches, identifying gaps in the literature, and considering innovative methodologies to address these gaps, this report provides the foundation to further consider how to best advance research in this critical area.

Part 1: Causal Effects

Executive Summary

Establishing the potential causal impact of smartphones and social media on children and adolescents — whether that is their wellbeing, health or educational outcomes — is challenging. While the bedrock of much of causal inference is experimental manipulation, ethical and logistical constraints can make it impractical to investigate this issue through an experimental approach. The ability to achieve causal evidence in this space therefore relies on triangulation across a range of different methodologies, each with its strengths and limitations. In this section, we discuss both experimental and non-experimental (observational) approaches to causality, highlighting their benefits and limitations.

Outlining Different Research Approaches

Current approaches to establishing causality in social media research can be grouped into two methodological categories.

A) Experimental research involves the direct manipulation of variables by researchers to examine cause-and-effect relationships, ideally using randomisation to address potential confounding. Experimental research can explore mechanisms of effect by manipulating a range of targets, including for example school-level or family-based interventions, specific components of social media platform content or design, or the use of device management applications that allow the user to modify and control their smartphone and social media activity, experience and usage. While experimental studies can provide strong evidence of cause and effect, manipulating certain exposures can be unethical or impractical in an experimental setting.

B) Non-experimental/observational studies involve research in the absence of direct manipulation by researchers. They include methods like surveys, interviews, focus groups, or analysing existing usage patterns without intervention. In the context of social media research, an observational study may examine differences between people who use social media to a greater or lesser degree. Natural experiment studies are a type of observational research that leverages naturally occurring events, such as the introduction of new policies (e.g. smartphone restrictions in school settings or for under-16s nationally) to make causal inferences. This type of research can provide valuable evidence on social media effects and policy impacts under real-world conditions. Observational studies are particularly useful for investigating relationships that cannot be ethically or practically explored through controlled experiments. However, they are susceptible to bias when potential differences (i.e. confounding factors) between comparison groups are not properly accounted for. To draw reliable causal inferences, researchers must carefully collect high-quality longitudinal data and rigorously identify and control for confounding factors.

Challenges of Establishing Causality

Experimental and Observational Research

Social media exposure measurement

Many researchers apply an inconsistent definition of 'social media use', creating difficulties when comparing and evaluating results across studies (Purba et al., 2023a). Additionally, much of the research in this field relies on simplistic measures, such as total 'screen time', which potentially conflate positive and negative experiences, obscuring meaningful patterns.

This focus on 'screen time' as a primary variable may mask important risk mechanisms and differential vulnerabilities across the population (Sonuga-Barke et al., 2024b). An analogy can be drawn to road safety: total driver mileage may show weak, inconsistent, or even negligible associations with accident risk. In contrast, more specific factors such as speeding, seatbelt use, driving under the influence of drugs, or the mechanical condition of the vehicle, are stronger predictors and would also provide clearer targets for safety interventions. Similarly, moving beyond simplistic exposure measures in social media research is critical for identifying nuanced risks and underpinning mechanisms to target evidence for public health and policy interventions.

Measures like 'screen time' exemplify a fundamental challenge in causal smartphone and social media research, highlighting the absence of well-developed theoretical frameworks and the necessary tools to identify the mechanisms through which social media exposure and engagement affect adolescent mental health, physical health and wellbeing (Orben, 2020a). These simplistic constructs fail to capture the complex, multifaceted nature of how the design and use of smartphones and social media shape their influence (Kaye et al., 2020) and lack a nuanced focus on the experience of using digital technologies (Dunne et al., 2024). There is a pressing need for more sophisticated theoretical frameworks, grounded in developmental, social and cognitive psychology, engineering and computer science, that can offer testable predictions about how changes in smartphone and social media use, along with platform content and design features, can mitigate harms and enhance benefits for users. Such frameworks would not only provide a clearer structure for understanding the nuanced effects of technology, its design and how it is used, but also equip researchers with the insight needed to develop robust causal questions. Without these frameworks, current research risks drawing overly simplistic or misleading conclusions about social media's impact on adolescent health and wellbeing.

Selection bias generalisability

Across both observational and experimental research, the composition of the studied sample is critical to the validity and generalisability of findings. Systematic biases in who participates or provides complete data can severely limit the applicability of results to the broader population. This issue is particularly pronounced in certain types of social media research. For instance, studies that require linking platform data or involve experimental interventions, such as social media detoxes, often attract specific groups of participants while excluding others, leading to selection bias (Radtke et al., 2022).

In large-scale observational studies, researchers can address this bias by using sampling weights, where underrepresented groups are assigned greater weight in analyses to better reflect the wider population (Pfeffermann, 1996). Evidence shows that properly weighted data can significantly improve the accuracy and representativeness of study findings (Bell et al., 2012). However, despite their importance, these weights are often underutilised due to limited researcher training, insufficient documentation and data, or accessibility issues, reducing the robustness of studies (Bell et al., 2012). Addressing these challenges is essential for producing reliable evidence that accurately informs policy and practice.

Furthermore, much of the discourse surrounding social media and smartphone use focuses on aggregate-level effects across the population, overlooking crucial individual differences and subgroup variations. It is likely that only a subset of individuals experiences significant harms or benefits. Therefore, understanding who is most vulnerable to the adverse effects of social media and smartphones, why, and how to mitigate these risks are key research priorities. One of the key challenges in generalising experimental findings from social media research to the broader population lies in the sampling methods employed (Lohmann & Zagheni, 2023). Volunteer-based samples, commonly used in such research, often fail to accurately represent the broader population, distorting any causal relationships observed. For example, these samples tend to overrepresent individuals with higher socioeconomic circumstance, greater technical ability and higher digital literacy (Hargittai, 2020), leading to skewed results that cannot be reliably generalised to broader populations, potentially leading to misleading conclusions about the true effects of social media use. Further, those populations most systematically underrepresented in social research have been argued to potentially be most at risk and are likely to experience unique, and potentially amplified, impacts from digital technologies (Coyne et al., 2023; Odgers, 2018).

To mitigate these biases, it is important to adopt more rigorous sampling methods. Representative sampling aims to capture the diverse characteristics of the broader population, ensuring that findings are applicable across different demographic groups. For instance, stratified random sampling can be employed, dividing the population into meaningful subgroups — based on factors such as age, socioeconomic circumstance and geographic region — and selecting participants randomly from each subgroup. By using such advanced sampling strategies, researchers can sample in ways that better mirror the real-world distribution of social media use, thus strengthening the generalisability of their findings and improving the robustness of causal inferences.

More targeted sampling approaches will be required when researchers want to examine specific factors of vulnerability which may only affect a small subset of the general population. Considerations on the target population and generalisability of findings should then inform the sampling approach used. To adequately capture the experiences of marginalised groups (e.g. non-native English speakers, children with disabilities, LGBTQ+ individuals), researchers will need to make concrete efforts to ensure their perspectives are represented through diverse outreach.

The current reliance on schools to facilitate the recruitment of children and young people also comes with specific limitations. This approach is efficient and safe, as it relies on safeguarding protocols from the institutions, and can target broad populations of children and young people. Yet the deployment of the study itself often results in a multi-tiered process of recruitment that includes the schools, parents and children. There is often substantial drop-out at each stage, which is non-random due to specific populations being more likely to, for example, not get approval to engage in research from parents. While schools therefore offer a good opportunity to get a broad population of young people involved, challenges to recruiting some populations remain.

Experimental Research

Experimental research remains the gold standard for establishing causality. However, descriptive approaches to social media research dominate the literature and attempts at generating causal evidence are limited as experimental research is challenging to implement in social media contexts (e.g. it is unethical to deliberately expose individuals to harmful content or investigate outcomes like adolescent alcohol use in trial settings). Further, society and mental health are complex systems, and small-scale, short-term interventions might not have noticeable impacts due to the outcome being influenced by a range of exogenous features. For example, if you remove a smartphone from one child, but all their friends still have one, the benefit of the intervention might be minimised, or even reversed, as the potential for the intervention to increase the child's social isolation could offset or reverse potential advantages.

Experimental research on smartphones and social media to understand their causal impact is inherently limited to manipulating social media or smartphone use across very constrained a) contexts (e.g. specific platforms or features), b) populations (e.g. only undergraduate students, those who feel inclined to give up smartphones or social media) and c) timescales (e.g. for 1–2 weeks). This creates difficulties when attempting to generalise conclusions from the experimental context to the real-world, where most users engage in several social media platforms and features, which may have complex and interdependent effects on them. Furthermore, one cannot replicate the impact of the smartphone beyond the context of the individual and the limited timescale of any intervention. For example, while one could force some young people to give up their smartphones for a week, the cumulative impact of many years of smartphone use might still influence their wellbeing and they will still live in a world where others use phones, and this use could indirectly impact them. Much research attempting to understand the impact of smartphones and social media has therefore relied on observational studies, but these have a variety of limitations of their own.

Population-level interventions

Despite the inherent challenges, significant opportunities exist to rigorously examine the causal effects of social media exposure. Population-level interventions in particular present powerful avenues for understanding these effects. One such example could be the staggered roll-out of smartphones, where the introduction of smartphones is delayed for a randomly selected subset of families, allowing researchers to compare children who receive their first phone earlier (control group) with those whose introduction is postponed (intervention group). This design could provide valuable information on the impact of smartphone use on various outcomes in children, from mental health to social development. Similarly, restricting smartphone use in schools could be evaluated in a cluster randomised controlled trial design where schools matched on social demographic factors are randomised to either restrict use within the school (intervention group) or maintain access as usual (control group) (Parker et al., 2021).

However, while these approaches offer potential, it is essential to acknowledge the challenges of examining effects across the population, which includes difficulties in isolating causal effects as part of complex real-world interventions, where contextual factors can complicate results (Christakis et al., 2004; Foster & Watkins, 2010; Schramm et al., 1961; Williams, 1986). Despite this, well-designed population-level interventions remain a promising strategy to investigate the causal links between social media exposure and its wide-reaching effects.

Observational Research

Confounding factors

Much of the research exploring the relationship between social media or smartphone use and adolescent wellbeing is observational. This means researchers study naturally occurring behaviours and outcomes without manipulating who is exposed to what. While observational studies are useful for identifying associations, they do not involve controlled intervention, making it difficult to determine whether one factor causes another. As a result, these studies are particularly vulnerable to bias from confounding variables — factors that influence both the exposure and the outcome.

Social media or smartphone use, the exposure in question, is closely linked with other factors that independently influence outcomes, such as wellbeing or health-risk behaviours in young people (Purba et al., 2025). These factors, known as confounders (or third variables) can lead to misleading conclusions if not accounted for in analyses. For example, while increased smartphone use (exposure) is correlated with lower wellbeing (outcome), socioeconomic circumstance may also influence both greater smartphone use and reduced wellbeing, making this a potential confounder. This raises the critical challenge of determining whether the relationship between smartphone use and wellbeing is causal or simply reflects the influence of a third factor such as socioeconomic circumstance. Similar complexities arise with variables such as age, sex and family environment, making it difficult to isolate the true causal effect of smartphone use on adolescent wellbeing.

Further, observational research often relies on secondary data — data that was originally collected for a different purpose or broader aim, which may not align perfectly with a researcher's specific research question. This can limit the availability or relevance of key variables, both in terms of what was collected and the time periods covered. As a result, secondary data can exacerbate issues of unmeasured or residual confounding — that is, bias that persists even after adjustment, due to missing, inaccurately measured, or improperly modelled confounding variables — especially when critical confounders are missing or poorly measured (Pederson et al., 2020).

Even if data is not available for specific confounders, it is crucial that researchers clearly identify and justify which confounding variables they control for in observational data analysis. One effective way to achieve this is by using Directed Acyclic Graphs (DAGs), which visually map the relationships between variables, helping to identify potential confounders as well as highlighting unmeasured confounders (Tennant et al., 2021). DAGs are particularly valuable for identifying confounding factors and improving the estimation of causal effects (VanderWeele et al., 2008). These tools strengthen causal reasoning in observational research by providing a structured way to map causal mechanisms and make explicit the assumptions underlying causal analyses. Other types of causal diagrams — such as causal loop diagrams — can also be employed, depending on the complexity of the system under study and the specific research questions being asked (Uleman et al., 2024).

However, the accuracy and utility of a DAG depends heavily on the theoretical assumptions and evidence behind it. Without proper theoretical backing, there is a risk that DAGs could be misused or biased, as variables can be classified as both confounders and mediators, leading to potentially skewed conclusions. This highlights the importance of co-production in

DAG development, ensuring that experts, policymakers and youth (whose lived experiences are directly impacted by the research) are involved in identifying and selecting the relevant variables, alongside reviewing the existing evidence base. Collaboratively co-creating DAGs based on both empirical evidence and lived experience helps safeguard against researcher-driven bias and ensures that the analysis better reflects the complexities of real-world settings.

Target Trial

There are additional methods that can be applied to observational dataset to enable causal inference, such as the Target Trial Approach (Hernán et al., 2022). This approach mimics the structure of an RCT by conceptualising the observational study as if it were a trial, with clearly defined treatment groups, outcomes and follow-up periods. This method improves the robustness of analyses by creating hypothetical randomised treatment and control groups (based on baseline data), thereby facilitating a more structured comparison. By establishing eligibility criteria, treatment assignment and outcome assessment protocols similar to those in RCTs, the Target Trial approach helps to reduce biases typically found in observational studies. It allows researchers to better approximate the conditions of an RCT, ensuring comparability between exposed and control groups and helping to account for confounding variables. This approach enhances the internal validity of observational studies, aligning them more closely with the rigour and structure of RCTs, thus improving causal inference in settings where randomisation is not possible.

Reverse causality

There is a risk of reverse causality, where changes in the outcome of interest, such as mental health, educational performance, or health behaviours, may directly influence social media use rather than the other way around (Sundar & Limperos, 2013). For instance, a child experiencing declining mental health might withdraw from face-to-face interactions and increasingly turn to social media as a coping mechanism. This complicates efforts to determine whether social media use is a driving factor behind mental health challenges or simply a consequence of pre-existing issues.

It is important to recognise that this relationship may be bidirectional, such that social media use and mental health outcomes may influence each other in a dynamic way. For instance, not only could social media use contribute to poorer mental health, but deteriorating mental health could also drive increased social media use. The potential bidirectional nature of these relationships makes it difficult to draw clear causal conclusions without sophisticated analytical approaches that can account for these reciprocal effects.

Natural experiments

A promising approach to improving the generalisability of social media research is the careful study of natural experiments. Researchers have long relied on natural experiment studies for causal inference, and this approach can be particularly valuable in social media and smartphone research where opportunities for experiments are limited (e.g. Saha et al., 2020). The opportunity to study natural experiments arise from real-world changes such as shifts in platform design, the introduction of new policies, or other variations in the social media and smartphone landscape that researchers cannot control (Crane et al., 2020; Ochoa & Been, 2023). Unlike traditional experimental studies that operate in controlled settings, natural experiment studies capture the effects of real-world changes, offering evidence that more closely mirrors the conditions of the broader population. For example, policies like

Australia's ban on social media platforms providing children under the age of 16 access can provide natural experimental conditions, allowing researchers to investigate the systematic effects of restricting social media access (Craig et al., 2012; Nogrady, 2024).

To fully capitalise on the potential of natural experiment studies, significant changes are needed in the current research infrastructure. Researchers must be equipped with flexible, rapid-response protocols to take advantage of emerging opportunities for causal inference (Leatherdale, 2019). The existing system, which often involves slow funding approval processes and rigid research protocols, has limited researchers' ability to respond quickly to natural experiment opportunities. Further, outcome measures need to be tracked at scale and across time to be linked to natural experiments taking place. A promising solution is to align natural experiment evaluations with ongoing longitudinal studies, or with effective and linked administrative data collection (e.g. school performance scores, crime registries, healthcare demand). These studies, with established ethical approvals, research protocols and participant pools, are well-positioned to swiftly capitalise on emerging real-world changes. For instance, an ongoing longitudinal study on the impact of digital media on adolescent health could be used to collect baseline data before a policy like a school phone ban is introduced. By continuing with longitudinal data collection after, this would allow researchers to examine the effects of such changes on digital media use and health outcomes before, during and after the intervention, providing robust, real-world evidence of causal effects. Integrating natural experiment research with these studies would greatly enhance the timeliness and relevance of social media research, enabling it to produce more actionable real-world evidence.

Summary

Key limitations:

- *Experimental constraints*: Experimental research on smartphones and social media is limited by the contexts, populations and timescales involved, making it at times difficult to generalise findings to the broader population or real-world situations.
- *Confounding factors*: Social media use is closely linked with other factors that independently influence outcomes like mental health or health-risk behaviours, potentially distorting observed associations.
- *Residual confounding*: Observational studies may suffer from unmeasured or residual confounding, influencing the validity of findings. This can be addressed using methods like DAGs, which help identify and manage confounding variables.
- *Reverse causality*: Changes in outcomes, such as mental health, can also influence social media or smartphone use rather than the reverse, which could lead to misleading causal conclusions if not considered using the appropriate causal and longitudinal research designs.
- *Selection bias and generalisability*: The composition of study samples may not represent the broader population, leading to systematic biases and limited generalisability.
- *Individual differences:* Studies often examine effects across the population and overlook crucial individual differences and subgroup variations, especially of those populations most at risk. The effects of social media likely differ between individuals and can be positive for some and negative for others.

- *Simplistic exposure measures*: Many studies rely on basic measures such as 'screen time', which can mask complex patterns in social media usage, making it difficult to identify specific risk mechanisms or meaningful effects.

Key opportunities:

- *Natural experiments*: Many natural experiments are currently underway, including changes to school smartphone policies in the UK or larger policy changes internationally, which offer unique opportunities for studies to explore causal effects in real-world scenarios. Evaluations of these (potentially linked to ongoing longitudinal or administrative data collection) can capture effects from real-life variations, offering evidence that is more applicable to broader populations than randomised controlled trials (RCTs).
- *Population-level interventions*: Beyond natural experiments, intervention studies and RCTs (e.g. those implementing different parenting interventions, implementing smartphone or social media restrictions or providing young people with types of phones that have different functionalities) can help isolate the impact of smartphone or social media use on mental health and development, providing evidence on long-term, population-wide consequences, even though they also have limitations that need to be considered.
- *Implementing causal approaches on observational data:* There are robust methods that can enable causal inference based on observational data (if used appropriately), such as DAGs or the Target Trial Approach (Hansford et al., 2023).
- *Rigorous sampling methods*: Use of representative sampling methods, such as stratified random sampling, can improve the generalisability of findings. When this is not possible, weighting procedures can be applied to adjust for underrepresented or overrepresented groups in the sample. This will help ensure that the study results are more applicable to a broader, more diverse population.

Part 2: Smartphone and Social Media Measures

Executive Summary

To understand smartphone and social media use, and provide usable causal evidence of its impact, from an epidemiological and medical science perspective, we need to measure and quantify engagement appropriately. However, due to commercial incentive structures, technological companies that produce platforms or products often have access to high-quality measurement data but do not share such data with public-facing researchers. Currently, research is reliant on measures such as total time spent on smartphones or social media or patterns in their use, limiting the ability to understand the causal impact of specific engagement metrics on health and wellbeing. Many of the measures used routinely in research are based on self-report by the young person (e.g., collected through questionnaires).

Self-report data are valuable for understanding children's and young people's lived and subjective experiences (e.g. if they felt they were impacted by a specific piece of social media content), which cannot be measured using objective data. However, too often, such self-report measures replace measures of exposure (e.g. amount of time spent on phones, or exact content seen on social media) that should — and in theory, could — be measured objectively and precisely to enable causal inference. This is problematic as these self-report measures are subject to a range of biases, including recall and social desirability bias.

There have been several efforts to develop better questionnaire measures of aspects of social media and smartphone use that go beyond 'time spent'. Further, new approaches have been used to enable access to objective social media and smartphone data (e.g. information recorded by platforms). Yet, these come with their own ethical and research infrastructure challenges. Measuring smartphone and social media use in accurate and acceptable ways remains an ongoing issue.

Well-defined Measurement

In causal inference, especially from an epidemiological perspective, it is crucial to have specific, high-quality, accurate and reliable measurements of the exposure being studied. The exposure (i.e. the factor potentially driving the causal effect) and the outcome need to be consistently measured across the population being studied. A well-defined exposure is essential for minimising measurement error, reducing bias, and ensuring that the relationship between exposure and outcome is accurately assessed. If the exposure is poorly defined, inconsistently measured, or too broad and subjective, it can introduce significant error and distort observed causal relationships (Igelström et al., 2022).

Further, the way individuals report their exposure can vary, which can introduce bias into the findings. This becomes especially problematic if there is a systematic difference in how different groups report their exposure. For example, high social media users might underreport the amount of time they spend on social media, while low social media users may overestimate their time spent (Parry et al., 2021).

Due to the need to have a consistent exposure measure across the population, most research on digital technologies that attempts to make causal claims measure aspects of digital technology use that can be consistently and accurately quantified across users. This includes, for example, assessing the applications participants have used that week or how much time they have used their phone overall. Such measures are difficult to capture with self-report tools such as questionnaires, as they can introduce bias.

Self-Report Measurement

Some researchers believe that quantified measurements of digital technology use will ultimately always fail to capture the complexity of the smartphone or social media experience (Dunne et al., 2024). While measurement for causal inference will require quantification and therefore, simplification, it is important that we are quantifying the right things and researchers are increasingly addressing this question by trying to understand the diversity of online experience, identifying causal mechanisms that should be measured and evaluated, and co-designing measures and research with children and other stakeholders (Bulbulia, 2024; Thabrew et al., 2018).

Due to the lack of high-quality objective data available, researchers have predominantly used subjective self-report measures of smartphone or social media use, asking individuals to estimate the average time spent on digital platforms (Verbeij et al., 2021), or report on the specific activities they undertake (Kostyrka-Allchorne et al., 2023). Self-report measures dominate much of the psychological and public health literature, and their utility is rooted in the fact that they are cheap, easy to design and complete, provide insights into subjective experiences, and can be implemented in large-scale data collection efforts (Black et al., 2024b; Dunne et al., 2024).

Self-reported screen time, due to its ease of application, is the most common self-report measure of digital engagement, although it has been shown to be an unreliable estimate (Parry et al., 2021). Moreover, it provides limited insight into the mechanisms that are driving positive or negative outcomes of online engagement and is more difficult to translate to concrete recommendations or benchmarks that can be used to inform evidence-based policies and interventions. Researchers have therefore questioned the conceptual relevance of screen time or time spent on social media in the first place (Kaye et al., 2020), stressing the importance of understanding what individuals do on social media (Winstone et al., 2022) and the content and context of what they are exposed to and engaging with (Kaye et al., 2020; Winstone et al., 2023). There are ongoing efforts to move beyond reductionistic screen time measures, considering context, designing in an age-appropriate manner and facilitating recall using digital tools (Kucirkova et al., 2023; Livingstone et al., 2018). There is an ongoing need to improve how we measure social media and smartphone use, even with self-reports, as some data collection efforts (especially those at scale) will have to rely on self-report measures due to their large data collection efforts, population or method of delivery.

When deciding what to measure and which method to use, researchers should consider the type of exposure being assessed and the level of causal inference they aim to achieve. Self-reported measures have inherent value for understanding the subjective realities and reflections of children and young people on their experiences with digital technologies. These subjective realities need not be outcomes of digital experiences but can also shape the effects of digital technologies. While these measures are difficult to standardise across users (therefore increasing the difficulty of causal inference) and link to policy options, they are valuable for understanding how the nature of technological experience impacts outcomes and for capturing children's or young people's perspectives on how the digital world affects them.

However, they need to be seen as a complementary measurement mechanism, with objective and behavioural measures still central to the application of causal inference.

There has been a proliferation of different self-report measures attempting to go beyond time spent, for example, by capturing the frequency of social media use and the potential problems associated with this (Duradoni et al., 2020; Ellis, 2019; Moretta et al., 2022). At times these efforts conflate whether the aims are to accurately predict measures of digital technology use that should best be measured objectively (e.g behaviours or exposures) or can only be achieved subjectively (e.g. interpretations or evaluations). There is also a lack of standardisation in measurement and the quick proliferation of new measures is problematic as it makes comparison across studies difficult (Purba et al., 2023a), disrupting the cumulative process of academic knowledge generation (Hargittai, 2020). The large number of measurement tools that are being created also reflects a fundamental absence of agreement on what exactly about the use and design of smartphones and social media matters when predicting our outcomes of interest (Shaw et al., 2020).

It is important to note that in order for a measure to be considered valid, it needs to be systematically evaluated on several key properties: internal consistency (different parts of the measure assess the same construct), test-retest reliability (stability in measurement over time), construct validity (reflects a theoretical construct), convergent validity (relates to established measures of the same construct), discriminant validity (does not relate to unrelated constructs), criterion validity (predicts behaviour or outcomes), and measurement invariance (functions similarly regardless of age, gender, or cultural background). At times the proliferation of measures also makes it difficult for researchers to appropriately ascertain if these thresholds have been reached.

However, similar measurement issues are also common across many areas of social and medical research, and therefore not unique to the exposures measured in this area. Specifically, they also related to our outcomes of interest (i.e. what digital technology use is impacting) (Flake & Fried, 2020; Fried et al., 2022). Whereas we have focused on the challenges of measuring the experiences and behaviours of users online, similar issues pertain to the outcome measures used to assess potential consequences of these experiences and behaviours. Both inconsistencies in how outcomes are quantified (Anvari et al., 2025; Davidson et al., 2022), as well as the validity of predominantly-used outcome measures create difficulties for inference and comparison of findings across studies (Bentley et al., 2019; Newson et al., 2020). Despite the critical importance of these outcome measurement issues, we do not discuss them in detail here as they pertain to psychological measurement more broadly and exceed the scope of this report. However, it is evident that to generate reliable insights into the effects of social media, one needs to employ valid measures of both social media as well as the outcomes of interest.

New Approaches to Objective Measurement

It is well established that self-report questionnaire estimates of certain technological behaviours are of low quality, especially when they try to replace aspects of technology use that should best be measured objectively (Kaye et al., 2020; Parry et al., 2021; Verbeij et al., 2021). There is therefore demand for objective smartphone and social media measures that provide data of the activities that users engage in on phones or social media. As noted above, the combination of such individual-level data with rich information about subjective user experiences would allow researchers to better study what happens on these technologies, what their causal impacts are and who is affected (e.g. Geyer et al., 2022).

Well-defined exposure measures (i.e. exposure to different types of content) are heavily reliant on objective metrics which are captured routinely on digital devices or applications and used by the parent companies in their product evaluation and marketisation. This could offer a substantial opportunity for researchers and companies to share data to understand the impact of their products. However, there are fundamental tensions between the commercial interests of technology companies and the academic interests of public-facing researchers, particularly when it comes to the use of social media and smartphone data. These tensions often prevent researchers from accessing the comprehensive data valuable for conducting rapid causal research to understand the impacts of new technologies (Bruns, 2021). External researchers' access to even low-level data has been limited, often due to frequent changes to Application Programming Interfaces (APIs) that enable such access, or increasingly, the complete removal of access altogether (Freelon, 2018).

If companies do collaborate with external researchers, and this entails a sharing of data, such collaborations are often very selective (i.e. only with a few high-power individuals), highlighting conflicts of interest and researcher bias issues (Livingstone et al., 2023a). This disparity creates a significant barrier to comprehensive research while raising questions about data quality, access and equity (Black et al., 2024b). Further, while platforms collect a wide array of high-resolution data essential for their operations, such as login patterns, user behaviour and targeted advertising, this data is typically not as extensive as required for independent researchers to effectively track and analyse the full impact of these technologies, and the most impactful research will therefore require in depth collaboration.

As there are real challenges to obtaining such objective data, a range of technological developments have aimed to address these, making objective data collection more feasible and scalable. We have reviewed some key developments below:

Data Donation Packages

A potential solution is the use of 'data donation packages', which involves users downloading their personal data from the platform and donating it to researchers. This approach aligns with the UK General Data Protection Regulation (previously EU General Data Protection Regulation) from 2018, which mandates platforms that store user data to make this data available to them upon request (Boeschoten et al., 2022; Cork et al., 2024). Data donation packages provide rich data on the online experiences and behaviours of social media users and provide a fuller overview of a user's activity across devices. Furthermore, data donation packages can provide data from the start of account creation and do not require the installation of additional applications, as is the case in other approaches to obtaining objective digital data (Geyer et al., 2022; Ohme et al., 2024).

However, not much is known yet about who donates their data and whether the effort required to do so is potentially too high for research participants of different backgrounds and situations, especially when parental consent is required. There might be significant attrition risks and biased samples. However, in feasibility studies this approach has already been used with adolescents (Yap et al., 2024).

More recently, changes in the EU regulatory landscape have introduced data portability APIs. These APIs allow for continuous and easier data donation in a standardised format. For example, users can request their data from a platform like TikTok and consent to share it with a research team via a secure and automated process. This approach is more scalable, secure, and simple to administer when integrated into a centralised data infrastructure.

Application Programming Interfaces

In the past, a common approach to obtaining objective social media and/or smartphone data has been the use of APIs. APIs are bridges that allow two or more software systems to communicate and transfer information. APIs enable sophisticated approaches to accessing social media data, and their advantages include scalability (allow for programmatic access to large datasets), customisability (specific data points can be accessed, reducing unnecessary data transfer), and content facilitation (user-authenticated APIs enable content transfer). However, most APIs are designed with developers and businesses in mind and are not tailored to the specific needs and requirements for use in a research context (Valkenburg et al., 2024). Moreover, social media platforms have increasingly restricted access to their APIs or priced them out of reach for most academic research budgets (Bruns, 2021). This has resulted in a fragmented research infrastructure that is vulnerable to platform changes and complicates efforts to conduct accurate, comprehensive and replicable social media research.

Applications for Data Collection

Another approach that has been used across the research landscape to collect objective social media data is in-built applications and tools in smartphones that track screen time (e.g. Apple Screen Time). Researchers or research software providers have also created custom software that tracks how much time is spent on specific applications, as well as data points such as location, light levels and whether the participant is typing or not. While these tools are utilised in research and enable some access to objective data, they tend to lack the detailed and accurate contextual information required for high-quality public health studies (Beukenhorst et al., 2017; Kuhlmann et al., 2021). Their primary limitation is that they often only measure time spent on devices or applications (or often only how long such devices were open or 'on' for, for example, not how long is spent looking at the specific content or device), offering little insight into the impact of — for example — types of content. Further, the applications can be cumbersome to download and use, drain battery life, use data which participants have to pay for through their network providers and come with increasing privacy concerns, leading to (as above) a risk of biased and selected study samples.

'Screenome' approaches have also been developed, which involve recording screenshots of participants' phone screens throughout the day (Reeves et al., 2020). The screenshots can be used to capture detailed, moment-by-moment records of individuals' smartphone use and can therefore provide a comprehensive description of the ways in which people interact with digital devices. This approach can be used to capture the content of screen interactions, such as the text, images, location and preceding activities. They still cannot collect data on aspects such as context and motivation. The approach also presents substantial challenges in data security, data ownership and ethics as the screenshots could involve third party individuals and applications who have not given their direct consent to be involved in research, and there are legal implications if — for example — illegal activity occurs on the phone and is captured by researchers' screen captures (van Driel et al., 2022).

When working with objective data, researchers do not just face challenges in data collection but also in data enrichment, analysis and transformation. Unlike subjective measures, which attempt to directly tap into specific constructs, objective data often arrives in raw, unstructured formats. For example, a user's TikTok history might consist of timestamped URLs, which require extensive further processing to extract meaningful information about the content consumed. Transforming raw data into measures is a multistage process (i.e. extracting types of content of interest, measuring length of exposure and then linking to outcomes of interest) that can be laborious and complex (Stier et al., 2020), as well as at times legally or ethically unclear (Taylor & Pagliari, 2018). This underscores the need for support not only in accessing data but also in facilitating its enrichment and transformation.

Legal Provisions for Researcher Data Access

The government (at the time of writing in January 2025) has included provisions in the Data (Use and Access) Bill (2025) which would give the Secretary of State for Science, Innovation and Technology the power to make regulations to establish a framework for researchers to access online safety data. Such a framework would give researchers a legislative footing to access the data they need from technology providers to conduct online safety research. The government's ambition is for improved access to online safety data to enable more comprehensive research into online safety risks, as well as the effectiveness of providers' processes to mitigate risks to users as part of meeting their duties under the Online Safety Act (OSA). The aim is for this research to inform future online safety interventions, such as updates to the online safety regulator Ofcom's codes of practice, and to contribute to a safer online experience for UK users.

The framework will be informed by a robust evidence base, including a report by Ofcom exploring the ways researchers can currently access information from technology providers, the challenges that currently constrain information sharing, and how greater access to information might be achieved. This report is currently being developed, and Ofcom has concluded a public call for evidence (Ofcom, 2024c), seeking the views of those a future framework might impact. The report will be published in July 2025. The government will be required to consult with Ofcom, the Information Commissioner, regulated service providers and those representing the interests of independent researchers on its proposals and expects to launch a public consultation on the framework as soon as possible after the publication of Ofcom's report.

Ethics

The use of objective social media data raises important issues regarding data security and ethics. For instance, whereas researchers used to be the owners storing participant data, data donation packages involve participants first downloading detailed social media data onto their own devices. Often, both researchers and participants are not trained to store, process and distribute the resulting data in a responsible manner. In addition, many research institutions lack the appropriate regulation, infrastructure, legal and technical expertise to deal with the emerging challenges of handling sensitive social media data (e.g. responses to extremist or suicidal content).

Further challenges arise from the fact that objective data collection approaches often provide detailed and sensitive user data that exceeds researchers' needs (Taylor & Pagliari, 2018). This stems from the fact that data donation protocols or other ways of obtaining objective social media data are often not designed with researchers in mind. Therefore, working with objective social media data necessitates substantial data filtering by research teams themselves.

The ethical challenges and need for data filtering follow from the extent to which the collection of objective data can be tailored to include the required level of granularity and is limited to the data that participants have consented to share. For example, screenome approaches that collect information presented on the participants' screens may inadvertently capture sensitive information from third parties (e.g. a friend's private post) who have not provided consent. In contrast, these consents are less relevant for data donation protocols, which involve collecting data that legally belong to the participant (van Driel et al., 2022). Therefore, the ethical considerations and filtering requirements differ substantially depending on the collection methodology employed. The ethics and implications of each data collection approach will need to be evaluated on a case-by-case basis.

In the future, more targeted approaches to obtaining objective social media data can help mitigate such risks, which could involve specifying the data that is collected or requested, and why, so that only a select amount of data gets provided to the research team (Boeschoten et al., 2022). In the meantime, given that approaches such as data donation collect retrospective and prospective data, it is important to have adequate protocols in place that consider at which points one can act if safeguarding issues were to arise. Ethics boards and regulatory frameworks have not kept pace with the rapidly evolving digital landscape, particularly regarding sensitive data handling (van Driel et al., 2022).

To allow for an ethical and responsible use of the increasingly detailed and sensitive information used to do social media research, we must ensure that innovation in research methodology is guided and supported by ethical frameworks and appropriate infrastructure.

Summary

Key limitations:

- *Data access*: There is limited access to high-quality and high-resolution data from social media platforms.
- *Self-report measures*: An overreliance on self-report measures for measures that should be measured objectively leads to unreliable results that fail to capture the complexity of online behaviours and experiences.
- *Transparency*: Forced reliance on collaborations with technology companies, APIs or data donation packages to get access to objective data about social media or smartphone use raises ethical risks for researchers.
- *Technical demands*: Increasingly complex and technical solutions to accessing objective social media use data require a technical skillset that is not as readily available in the research community, and difficult to apply in large-scale complex studies.

- *Youth participation*: The lack of children's and young people's engagement in the design of measurement, and the inconsistent measurement of social media use and experience, creates substantial heterogeneity in the literature, limiting comparability amongst studies, and thus the development of high-quality evidence syntheses in this area.

Key opportunities:

- *Objective data*: New technologies allow for collecting detailed social media use data that provide rich insights into children's and adolescents' online experiences that can complement other more subjective measures. Furthermore, new regulations aim to facilitate researchers' access to objective data.
- *Granular data*: High-resolution objective social media use data can enable researchers to better understand the causal mechanisms behind the impact of smartphones and social media use.
- *Scalability*: Technological advancements allow for scalable and customisable ways to collect objective social media use data.

Part 3: Intervention Studies

Executive summary

Experimental and intervention studies can — if deployed correctly — help researchers cut through the complexity of observational research and get closer to drawing causal inferences about the effects of smartphones and social media on children and adolescents. Yet, as already discussed in the 'Causal Effects' section, they come with real and distinct challenges. A recent report classified 96% of reviewed social media intervention studies on mental health to be of poor methodological quality (Plackett et al., 2023). The limitations of current work include non-representative sampling approaches limiting the generalisability of findings, and expectancy effects, where participants' awareness of the intervention biases outcomes. A lack of theoretically informed measurement and research design further undermines the reliability and comparability of results.

Methodology

Intervention studies test the effects of a treatment, activity or procedure on a behavioural and/or health-related outcome. Participants are assigned to groups and the results of intervention/experimental groups (i.e. the participants that receive the intervention) and control or comparator groups (i.e. participants that do not receive the intervention) are compared. In smartphone and social media research, intervention studies focus on changing or manipulating behaviours to prevent negative impacts (e.g. techniques to address problematic use) or promote health-related behaviours (e.g. providing real-time social support). Example intervention studies include therapy-based techniques (Plackett et al., 2023), digital detoxes (Radtke et al., 2022), physical activity (Goodyear et al., 2023) and curriculum interventions (Weinstein et al., 2023). Due to the manipulation of the technology of interest, well-performed intervention studies can provide high-quality causal evidence in a systematic and controlled manner.

While intervention research has the potential to generate causal evidence, substantial methodological challenges have limited its value in generating evidence on the effects of smartphones and social media on users. According to research by Plackett et al. (2023b), 96% of studies examining social media interventions for mental health failed to meet adequate quality standards. Methodological shortcomings included a) the use of convenience samples (i.e. non-representative samples, 70%), which can introduce selection biases and limit the generalisability of findings, b) the failure to account for confounding variables (61%), which can lead to incorrect conclusions, and c) failure to detail study methodology and randomisation processes, which reduces transparency and others' ability to evaluate the quality of results. Moreover, the review concluded that many researchers failed to appreciate how research designs affected the inferences one could or could not make (Plackett et al., 2023). In other types of interventions (e.g. digital detoxes and social media-based physical activity interventions), systematic reviews have identified additional methodological challenges such as a lack of evidence or conceptually informed justification for research design, non-robust data collection methods and a lack of ethical detail (Goodyear et al., 2023; Radtke et al., 2022).

Intervention studies on social media tend to be exploratory in nature. They often pilot or feasibility-test new interventions to generate hypotheses and programmes of action. In turn, several intervention studies are not underpinned by a strong theoretical foundation, and this can limit the robust evaluation of how an intervention is expected to work. Many of these studies also suffer from using non-validated self-report measures (i.e., measures that have not been rigorously tested to confirm they accurately measure what they intend to) that are impacted by unreliable estimates, recall bias, and misinterpretation, as discussed in the section on measurement above (Orben, 2020a). Similarly to observational studies, many intervention approaches are also constrained by their simplistic focus on overarching time spent on phones or social media, while there is limited evaluation of other components (e.g. interactions, information and gamification).

Similar to the observational literature, the lack of consistent measurement of smartphone or social media use, and the outcomes of interest prevents meaningful comparison across studies (Marciano et al., 2024). For example, studies examining the effect of smartphone use on stress in the classroom may assess student self-reports or cortisol measures. Whereas both measures are valid, if one study uses one measure while the other uses another, one cannot determine whether differences in intervention effectiveness result from the difference in intervention or are due to different outcome measures. This is important as many existing intervention studies paint a mixed picture regarding the effects — positive, negative and null — of social media interventions on mental health and other wellbeing outcomes, such as physical activity and diet (Goodyear et al., 2023; Plackett et al., 2023; Radtke et al., 2022).

Moreover, intervention studies often assess a diverse range of outcomes with relevance to mental health and wellbeing (Y. Liu et al., 2025) to more specific indicators such as fear of missing out (Hunt et al., 2018), social comparison (Vogel et al., 2015), and sleep quality (Scott et al., 2022). This methodological heterogeneity creates difficulties when comparing results across studies and can create concerns regarding selective outcome reporting or outcome switching within studies, for example if only one out of many outcomes is reported (Kampman et al., 2021; Plackett et al., 2023).

Temporal Considerations

As discussed in previous sections, intervention studies also tend to focus on the short-term impacts of social media use, reflected in exposures that involve a few days or weeks with limited follow-up (van Wezel et al., 2021). However, social media's effect may involve cumulative processes that develop over extended periods. As such, short-term studies miss critical periods where initial effects might stabilise, reverse or disappear, and cannot capture how different usage patterns or outcomes emerge. This is further complicated by research often being interested in outcomes that will be impacted by many different factors. Some therefore argue that researchers should only expect small effect sizes (e.g. small differences between groups) for any individual intervention.

Effect size refers to the magnitude of the difference between two groups or the strength of the relationship between variables. In public health interventions, especially those aimed at large populations, effect sizes are often modest (Carey et al., 2023; Matthay et al., 2021). For example, a public health intervention might lead to only a small difference in social media use or wellbeing between the intervention and control groups. This is not necessarily a failure of the intervention but rather a reflection of the complexity of human behaviour and the many factors influencing health outcomes.

Moreover, the effects of interventions may not be linear. Complex system effects, such as changes in the online behaviour of entire communities or families, could result in broader impacts, whereas individual-level changes may not show the same patterns. For instance, while a small change in the social media habits of a few individuals might not yield noticeable outcomes, systemic shifts in how communities engage with social media could have more significant, cumulative effects (Sunstein, 2025).

Control Group

Another challenge for the design of robust intervention studies is the use of appropriate control groups. The widespread and interconnected use of social media means that control group participants often have indirect exposure to intervention effects through their social networks. For instance, if the intervention group reduces their social media use this may affect their online interactions with the control group, creating contamination effects. Furthermore, because participants are often aware of which condition they are in (e.g. participants who are asked to do a digital detox for a week are aware of this), social media interventions may introduce effects based on participants' expectations of the intended impacts, which may substantially undermine causal interpretations.

Sampling

A further limitation of previous intervention studies is that they predominantly include small sample sizes of participants, and they often study mainly individuals above the age of 18 (see Appendix 1). While this does not have to be the case, this current sampling approach is driven by pragmatic considerations around consent, with younger populations requiring parental consent and therefore substantially increasing the administrative load. This, however, creates substantial knowledge gaps regarding the effects of smartphones and social media interventions on younger users, their developmental trajectories and age-specific vulnerability factors (Emerson, 2021).

Furthermore, intervention studies need to emphasise participant recruitment that is representative to allow for generalisable claims about intervention effects to be made. A widespread problem is the use of convenience samples that recruit participants who are highly motivated to change their behaviour at the onset of the intervention (Skeggs & Orben, 2024). For example, most intervention studies find it easiest to target and recruit young female adults (aged 18–35 years) attending college/university. However, by focusing recruitment on this group, it is more difficult to ensure the results are generalisable to other parts of this population. There is also a lack of consistency in reporting ethnicity and socio-economic factors, and when ethnicity is reported, the samples often insufficiently represent the ethnic composition of the population (Hargittai, 2020).

Summary

Key limitations:

- *Complexity*: Given that social media and smartphone engagement is a heterogeneous behavioural phenomenon, it may be difficult to assess with confidence the impact of any given intervention on target behaviours or outcomes.
- *Sampling*: Research is based on small and non-representative samples predominately focused on older adolescents or adults. This limits the extent to which findings can be generalised to children.

- *Measurement heterogeneity*: Evidence on the impact of interventions is inconclusive, in part due to variability in reported effects and non-standardisation of measurement. This complicates meaningful comparison across studies and raises the question of whether differences in results are the consequence of the different measurement approaches, or true differences in the assessed populations.

Key opportunities:

- *Interventions*: Do intervention research with children and young people despite the inherent challenges.
- *Cost*: Consider the scale required to generate meaningful and robust conclusions and if necessary implement smaller-scale and less resource-intense interventions where possible.
- *Valid and transparent measurement*: Use validated measures to enable comparison of findings across interventions and disclose the outcome variables that were assessed.
- *Theoretical framework*: Employ behavioural science to underpin the conceptual framing and design of interventions, to explore mechanisms of change.

Part 4: Existing Datasets

Executive Summary

The UK is world-leading in the development and collection of cohort studies that allow for science to support policymaking across a wide range of areas. Indeed, UK population cohort studies constitute an annual governmental investment of approximately £30 million, encompassing over 2.2 million participants across the 34 largest cohorts (Pell et al., 2014). These cohorts have the potential to offer valuable evidence because their longitudinal samples comprise well-characterised participants with high-quality life course data on outcome measures, allowing time-course analyses that account for a wide range of demographic confounders.

However, significant challenges remain in accessing detailed data (especially about digital technology use) while preserving participant privacy. Social media, smartphone and adolescent data remain relatively rare, and effectively collecting this data requires greater administrative overhead and technical expertise among cohort staff. Coordinated efforts across research institutions and regulatory bodies, as well as attention to ethical and participant privacy considerations, are also required (Di Cara et al., 2020; Shiells et al., 2022).

The potential of cohort studies to provide information about causal mechanisms of smartphone and social media use depends on developing robust and sustainable infrastructure for both sustainable data collection from smartphones/social media and sharing while maintaining high standards of privacy and ethical conduct. Continued investment in technical capabilities and stakeholder engagement will be crucial to this effort.

Smartphone and Social Media Measurement

Cohort studies are longitudinal studies that follow a cohort of participants over a prolonged duration and take measurements from individuals at regular time intervals. Whereas cohort studies allow for the modelling of developments across time, the level of granularity of smartphone or social media data currently collected generally lacks the detail required to provide evidence of causal mechanisms underlying the positive and negative effects of these technologies.

The technical complexities of linking detailed smartphone or social media data have resulted in most cohort studies limiting assessments of smartphone or social media use to self-report questions asking participants to estimate the ‘time spent’ on their phone or on specific applications. Self-reported measures of screen time are, however, poor estimates of usage behaviour (Parry et al., 2021; 2022), and data linkage approaches have been proposed as a solution to gathering more detailed and accurate information (Tanner et al., 2023).

Data linkage combines data from different sources that relate to the same individual, and in the context of smartphone or social media research, this often relates to the collection of digital footprint data (e.g. directly from platforms) (Di Cara et al., 2024). However, data linkage requires increased financial and technical support to overcome methodological complexities and make the data accessible to researchers responsibly and securely (Harron et al., 2020). Data linkage can also introduce sampling biases (i.e. the sample may not be representative of the general population as some members have a greater sampling probability than others), which may limit the generalisability of resulting inferences (Bohensky et al., 2010). However, one advantage that cohort studies have over other samples of opportunity is that the participants often have associated detailed demographic information, which allows researchers to address sampling bias through survey weighting.

Lack of Child and Adolescent Data

Another challenge in examining the causal effects of digital media on children and young people is the lack of children and adolescents in the ongoing cohorts. About 92% of all current cohort study participants are now over the age of 45 (Pell et al., 2014). This creates challenges for drawing meaningful conclusions based on data from individuals of a different generation and using very different digital platforms and technologies. Although it is often possible to link historical digital technology or social media data, the lack of cohort studies covering the generations of children growing up with new and more intensive forms of digital media (2010s and 2020s) poses a fundamental challenge for cohort studies providing evidence into the effects of growing up in a rapidly evolving digital world.

The 'Adolescent Health Study' and 'Children of the 2020s' studies are exciting opportunities to provide crucial information on the digital lives of children and young people today (Karcher & Barch, 2021; Raynor & Born in Bradford Collaborative Group, 2008). However, with pressures for the Adolescent Health Study to recruit an exceptionally large sample on a relatively small budget, it is likely that collecting digital data will (at least initially) not be prioritised. There is however a real potential for these two cohorts to be among the first to collect detailed smartphone and social media data longitudinally in a cohort of adolescents.

Data Access and Privacy

Barriers to maximising cohort studies' utility also lie in the difficulties surrounding data access. Data donation packages, which are one solution to obtaining objective social media data, are restricted to 'anonymous' data which often exclude more detailed information about the use of and interactions on social media platforms (Ohme et al., 2024). Similarly, although cohorts may be able to draw on the long-term trust relationship between the cohort and participants to link their detailed social media data, the cohorts are likely to be reluctant to share this detailed information with outside researchers because of the risk to participants' privacy, legal and data protection issues (Di Cara et al., 2020). For example, if the cohort shared the full text or exact timings of participants' X (previously Twitter) posts with researchers, it would be possible for the researchers to use public information from X to identify cohort participants.

There are several promising solutions to the complexities surrounding access to potentially identifiable information of cohort study members. For example, a cohort might choose to share only information derived from social media data, such as ratings of emotional language based on computational large language models, rather than the raw data itself (Tanner et al., 2023). Alternatively, cohorts might choose to generate and share synthetic datasets based on the original smartphone or social media data. Privacy-preserving synthetic data approaches use techniques such as machine learning to create a new data set that retains as much as possible the utility of the original data set while protecting the privacy of the data (Jordon et al., 2022). Other solutions to enabling access to sensitive social media data include the use of data controllers, secure data access points, or trusted research environments. While there is still no gold standard way of linking objective social media or smartphone data to cohorts, there are many potential avenues that merit further exploration and support.

Temporal Resolution

Most cohort studies involve annual measurements that leave substantial gaps in our understanding of a rapidly evolving digital landscape. While this measurement frequency is insufficient for capturing causal impacts of digital media use that manifest over shorter time intervals, it does offer the possibility of tracking the causal influence of smartphone or social media use over the longer term. For example, cohorts have often followed participants from before they were first exposed to social media, and annual outcome measures can be combined with long-term social media data linkage. Multi-tiered data collection approaches that combine different sources of data are promising and can supplement annual measurements with other data sources that provide granular information, such as detailed baseline measurements, digital footprint data linkage or ecological momentary assessments.

Summary

Key limitations:

- *Timeline mismatch*: Key online behaviours may be difficult or impossible to measure because of the mismatch between the timelines of rapid technological adoption and the time to set up and revise birth cohort and panel studies.
- *Sensitive data*: There are ethical implications, particularly around anonymity and participant retention, when social media or digital technology use information is linked to a wide range of other social and biomedical data held on cohort participants.
- *Costs*: Developing the platforms for large-scale digital footprint data collection, linkage and sharing requires specific and substantial investment in the resources and technical skills available to cohort staff.

Key opportunities:

- *Existing datasets*: Much of human behaviour and interaction happens online and augmenting existing datasets is useful for researchers interested in both online harms and human behaviour in general.
- *Representative samples*: Cohort studies can offer a wealth of linked data that allows for sample representativeness to be assessed and adjusted for if necessary. Furthermore, cohort participants are generally well-characterised in terms of demographics and potential confounders, which means potential sources of bias can be investigated and accounted for in analyses.
- *Baseline measures*: The gold standard outcome measures that cohorts collect on a regular basis can provide the reference points necessary for developing and validating new approaches for social media analysis and can also be leveraged for evaluations of natural experiments.
- *Long-term effects*: The life course data collected by cohorts, including data from before participants were exposed to social media or other digital technologies, is likely to be valuable for investigating the long-term causal influences of social media and digital technologies on children and young people.

Part 5: Ethics and Responsible Innovation

Executive Summary

Social media platforms and other digital technology providers have historically resisted sharing data that could establish causal links between their services and potential harms. In response, researchers have developed innovative methods to access increasingly detailed user data as discussed above. These developments have created unique ethical challenges. Ethical considerations must now go beyond pre-emptive measures to encourage responsible innovation in this space (Shaw et al., 2023), requiring ongoing review as data collection methods and capabilities evolve.

Responsible innovation principles also apply to the design and deployment of social media platforms and other digital technologies where child and adolescent wellbeing and positive mental health are often not incentivised in business models and incorporated into design and regulation. This will require a shift from retrospective to anticipatory approaches, to ultimately understand and mitigate the potential harms of smartphones and social media. In this section we highlight the need for ethical procedures that ensure inclusive research, emphasising that children and young people should be involved not only as participants but throughout the entire research process from planning to dissemination.

Current Landscape

Social media platforms and other digital technologies have historically been resistant to sharing data that could establish causal links between their services and potential harms, creating what economists term an ‘externality’ — where costs are created in one location but borne elsewhere. This resistance stems from the incentive structure that does not reward platforms for sharing data. For instance, concerns around the liability of platforms parallel historical cases in other industries where evidence of harm was initially obscured.

To overcome the difficulties with accessing detailed social media data or data on use of smartphones, researchers have started to develop innovative methods to circumvent these issues, the ethical challenges and implications of which we are yet to fully appreciate (van Driel et al., 2022). These developments are described in detail in ‘New Approaches to Objective Measures’ above. The new avenues for obtaining detailed user data and the detailed user data itself have created unique challenges for ethical procedures and guidelines. Adequate support and regulation for responsible research, considering increasingly complex data and data collection methods, has been difficult and is important to get right (Hinds et al., 2020). The hidden dangers of collecting digital user data are difficult to anticipate. For instance, smartphone app usage logs alone could be used to identify individual users among hundreds of individuals (Shaw et al., 2022).

The difficulties surrounding harm anticipation often render one-off pre-emptive ethical considerations insufficient, for example, it might have been impossible in the past to re-identify participants from certain forms of detailed digital data, but the risks are now higher since AI can analyse large data loads at high speed and low costs. Continued ethical review and examination throughout the research process will therefore be necessary (Shaw et al., 2023).

Stakeholder Engagement

Stakeholder involvement throughout the research lifecycle can strengthen ethical considerations and establish research priorities. The relevant stakeholders include children and young people, parents, educators, health and social care professionals, and policymakers, all of whom stand to provide unique perspectives. Importantly, involvement should not be limited to participation in research, but also planning, completing and the evaluation of the research (Levac et al., 2019). For research attempting to understand the impact of smartphones and social media on children and young people, this would mean involving children and young people themselves, as well as their parents and educators. Special attention should be devoted to children's and young people's perspectives as these are important for understanding the real-world impact of smartphone and social media use, which is dynamic, individual, place-specific and fast-moving. The NIHR James Lind Alliance Priority Setting Partnerships (PSPs) provide an established methodology for engaging the public in setting research priorities (Hollis et al., 2018).

Current research practices often inadvertently exclude populations who may be most affected by smartphones and social media, in either positive or negative ways (Fassi et al., 2024). For instance, individuals deemed to be 'at-risk' (e.g. children or adolescents with a current mental health diagnosis, or young children) are often excluded from research instead of making the necessary accommodations that would enable 'at-risk' individuals to contribute to or participate in the research (Schroeder et al., 2024). The exclusion of 'at-risk' individuals does not reflect the fact that they continue to have access to digital platforms. This creates a paradoxical — indeed, at times unjust and discriminatory — situation where the individuals potentially most affected by use of smartphones and social media are least considered in research.

Developing a supportive and inclusive approach to research design and participation will be crucial for conducting causal research that is generalisable to the individuals potentially most affected, rather than defaulting to exclusion. This effort could be guided by the UK Standards for Public Involvement, which encompass inclusion, working together, support and learning, governance, communication, and impact (National Institute for Health and Care Research, 2019). Establishing Young Person Advisory Groups to guide and inform research is another important option to ensure that research methods and practices are appropriate to the children and young people most impacted. This requires funding for involvement and dedicated professional staff to support children and young people in this process.

Summary

Key limitations:

- *Reactive approach*: Current digital ethical decision-making processes are often reactive and might fail to adequately prevent harm.
- *Training needs*: Current training around ethics and ethical processes requires an increasing level of interdisciplinary expertise, and institutions are often behind the cutting edge of current research and technology practices.
- *Participatory research*: Research practices often fail to consider the voices of individuals who might be most affected by smartphone and social media, resulting in potential health inequalities. Furthermore, vulnerable populations are often excluded from research despite their continued access to digital platforms.

Key opportunities:

- *Youth and stakeholder involvement*: Establishing Children and Adolescent Advisory Groups is essential for effective involvement and requires expert support and funding. Engaging with diverse stakeholder groups is challenging but can be achieved by working with community partners.
- *Ethical research*: Involving stakeholders and boosting training in ethics at research institutions helps ensure that research is appropriate, responsible, ethical and impactful.
- *Evaluation throughout the research process*: Develop resources to support ethical reflection as a more proactive endeavour, which occurs throughout the research process, rather than at one point during research design, reducing the risk of potential harm to individuals.

Part 6: Timeliness and Response to Emerging Harms

Executive Summary

An ongoing challenge regarding smartphone and social media research is its ability to respond quickly to emerging threats arising or thought to be arising from new technologies such as smartphones, social media and AI. There is a clear tension between policymakers' present need for evidence regarding the influence of smartphones smartphone and social media on children and adolescents, and the pace and practical requirements of rigorous academic research. This unmet need is exacerbated because existing technologies change quickly, and new platforms can become popular with children and adolescents in very short timeframes.

Addressing these challenges requires fundamental changes to research infrastructure and the way research is used to inform policy. While this is a difficult and deep-seated issue, potential recommendations discussed in the consortium include a) establishing pre-approved research protocols, b) implementing flexible evidence thresholds based on harm and severity, and c) developing sustainable funding mechanisms and research infrastructure for rapid response capabilities. These recommendations can improve research practices and abilities to address a potential evidence bottleneck in the face of rapid technological change and support timely, evidence-based policy responses for emerging digital harms.

Timeline Mismatch

The academic research cycle often operates on a timeline of years, whereas policymakers sometimes require evidence within weeks or months in light of technological changes. Reliable research is most often not available on this shorter timescale because: a) grant funding cycles that are required before research commences (Hippel & Hippel, 2015), b) extended ethical and legal university review processes, c) in-depth research design, data collection, analysis and review, d) longitudinal evidence routinely requiring more than three waves (often years or months) of data collection to address causal relationships (Zyphur et al., 2020), and e) peer-review and publication delays (Andersen et al., 2021). The length of time it takes to do high-quality academic research is therefore at odds with the accelerating timelines of technological change where new platforms or features can gain massive adoption within days and fundamentally change the digital ecosystem that shapes children's and adolescents' lives across only a few weeks.

In the following section, we propose several potential changes to the prevailing research infrastructure and approach to evidence-based policy that may address the mismatch in timelines. This is, however, not a comprehensive overview, and the problem will need standalone work and interdisciplinary consultation to fully address, potentially as part of a National Research Strategy on Online Harms.

Research Infrastructure

There is substantial disagreement on the best approach to address the mismatch in timelines between policy, technology and research. However, there are promising examples from other areas of research that have successfully accelerated the research process, for instance, in the case of climate research (Solecki et al., 2021). The case of climate research illustrates how research infrastructure changes, such as strategic science-policy partnerships, can accelerate and support the production of research outputs.

Changes to the prevailing research infrastructure can be implemented to accelerate the research process while maintaining scientific rigour (Sigfrid et al., 2020). One such development could be the use of pre-approved research protocols. Research institutions could develop study templates of common research study designs and undergo preliminary ethical review (Saxena et al., 2019). These templates would include specific methodological frameworks for common research scenarios, such as the examination of the impact of new social media features. Legal and ethical concerns about studies of such features using children and young people, as well as sensitive or proprietary data could be addressed beforehand. This would involve review boards, legal services, research services, contracts, technical experts, as well as children and young people, teachers, parents, or those with lived experience. For instance, a pre-approved protocol could include predetermined sampling strategies, standardised measurement scales and drafted materials that require only minor modifications for specific applications or new technologies.

Standing participant pools should be maintained through ongoing recruitment and engagement programmes (e.g. *Games & Mental Health in the Spotlight as D-CYPHR Brings in Study Participants for SPARX UK*, 2024). These pools would include pre-screened participants across different demographic groups who have provided baseline data and confirmed their willingness to participate in rapid-response research (if deemed appropriate, this could also include prospective consent procedures). Given appropriate infrastructure and support, this could reduce participant recruitment times, even though biases in participant recruitment and retention need to also be considered.

Regulation and Anticipation

Responsible innovation and regulation in social media research will also require moving from a retrospective perspective on smartphones and social media to increased anticipatory thinking about the potential dangers and implications for both research and regulation. Several factors currently hinder such an anticipatory approach.

First, accurate measurement and definition of the potential impacts of smartphones and social media are crucial. Both the UK and EU are moving toward an increasingly regulatory approach that requires platforms to demonstrate a level of viability and accountability for their effects in order to operate. For this approach to function, accurate data and measurement are paramount (Shavell, 1984). This also requires a shift in responsibility onto social media and other digital technology platform providers to demonstrate, with independent verification, the safety of their platforms for children and young people, such as 'safety by design and default', and enforcement of regulations such as age and content restrictions. Responsible regulation should ensure that platform providers are held legally responsible for harm caused through exposure to smartphones or social media.

One of the ongoing efforts is focused on increased data access for researchers, such as through the Data (Use and Access) Bill (2025). This condition is necessary but not sufficient, as reflected in other domains such as misinformation research, where an increase in misinformation prevalence has paralleled researchers' access to detailed data on misinformation (Clark et al., 2023; Pfender et al., 2024; Pilgrim & Bohnet-Joschko, 2019). Driving regulation that has positive effects will require clear definitions of what data and oversight are needed, what and how outcomes are measured, close collaboration between research, regulators and the affected stakeholders, and consideration of the costs and potential unintended consequences of regulation.

Long-term Objectives

The long-term focus should be on developing predictive capabilities and establishing sustainable research infrastructure. This includes:

a) Building comprehensive databases of historical threats and responses, enabling better prediction of future challenges. These databases should include detailed documentation of research methods, findings and policy impacts.
b) Developing advanced analytical capabilities, including machine learning models that can identify potential threats before they become widespread. These capabilities should be integrated with monitoring systems to provide automated alerts and preliminary impact assessments.
c) Creating sustainable funding mechanisms for maintaining rapid response capabilities, including dedicated budget lines and emergency funding protocols, for example as part of a National Research Strategy on Online Harms. These mechanisms should ensure that research teams can respond quickly to emerging threats without disrupting ongoing research programmes.

Summary

Key limitations:

- *Timeline mismatch*: Research timelines often take years, whereas policymakers sometimes require evidence within weeks or months.
- *Research timelines*: Research timelines (especially for work funded through response-mode grant funding) are long due to grant approval, ethical reviews, research design and deployment, and peer review all taking substantial periods of time.
- *Technological timelines*: The digital landscape changes rapidly, with the adoption of new features or platforms.

Key opportunities:

- *Pre-approved protocols*: Pre-approved research protocols with standardised methodologies can accelerate the research process while retaining scientific and ethical standards.
- *Standing participant pools*: Standing participant pools can be used to facilitate recruitment, yet selection bias of these will need to be considered.
- *Risk identification*: A coherent process for identifying, estimating and intervening on potential risks and harms will empower policymakers (and other stakeholders) to make consistent and evidence-based trade-offs.
- *Sustainable funding*: A long-term and sustainable funding mechanism to provide the foundation for prospective online harms research. This could be scoped through a National Research Strategy on Online Harms.

Appendix 4: Expert Roundtable Discussion Report

March 2025

Introduction

This report provides an overview of a two-day workshop designed to explore methods to generate causal evidence on the impact of social media and smartphone use on the development of children and young people (CYP; 3–21yrs; including physical and mental health, wellbeing, lifestyle and health behaviours and educational attainment). Hosted at the University of Cambridge on 12–13 February 2025, the workshop brought together a diverse group of stakeholders including representatives from government, regulatory bodies, and academic researchers. The primary objective was to collaboratively identify research strategies capable of delivering causal evidence within a two-to-three-year timeframe.

Workshop Design and Structure

The workshop was co-designed with Dr Myriam Hadnes (*workshops.work*) to maximise engagement, interdisciplinary collaboration and outcome-driven discussions. The structure was carefully planned to facilitate:

1. A shared understanding of research challenges and opportunities through panel discussions and small-group reflections.
2. Brainstorming and solution generation using templates to identify innovative research approaches.
3. Critical evaluation of feasibility of research approaches by incorporating ethical, methodological and policy considerations.
4. Consensus-building and prioritisation through ensuring that proposed solutions were both scientifically rigorous and practically actionable.

The two-day agenda combined plenary discussions, structured brainstorming exercises, small-group work, and iterative refinement of research ideas. The workshop emphasised interdisciplinary dialogue: scientists, policymakers and regulatory stakeholders should work together to develop solutions that are both methodologically robust and policy relevant.

Workshop Attendees

A key strength of this workshop was the diversity and deep expertise of its attendees, who brought a range of areas of specialism and perspectives to the discussion. Attendees were categorised into three main groups:

1. Scientific Consortium

The Scientific Consortium brought together leading researchers in psychology, mental health science, public health, information systems and behavioural science to ensure that discussions were informed by high-quality scientific evidence and methodology. Selection was based on prior UKRI funding awarded in this area, methodological expertise in public health, and expertise in social media's impact on young people, with a focus on inclusivity across national research leads rather than specific subject backgrounds or methodological preferences.

Name	Affiliation	Role

Professor David Ellis	University of Bath	Professor of Behavioural Science
Professor Adam Joinson	University of Bath	Professor of Information Systems
Dr Victoria Goodyear	University of Birmingham	Associate Professor in Pedagogy in Sport, Physical Activity and Health
Dr Oliver Davis	University of Bristol	Associate Professor and Mental Health Data Scientist
Professor Vittal Katikireddi	University of Glasgow	Professor of Public Health and Health Inequalities
Dr Margarita Panayiotou	University of Manchester	Senior Lecturer in Educational Psychology
Professor Chris Hollis	University of Nottingham	Professor of Child & Adolescent Psychiatry and Digital Mental Health
Professor Ellen Townsend	University of Nottingham	Professor of Psychology
Professor Andrew Przybylski	University of Oxford	Professor of Human Behaviour and Technology

2. Policy Partners

Policymakers and representatives from government and regulatory bodies provided policy expertise, ensuring that proposed research approaches aligned with priorities, policy needs and real-world implementation challenges.

Name	Affiliation	Role
Professor Russell Viner	Department for Education	Chief Scientific Adviser
Dr Alma Chapet-Batlle	Department for Education	Senior Scientific Adviser
Alex Huth	Department for Science, Innovation and Technology	Senior Economist, Analysis Team, Security and Online Harms
Sarah Marigold	Department for Science, Innovation and Technology	Head of User Safety, Security and Online Harms
Lisa Etwell	Ofcom	Head of Consumer Research
Jonathan Porter	Ofcom	Head of BI Economics

3. Project Delivery Team

The Project Delivery Team, who carry out research on social media and young people's mental health within Dr Amy Orben's University of Cambridge research group, contributed their expertise to chair discussions, take notes, and ensure the smooth execution of the workshop. Dr Amy Orben and Dr Amrit Kaur Purba also participated as members of the Scientific Consortium.

Name	Affiliation	Role

Dr Amy Orben	University of Cambridge	Project Lead
Dr Amrit Kaur Purba	University of Cambridge	Deputy Project Lead
Lukas Gunschera	University of Cambridge	Researcher/Group Facilitator
Ioanna Fokas	University of Cambridge	Researcher/Group Facilitator
Zhuo Yao Yap	University of Cambridge	Project Manager
Matthew Richards	University of Cambridge	Group Facilitator
Brandon Davidson	University of Cambridge	Group Facilitator

Workshop Agenda

Day 1 — 12 February 2025

Time	Room	Activity	Details
10:00–10:30	Central Hall	Registration and Coffee	Sign in at Reception and networking.
10:30–10:50	Lightfoot Room	Opening Welcome by Dr Amy Orben (AO) & Dr Amrit Kaur Purba (AKP)	Introduce workshop goals and attendees' roles.
10:50–11:30	Lightfoot Room	Small Group Discussion	Reflect on 'Limitations and Opportunities Report' in groups.
11:30–12:30	Lightfoot Room	Roundtable Discussion on Achieving Causal Evidence	Overview of causal methodologies by AKP, then explore feasibility, risks, and mitigation strategies.
12:30–13:30	Central Hall	Lunch	
13:30–14:30	Lightfoot Room	Collaborative Thinking Session	Brainstorm and refine best research idea per individual that would get us to causal evidence in two to three years.
14:30–15:30	Lightfoot Room	Formalising Potential Solutions	Teams develop and document approaches using a structured framework (e.g. SWOT analysis).
15:30–15:50	Central Hall	Coffee Break	Group photo
15:50–16:30	Lightfoot Room	Peer Feedback Round	Teams present approaches and receive constructive peer feedback.
16:30–17:00	Lightfoot Room	Voting on Top Approaches	Attendees identify and refine the most promising approaches through voting or further discussion.
17:15–18:15	Lightfoot Room	Fireside Chat: Professor Russell Viner & Dr Amy Orben	Expert perspectives on research-policy intersections. Followed by open discussion and queries.
18:15–19:30	Wordsworth Room	Drinks Reception	
19:30–21:30	Wordsworth Room	Dinner	

Day 2 - 13 February 2025

Time	Room	Activity	Details
09:30–09:45	Central Hall	Registration and Coffee	Sign in at Reception and sharing insights from Day 1.
09:45–11:00	Lightfoot Room	Collaborative Project Scoping and Feasibility Assessment	Collaborative scoping to evaluate methods, limitations, challenges/risks, timeframe, ethics, emerging technologies, vulnerability considerations, and cost/resources to recommend a balanced, feasible approach for DSIT's next research phase.
11:00–11:30	Central Hall	Coffee Break	
11:30–12:30	Lightfoot Room	Pitches and Moderated Discussions	Evaluate pitches, providing conceptual and practical feedback. Clearly identify potential concerns and obstacles in each project idea.
12:30–13:00	Lightfoot Room	Group Discussion	Teams regroup to refine their ideas, incorporating feedback and addressing identified challenges and suggestions.
13:00–14:00	Central Hall	Lunch	
14:00–15:00	Lightfoot Room	Final Refinement & Feasibility Review	Teams present refined ideas, focusing on how they can be made feasible. Final questions addressed, and the most viable approaches will be prioritised and documented.
15:00–15:15	Lightfoot Room	Ranking	Workshop attendees reach a consensus on the four most feasible approaches.
15:15–15:30	Lightfoot Room	Workshop Close	Closing remarks.

Session 1: Introduction

The workshop began with Dr Amy Orben outlining the objectives and schedule to align all attendees on the workshop’s purpose. Dr Amrit Kaur Purba then highlighted the importance of the diverse expertise in the room, emphasising that each attendee brings valuable insights essential for a well-rounded discussion. Active engagement was key to fostering interdisciplinary exchange and a comprehensive understanding of the challenges. Dr Orben then led a brief introduction round, where attendees shared their names, affiliations and three words describing their expertise.

Figure 12. Opening of the Workshop by Dr Amy Orben and Dr Amrit Kaur Purba.

Session 2: Reflections on Limitation and Opportunities Report

This session aimed to promote critical reflection on the Limitations and Opportunities Report to outline the challenges and opportunities in researching the impact of social media and smartphone use on young people's mental health and development. Attendees were split into four interdisciplinary groups to review the report, which was included in the pre-reading materials. This report outlined key challenges and future directions for evidence provision on the impact of social media on children and young people. Each group identified the top three limitations and opportunities, noted any gaps and highlighted any unexpected insights from the report. Using sticky notes and guided by group facilitators, groups captured their insights, which were then summarised and presented to the wider group.

Session 3: Establishing Feasibility and Anticipating Risks

The next session included a presentation and subsequent facilitated discussion. Dr Amrit Kaur Purba opened with a 15-minute overview of causal inference methodologies, focusing on how researchers can infer causality in the absence of experimental studies. She outlined the strengths and limitations of various approaches and explored the level of evidence that could realistically be achieved within the next two to three years. This presentation set the stage for a broader discussion on potential risks that could undermine these efforts.

Session 4: Collaborative Thinking Session

The goal of this session was to explore general methodological approaches to achieving causal evidence of the impact of social media usage on mental health and wellbeing in two to three years.

Phase 1: Idea Generation and Refinement

The session began with structured solo brainstorming, where attendees individually generated four to ten potential strategies of achieving causal evidence of the impact of social media usage on mental health on sticky notes. This approach encouraged independent thinking and the generation of a broad range of ideas.

Attendees then moved into pre-assigned discussion groups, designed to bring together diverse expertise and backgrounds. Within these groups, attendees refined their ideas, critically assessing their strengths and weaknesses. Attendees were then asked to personally choose one or two of the most viable approaches.

The process then shifted to whole-group synthesis, where similar individual 'top' ideas were clustered to reveal overarching themes and research directions. This step was crucial in identifying key methodological priorities and eliminating redundancy. The session concluded with self-selection into focused teams that would each develop one of the methodological clusters further in the next phase.

While the four-project team covered key areas (natural experiments, theory, interventions and existing datasets), some research approaches, such as multiple feature manipulations, micro-RCTs, and individual-level meta-analysis, remained unexplored.

Phase 2: Formalising Research Approaches

With teams established, each group further discussed their research approach and conducted a Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis to critically assess its effectivity and viability. This step ensured that ideas were not only innovative but also methodologically sound, scalable and practical within the given timeframe.

Phase 3: Collaborative Scoping and Evaluation

On the second day, teams reconvened to design a concrete implementation of their idea and examine key considerations that would shape the feasibility and impact of their proposed methods. This collaborative scoping exercise covered essential aspects such as benefits, limitations, risks, ethics, resilience to rapid changes and emerging technologies, timeframe and resource requirements. By working through these elements, teams developed a clearer understanding of the practical challenges their approach might face and how to navigate them effectively.

Following this, group facilitators gave two-minute pitches to the other three groups, outlining their group's approach for the ideas to be peer-reviewed. Feedback focused on both conceptual soundness and practical execution, with an emphasis on identifying critical weaknesses and barriers to implementation. Teams then regrouped to incorporate this feedback, making necessary adjustments to strengthen their proposals. This iterative process ensured that every approach was stress-tested, improved and feasible for real-world application.

Phase 4: Final Presentations and Prioritisation

The session concluded with teams presenting their final, refined research approaches, focusing on how they could be realistically implemented in the science-policy landscape. Attendees had the chance to respond to feedback and clarify their proposals, ensuring that all outstanding questions were addressed.

In the final discussions, four viable approaches (natural experiments, theory, intervention and existing datasets) were prioritised and documented. The outcome was not just a collection of ideas but a clear, evidence-based roadmap for possibilities to advance causal research in the coming years. The Project Delivery Team will use these as a foundation for their main report to DSIT.

Figure 13. Collage of Attendees Actively Engaging in Collaborative Discussions and Idea Development.

Session 5: Fireside Chat with Russell Viner

The fireside chat between Professor Russell Viner and Dr Amy Orben, which included a wider discussion across all attendees, explored the challenges and opportunities in using scientific research to inform policy on smartphones, social media and child development. The discussion highlighted the pressures shaping policymaking, the potential disconnects between scientists and policymakers and the need for stronger engagement between the two.

Figure 14. Fireside Chat Between Professor Russell Viner and Dr Amy Orben.

Session 6: Voting

Once the four main approaches had been finalised, and groups had presented their refined ideas to the wider group, attendees were given the opportunity to vote on two main questions. First, attendees were given three stickers to allocate between ‘experimental’ and ‘observational’ approaches, based on which they believed would be most likely to achieve causal evidence within two to three years. Attendees could distribute their stickers across both categories, depending on their confidence in each approach. ‘Experimental’ approaches received 23 stickers and ‘observational’ approaches received 25 stickers.

In the second voting question, attendees were asked to select which of the four approaches presented by each group they believed would most likely produce causal evidence within two to three years, with an emphasis on generating evidence that could be directly used by policymakers. The voting results showed the ‘experimental’ approaches received the most support, with 15 stickers, followed by ‘theoretical’ approaches with 13 stickers, and then the ‘natural experiment evaluations’ and ‘existing data’ approaches, both with 10 stickers.

Feedback from Attendees

The workshop was very well received by attendees, as evidenced by positive feedback via an anonymous feedback exercise. Many appreciated the complementary expertise in the room, noting how the group dynamic fostered meaningful discussions without redundancy. The sessions reinforced the potential for collective progress with the right resources, and the structured format was particularly welcomed. The facilitation was also praised for keeping discussions focused and ensuring that diverse perspectives were heard. There was a shared sense of momentum and optimism, with many attendees reflecting on how the workshop reinforced the potential for meaningful progress in this space. It served as a reminder of what could be accomplished through sustained collaboration and adequate resources. Overall, the feedback highlighted the value of bringing together a diverse group to shape a clearer path forward for generating robust, policy-relevant evidence in this evolving field.

Appendix 5: Scientific Consortium Members

Dr Amy Orben
Affiliation: University of Cambridge
Role: Programme Leader
Subject: Project Lead
Professional Biography:
Dr Amy Orben leads the internationally recognised 'Digital Mental Health' research programme investigating the links between digital technology use and adolescent developmental outcomes. She has won multiple awards and sits on the Department for Education Science Advisory Council.

Dr Amrit Kaur Purba
Affiliation: University of Cambridge
Role: Senior Research Associate
Subject: Causal Methods
Professional Biography:
Dr Amrit Kaur Purba is an expert in public health/policy and epidemiology. Her MRC/CSO-funded research applies causal inference methods to observational data to investigate social media's impacts on adolescent health, employing social media data donation methods. She serves on the Department for Education's Technical Advisory Group and advises the UN, Met, and No.10 Downing St.

Professor Oliver Davis
Affiliation: MRC Integrative Epidemiology Unit at the University of Bristol
Role: Associate Professor and Mental Health Data Scientist
Subject: Existing Datasets
Professional Biography:
Professor Oliver Davis is a former Turing Fellow and expert in social media measurement and linkage to pre-existing data. He has led EPSRC, MRC and ESRC-funded work on digital data linkage, including developing tools that allow leading cohort studies to link millions of social media interactions, and leading CLOSER Work Package 21 on digital footprint data.

Professor David Ellis
Affiliation: University of Bath
Role: Professor of Behavioural Science
Subject: Ethics & Responsible Innovation
Professional Biography:
Professor David Ellis is an expert in psychology, computer science and cybersecurity, with an emphasis on innovative measurement of digital technology engagement. He is a project lead on the ESPRC-funded National Research Centre on Privacy, Harm Reduction and Adversarial Influence Online.

Dr Victoria Goodyear
Affiliation: University of Birmingham
Role: Associate Professor in Pedagogy in Sport, Physical Activity and Health
Subject: Ethics & Responsible Innovation
Professional Biography:

Dr Victoria Goodyear has led award-winning research examining smartphone and social media use in schools, and its relation to adolescent health and physical activity. She serves on the UK Chief Medical Officers' Physical Activity Guidelines panel.

Professor Claire Haworth
Affiliation: University of Bristol
Role: Professor in Psychological Science and Mental Health
Subject: Existing Datasets
Professional Biography:

Professor Claire Haworth is a former Turing Fellow and expert in mental health and social media measurement and linkage in cohort studies, with experience in causal analysis approaches. She has led cross-council funded work analysing social media data to assess its benefits and challenges for mental health and wellbeing, while considering ethical implications of such research.

Professor Chris Hollis
Affiliation: University of Nottingham
Role: Professor of Child and Adolescent Psychiatry and Digital Mental Health
Subject: Ethics & Responsible Innovation
Professional Biography:

Professor Chris Hollis co-leads the UKRI-MRC Digital Youth Programme as a leading expert in child and adolescent mental health, online behavioural interventions and digital technologies for mental healthcare. He is also Director of NIHR MindTech HealthTech Research Centre, expert advisor to NICE and serves on NHS England's Digital Mental Health Innovation Working Group.

Professor Adam Joinson
Affiliation: University of Bath
Role: Professor of Information Systems
Subject: Ethics & Responsible Innovation
Professional Biography:

Professor Adam Joinson leads the ESRC Digital Security by Design Social Science Hub+ and the 'risk and online behaviour' programme for the National Centre for Research and Evidence on Security Threats, focusing on susceptibility to malevolent influence and technological behaviour change.

Professor S. Vittal Katikireddi
Affiliation: University of Glasgow
Role: Professor of Public Health and Health Inequalities
Subject: Causal Methods
Professional Biography:

Professor Vittal Katikireddi is an epidemiologist and leading expert in causal inference through quantitative methods and evidence-based policy. He sits on the MRC/NIHR Better Methods, Better Research panel.

Professor Sonia Livingstone
Affiliation: London School of Economics and Political Science
Role: Professor of Social Psychology and Director of Digital Futures for Children Centre
Subject: Social Media Measures
Professional Biography:

Professor Sonia Livingstone has led many nationally important research and policy initiatives regarding child development, communications and digital technologies, such as the Digital Futures for Children Centre, and has advised organisations such as UNICEF on children's rights in the digital age.

Dr Margarita Panayiotou
Affiliation: University of Manchester
Role: Senior Lecturer in Educational Psychology
Subject: Social Media Measures
Professional Biography:

Dr Margarita Panayioutou is expert in measurement and psychometric analyses, leading MRC-funded research to improve the measurement of social media use through data donation, app tracking and novel questionnaire measures.

Professor Andrew Przybylski
Affiliation: University of Oxford
Role: Professor of Human Behaviour and Technology
Subject: Timelines and Response to Emerging Threats
Professional Biography:

Professor Andrew Przybylski has international influence through collaboration with policymakers to tackle emerging health challenges in the digital age. He is expert in the use of innovative data obtained through industry collaboration and data donation.

Professor Ellen Townsend
Affiliation: University of Nottingham
Role: Professor of Psychology
Subject: Ethics & Responsible Innovation
Professional Biography:

Professor Ellen Townsend co-leads the UKRI MRC-funded Digital Youth programme, a national investment to understand how digitalisation impacts adolescent health. She is also Co-investigator and Co-Lead of the Children and Young People research theme at MindTech. She is expert in self-harm and ethical and responsible innovation.

Dr David Zendle
Affiliation: University of York
Role: Lecturer in Computer Science
Subject: Social Media Measures
Professional Biography:

Dr David Zendle is a computer scientist and newly appointed director of the ESRC Data Donation Service, where he will build national data infrastructure to allow researchers to access smart data to address policy-relevant questions.

Appendix 6: Glossary of Technical Terms

Term	Definition	Reference (page no.)
Alberta Research Centre for Health Evidence (ARCHE) decision tool	A decision tool used to guide inclusion and reporting of systematic reviews in overviews of reviews and healthcare interventions.	Appendix 1, p. 91
Artificial intelligence (AI) chat applications	Defined by the UK government as any chatbot that 'makes the use of digital technology to create systems capable of performing tasks commonly thought to require intelligence'.	Appendix 1, p. 89
Application programming interfaces (APIs)	Technological 'bridges' that allow two or more software systems to communicate and transfer information, enabling access to social media data.	Appendix 3, p. 234
A/B testing	A research method used to compare two versions of something, typically before and after a key component of a platform has been changed, to determine which performs better against a set of certain criteria.	Main report, p. 34
Begg's Test	A statistical test used in meta-analyses to check for publication bias by looking at the relationship between the effect size of study results and their precision (referring to their 'standard error'). If a pattern is found, it might suggest that studies with certain results are more likely to be published.	Appendix 1, p. 99
Bradford Hill	A set of nine viewpoints used to assess if an association between an exposure and an outcome is likely to be a causal one in epidemiological research (Shimonovich et al., 2020; Hill, 1965).	Appendix 1, p. 99
Causation	A cause-and-effect relationship between two variables, where one directly influences the other.	Appendix 1, p. 99
Cluster randomised control trial	A type of randomised control trial where groups of individuals (rather than individuals) are randomly assigned to different exposure, intervention or treatment groups.	Appendix 3, p. 226
Cohort	A type of research design in which researchers collect data from a group of individuals sharing a common characteristic over time at several timepoints to assess how certain factors and exposures affect their health outcomes.	Main Report, p. 13
Confidence Interval	A range of values defined so that there is a specified probability that the value of a parameter lies within it. Denoted in-text by CI.	Appendix 1, p. 108
Confounder	A third variable that influences both the independent and dependent variables.	Main Report, p. 27
Correlation	A statistical measure that expresses the extent to which two variables change together constantly, denoting	Main Report, p. 28

	the statistical association between two variables.	
Cross-sectional	A type of research design in which researchers collect data at a single point in time (i.e. precluding observations across time).	Main Report, p. 39
Data donation	The process by which users manually download their personal data from the platform and donate it to researchers.	Main Report, p. 57
Data linkage	Combining data from different sources that relate to the individual. In the context of smartphone or social media research, this often relates to the collection of digital footprint data.	Main Report, p. 57
Difference-in-differences analysis	A quasi-experimental method used to estimate the causal effect of an intervention by comparing changes in outcomes between a treatment group and a control group, both before and after the intervention.	Main Report, p. 68
Delphi studies	A well-established approach to answering a research question through the identification of a consensus view across subject experts (Barrett & Heale, 2020).	Main Report, p. 72
Digital footprint data	The data left by an individual whenever digital technologies, especially the internet, are used. This includes both the information actively shared and that passively left behind.	Appendix 3, p. 243
Directed acylic graph (DAG)	A graph in which nodes are linked by one-way connections, with no cycles. It is used to illustrate dependencies and causal relationships, and visualise relationship between nodes representing data.	Main Report, p. 54
Ecological momentary assessment (EMA)	A research method involving collecting real time data from individuals in their natural environment, in order to study naturalised mood, thoughts and behaviours, thereby minimising recall bias and maximising ecological validity.	Main Report, p. 45
Eggers' regression	A statistical method used to detect publication bias in meta-analyses. Specifically, it assesses whether smaller studies tend to show larger effects than larger ones, which may indicate bias in the published literature (e.g. selective reporting of positive results).	Appendix 1, p. 99
Externalising symptoms	A subset of mental health issues where distress and negative feelings are directed outwards: aggression, rule-breaking, defiance.	Appendix 1, p. 119
Expectancy effects	A type of bias introduced when participant's awareness of the intervention affects outcomes.	Appendix 3, p. 239
Heterogeneity	The degree of variation in results across individual studies included in a systematic review or meta-analysis. Denoted in the text as I^2.	Appendix 3, p. 240

Internalising symptoms	A subset of mental health issues where distress and negative feelings are directed inwards: anxiety, depression, somatic complaints.	Main Report, p. 31
Mediator	A variable that explains how an independent variable affects a dependent variable in a system or relationship.	Appendix 3, p. 12
Meta-analysis	A quantitative synthesis of data from several independent studies on the same subject, in order to determine overall effects and trends.	Main Report, p. 48
Moderator	A variable that influences the strength or direction of the relationship between two other variables.	Appendix 1, p. 112
Natural experiment study/evaluation	An observational study where individuals are naturally exposed to different conditions as if they were randomly assigned to different experimental groups.	Appendix 1, p. 121
Newcastle-Ottawa Scale	A tool utilised to assess the quality of non-randomised studies in a meta-analysis or systematic review (Purba et al., 2023b; Wells et al. 2000).	Appendix 1, p. 112
Path-by-path analysis	Also known as causal modelling, this statistical technique is used only for models of observed, rather than latent, modelling. It is used to describe both the direct and indirect relationships between a set of variables, using diagrams to show these visually.	Appendix 1, p. 119
Pearson’s r	A correlation coefficient that denotes the strength and direction of the relationship between two variables, lying between -1 and 1. Presented in the text as r.	Appendix 1, p. 95
Preferred Reporting Items for Meta-analyses and Systematic Reviews (PRISMA) tool	A standardised checklist widely used to ensure researchers properly report the conduct of a systematic review or a meta-analysis.	Appendix 1, p. 114
Preferred Reporting Items for Overview of Reviews (PRIOR) tool	A standardised checklist widely used to ensure researchers properly report the conduct of an overview of reviews.	Appendix 1, p. 114
Preregistration	The practice by which a researcher records and publishes their research plan in advance, before beginning to collect data or analyse results. This is aimed to prevent bias through ‘cherry-picking’, making research more transparent, and trustworthy.	Main Report, p. 50
Probability Level	The likelihood that an observed result would be obtained if the null hypothesis (the assumption that there is no effect) were true.	Appendix 1, p. 94
Randomised Control Trial (RCT)	A scientific experiment where participants are randomly assigned to different exposure or intervention groups, with one group receiving the given intervention and the other serving as a control group. Commonly considered the gold standard for establishing causality.	Main Report, p. 28

Reverse causality	Changes in the outcomes of interest influence the exposure of interest, rather than the other way around.	Main Report, p. 29
Sampling weights	A statistical technique by which underrepresented groups are assigned greater weight in analyses to better reflect the wider population.	Appendix 3, p. 224
Selection bias	A type of sample bias that arises from how subjects are selected (or self-select) into the study, leading to skewed results.	Appendix 3, p. 229
Sensitivity analysis	A statistical test used to understand how changes in model variables affect outcomes, helping identify how the outcome might change when those variables are varied, and therefore which variable is most critical to the outcome.	Appendix 1, p. 16
Social desirability bias	A type of bias that occurs when respondents provide answers they perceive as socially acceptable, rather than being honest. This systematically leads to the under-reporting of socially ‘undesirable’ behaviours or outcomes.	Main Report, p. 22
Social media	Defined as ‘websites and applications that allow users to create and share content or to participate in social networking’.	Appendix 1, p. 13
Smartphones	Defined as portable cellular devices with internet access and capacity to host applications.	Appendix 1, p. 13
Stakeholder engagement	The process of involving all individuals or groups who are affected by a given policy in design of the given project, policy or decision.	Appendix 3, p. 29
Standing participant pools	Pools of pre-screened participants across different demographic groups who have provided baseline data and confirmed their willingness to participate in rapid response research.	Appendix 3, p. 39
Subgroup analysis	A statistical technique used to examine whether the effects of an intervention, treatment or exposure change across different groups within a population.	Appendix 1, p. 132
Synthetic datasets	Privacy-preserving datasets based on original smartphone data, which uses techniques such as machine learning to create a new dataset that retains the utility of the original dataset.	Appendix 3, p. 244
Target trial approach	A framework for designing observational studies to emulate the features of a hypothetical RCT, thereby allowing for better estimation of the causal effects of intervention.	Main Report, p. 54
Technological affordances	Potential tasks and activities users can perform with new technologies.	Main Report, p. 30
Triangulation	Combining multiple sources, methods or perspectives to increase the validity and reliability of findings.	Main Report, p. 37
Trim-and-fill	An analysis method used in meta-analyses to estimate how many studies	Appendix 1, p. 99

	might be ‘missing’ — usually those with less favorable or non-significant results — and adjust the overall findings to give a more accurate picture (Lin et al., 2018).	
Young person advisory groups	Providing funding to support dedicated youth groups that help ensure the perspectives of research participants are heard and meaningfully integrated throughout the research process.	Main Report, p. 76

Appendix 7: Causal Approaches Table

Classification System for Table 3 in Main Report

Cost Considerations: Cost was assessed in terms of total project budget, informed by personnel requirements, data access costs, technological infrastructure, and the scale of participant involvement. Lower-cost methods typically relied on existing data or small-scale qualitative work. More resource-intensive methods included those requiring real-time data tracking, participant recruitment across large samples, or bespoke technical solutions (e.g. custom apps, wearable integration or experimental platforms).

Ethical Risk: The ethical risk was judged based on the sensitivity of data collected, the degree of intrusion into participants' lives, and the vulnerability of the population involved. Methods that involve passive data collection, real-time monitoring or that target young people in sensitive contexts were seen as requiring more robust ethical safeguards. Considerations included the difficulty of achieving informed consent, risks of distress, challenges in anonymising data and the adequacy of safeguarding protocols. Where methods used only de-identified, publicly available or previously consented data, ethical risks were deemed substantially lower.

Extended Table 3

Methods	Description	Benefits	Challenges	Ethical Consideration	Cost Consideration
Method 1. Systematic Reviews of Pre-Existing Literature	Systematic reviews and meta-analyses are considered the gold standard for evaluating the strength, consistency and reliability of pre-existing evidence. They involve a transparent, structured search and synthesis of relevant literature. Meta-analysis specifically quantitatively combines effect sizes from	• Cost effective by pooling existing literature. • Enhances statistical power and generalisability by aggregating findings across multiple studies. • Allows for the identification of research gaps.	• Poor-quality studies can skew results and limit the effectiveness of reviews. • Limited studies available on the topic of interest will restrict the applicability of systematic reviews to inform policy decisions. • Reviews are not inherently causal; they approximate causality	• Low ethical risk as they do not involve primary data collection, but adherence to standardised guidelines like PRISMA and preregistration would boost transparency. • Ethical safeguards include declaring conflicts of interest, double-coding quality assessments by at least	Approximate total cost of project: £250,000–£400,000 Major factors that determine cost level: 1. Extent of literature under review. 2. Number of different sub-analyses requested.

	multiple studies to produce an overall estimate.		from previous studies, which can be difficult when studies don't achieve high levels of causal inference.	two reviewers, and ensuring consistency throughout the review process.	3. Use of GRADE methodology.
Method 2. Qualitative approaches and interviews	Qualitative approaches, such as interviews and thematic analysis do not establish causality alone. However, when adequately designed, they can complement existing causal research by 1) refining causal hypotheses by elucidating underlying mechanisms, and 2) generating new theories that can be tested subsequently in studies designed with causal inference in mind.	• Low-cost. • Qualitative methods provide valuable insights into participants' perspectives. • The integration of qualitative and quantitative approaches allows for the generation of rich primary data that can elucidate the underlying mechanisms between exposure and outcome. • Qualitative approaches can help integrate views of vulnerable populations, pinpointing important contextual factors or the significance of social media platform features.	• Are exploratory when used alone and do not provide causal inference. • Typically involve rich, in-depth research on a small sample, meaning findings may not be easily generalisable. • Due to its subjective nature, qualitative research needs strategies (e.g. reflexivity, transparency) to enhance validity and reliability, especially compared to more objective statistical or experimental methods. • Conducting qualitative research can be time and labour intensive.	• Low to medium ethical risk. • Consent and assent must be obtained, either opt-in or opt-out depending on risk. • Distress and safeguarding protocols needed, particularly when discussing sensitive topics. • Researchers must ensure appropriate support, especially for children and young people, with schools offering potential safeguarding structures. • Sharing qualitative data requires caution, ensuring full anonymisation is challenging.	Approximate total cost of project: £250,000–£600,000 Major factors that determine cost level: 1. Type of qualitative research methods applied. 2. Diversity and representativeness of populations studied, and the proportion of which is 'hard to reach' (e.g. care experienced children).
Method 3: Observational Analysis Using	This method uses pre-existing observational data from cohort studies, health surveys, or	• Cost and time-efficient, reducing the need for new data collection.	• Lack of high-quality and precise digital trace data in UK cohorts.	• Low ethical risk since data is already collected and managed by	Approximate total cost of project: £400,000–£800,000

Existing National Data Assets	administrative datasets to track trends and identify long-term patterns.	• Large sample sizes enhance statistical power, supporting generalisable findings and subgroup analysis. • Provides long-term insights into the effects of social media and identifies early risk factors. • Combined with DAGs, this approach produces high-quality, transparent research that can inform policy decisions.	• Established cohorts are aging, and new cohorts are still in early stages, reducing their ability to provide timely insights on child and adolescent age groups. • Additional challenges like lack of experimental controls, confounding variables, slow adaptability to new research questions and high participant attrition, which affects reliability.	experienced research teams. • Ethical safeguards include informed consent, participant withdrawal rights, data anonymisation, strict GDPR compliance, and ongoing audits to ensure privacy and data security throughout the research process.	Major factors that determine cost level: 1. Type of observational data analysis applied (which will determine expertise and size of team required). 2. Number of different analyses requested. 3. Data access costs for observational datasets.
Method 4: Augmenting existing observational or cohort datasets	This method augments existing cohort/panel datasets with precise, objective digital behaviour measures. It aims to improve causal inference by addressing limitations of self-reported, infrequent exposure data. Methods include data donation,* passive smartphone sensing, and GDPR-enabled APIs, enabling researchers to fuse rich behavioural data with existing self-reports and health records.	• Builds on strengths of Method 3 while addressing limitations. • Enables granular analysis of how specific patterns of digital technology use relate to short- and long-term outcomes. • Existing pilot efforts exist to integrate objective digital metrics into cohorts. • Scalable potential for rollout across cohorts if funding and	• High participant burden due to tracking apps, continuous data collection or frequent surveys. • Intrusiveness and privacy concerns may lead to opt-out or disengagement, risking low representativeness. • Requires significant infrastructure investment and logistical challenges. • Data donation* faces issues like incomplete data and reliance on	• High ethical concerns due to risks around privacy, data misuse, and sensitive information being collected, often passively without full participant awareness. • High effort means vulnerable groups may be underrepresented. • Clear, informed consent processes, strong data anonymisation and security, efforts to ensure diverse participation and systems to detect and	Approximate total cost of project: £500,000–£1,500,000 Major factors that determine cost level: 1. Type of linkage mechanism. 2. Number of participants linked. 3. Amount of linkage points. 4. Infrastructure and personnel costs for different large-scale datasets.

		prioritisation issues are addressed.	unstable third-party platforms. - Complex data requires advanced processing. - Not quick to deliver.	respond to serious harms all needed.	5. Alignment of digital trace data collection with pre-existing data asset strategic priorities.
Method 5: Ecological Momentary Assessment Studies	Ecological Momentary Assessment (EMA) capture individual' daily experiences and behaviours using short-term questionnaires often on a smartphone. It often complements traditional longitudinal designs by offering high-resolution data on immediate experiences. Temporal design of EMA can enhance causal inference, especially when combined with techniques like DAGs, experimental designs or objective digital use tracking.	- Reduces recall bias by capturing real-time outcomes. - Enhances ecological validity by collecting data in natural settings, providing insights into real-life emotions, behaviours and contexts. - Produces rich short-term datasets, allowing for within-person analysis, useful for identifying vulnerabilities and tracking intervention effects.	- EMA provides limited causal inference, remaining correlational without experimental designs and advanced modelling (e.g. DAGs). - EMA relies on smartphone access, limiting participation among younger children and potentially introducing sampling bias. - School restrictions on smartphone use could compromise data validity. - Challenges if linked with complex digital or health data, requiring expertise, funding and secure infrastructure.	- Medium ethical risk, varying with design factors (e.g. passive technology data collection). - Collecting objective digital or health data raises ethical and security concerns, requiring transparent planning, strict safeguards, and may be perceived as invasive. - Access and participant burden must be managed, protocols can be codesigned to ensure feasibility. - Data management, safeguarding and risk management protocols needed. - Careful balancing of participant burden against study benefit needed.	Approximate total cost of project: £300,000–£500,000 Major factors that determine cost level: 1. Smartphone EMA app (cost per participant) and whether objective tracking assessment is required. 2. Vouchers for participation. 3. Analyses required and linkage to other objective data. 4. Researcher expertise.

Method 6: Natural Experiment Studies	Natural experiment studies use real-world events or policy changes (e.g. platform restrictions) to create conditions like experimental and control groups. They approximate randomisation, reducing confounding and isolating the impact of digital media from individual differences.	• Provide stronger causal inference with real-world, quasi-randomised exposure. • Cost-efficient by utilising existing data, though new data may be needed for tracking outcomes before and after interventions.	• Rely on external events or policy changes, which may not align with research needs. • High-quality, high-frequency outcome data is often unavailable. • Researcher expertise is needed for valid evaluation, and unmeasured confounders still pose a risk, even with statistical methods like difference-in-differences analysis. • Concurrent changes beyond the natural experiment may complicate isolating the effects of the natural experiment.	• Low ethical risk as they observe participants in existing conditions, without researcher-imposed interventions. • Researchers must comply with data protection laws (e.g. GDPR) and manage data-sharing agreements to ensure responsible use of pre-existing or third-party data.	Approximate total cost of project: £500,000–£1,000,000 Major factors that determine cost level: 1. Whether there is pre-existing data available to monitor impact of natural experiment. 2. If the natural experiment has not yet occurred, but will, substantial costs can arise if more data collection is required.

Method 7: Randomised Controlled Trials (RCTs)	RCTs are considered gold standard for assessing causal relationships, involving random assignment to different intervention arms, which allows researchers to control for confounding. The method ensures balanced distribution of characteristics across groups, which allows causal effects to be attributed to interventions. Multi-arm RCT** approaches can test various interventions in one study.	• RCTs eliminate bias and confounding, isolating the causal effect of an intervention and providing strong evidence for causal relationships. • They offer a controlled environment to pilot interventions or policies, allowing researchers to fine-tune and link interventions to causal pathways. • Multi-arm RCTs** can enable the comparison of multiple interventions within a single study.	• RCTs may not be feasible for some topics and often face challenges in intervening directly in children's lives. • Recruitment can be biased. • Pilot trials are often required to assess feasibility. • Often expensive, logistically complex, and take time to design and implement. • Difficult to complete quickly in fast-moving areas like online safety, thus findings risk becoming outdated. • Results from small-scale or short-term interventions may not reflect effects at national scale or over longer periods. • Those RCTs that take communities into account will need much bigger samples to achieve statistical power.	• RCTs carry ethical risks as interventions that restrict social media use may negatively affect mental health and handling sensitive data (e.g. mental health, personal habits) raises privacy concerns. • Ethical safeguards include adverse event monitoring, secure data storage, anonymisation, and informed consent, with a focus on transparency, especially for studies involving children or vulnerable populations.	Approximate total cost of project: £2,000,000–£4,000,000 Major factors that determine cost level: 1. Whether feasibility/acceptability study is needed before main RCT. 2. Type of RCT applied, e.g. single or multi-arm RCT and simple or cluster RCT. 3. If complex interventions are studied.

***data donation:** a process whereby individuals voluntarily share data from their social media accounts or smartphone usage, either via manually uploading and sharing it with research, or with newer application programming interface (API) approaches that allow automatic collection of data in a structured and automated manner.
****multi-arm RCT:** randomised experiments in which individuals are randomly assigned to one of multiple treatment, exposure or intervention variants. It allows for the efficient evaluation of multiple interventions within a single-trial framework.

Appendix 8: ICMJE Conflict of Interest Disclosure Forms

Amy Orben

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: Amy Orben

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Paid to my institution
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		Jacobs Foundation	Paid to my institution via the CERES Network
		UK Research and Innovation (incl. Medical Research Council, Economic and Social Research Council and Engineering and Physical Sciences Research Council)	Paid to my institution
		National Institute of Health	Paid to UC Irvine and to myself through consultancy payments
		University of Cambridge	Paid to my institution
		Livelihood Impact Fund	Paid to my institution
		Emmanuel College, University of Cambridge	Paid to my institution
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☐ **None**	
		Digital Futures for Children Centre, London School of Economics and Political Science	Payment to myself for membership of advisory committee
		Opalescent LTD	Payment to myself, funded by Innovate UK
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☐ **None**	
		SWGfL	Payment to myself for panel attendance (November 2023)
		Apple University	Payment to myself for lecture (September 2023)
6	Payment for expert testimony	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
7	Support for attending meetings and/or travel	☒ **None**	
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☐ **None**	
		Digital Futures for Children Centre, London School of Economics and Political Science	Advisory board member, paid (see above)
		ESRC Smart Data Research UK	Programme Board member, unpaid
		British Academy	Public Policy Committee member, unpaid
		UK Department for Education	Science Advisory Council member, unpaid
		UK Department for Science, Innovation and Technology	College of Experts member, unpaid
		UK Department for Digital, Culture, Media & Sport	College of Experts member, unpaid
		Australian eSafety Commissioner	eSafety Social Media Minimum Age Evaluation Academic Advisory Group member, unpaid
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	
		Meta Inc.	Working dinner with agenda and guest list with a group of researchers and Nick Clegg at Magenta Restaurant/The Megaro Hotel, London, on the topic of "Data Sharing for Researchers" (December 2022, approximate value £75)
		Parent Zone	Working dinner with agenda and guest list before Digital Families Conference at Sea Containers Restaurant, London (October 2022, approximate value £60)

Please place an "X" next to the following statement to indicate your agreement:

☒ I certify that I have answered every question and have not altered the wording of any of the questions on this form.

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: Amrit Kaur Purba

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

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Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Payment made to my institution
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		Huo Family Foundation Pilot Grant	G132182 payment made to institution
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☐ **None**	
		Anthropy 2025 Conference	Payment to act as a panelist for session on media and misinformation on social media
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☐ **None**	
		Medical Research Council support to attend: -LSE Roundtable on social media harms -Centre for Countering Digital Hate Roundtable on social media harms -Home Office and No 10 Downing Street Roundtables on social media and knife crime	MC_UU_00030/13 payments made to institution

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☐ **None**	
		UK Department for Education	Unpaid technical advisory board member
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☐ **None**	
		UK Government	Unpaid Anti-Knife Crime Coalition member
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
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ICMJE DISCLOSURE FORM

Date: 4/30/2025

Your Name: Ioanna Fokas

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

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1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Payments were made to my institution, The University of Cambridge.
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒ I certify that I have answered every question and have not altered the wording of any of the questions on this form.		

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: Lukas J. Gunschera

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

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The author’s relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

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Time frame: Since the initial planning of the work			
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		Medical Research Council Studentship	
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☐ **None**	
		Medical Research Council, Cognition and Brain Sciences Unit	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☐ **None**	
		Wolfson College, Cambridge	
		Medical Research Council	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

Department for
Science, Innovation,
& Technology

UNIVERSITY OF
CAMBRIDGE

Zhuo Yao Yap

ICMJE DISCLOSURE FORM

Date: 5/1/2024

Your Name: Zhuo Yao Yap

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. “Related” means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author’s relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Payments were made to my institution, University of Cambridge
		UKRI Medical Research Council	Paid to the department for the project led by Dr. Amy Orben. Core funding, code SUAG/091
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

Brandon Davidson

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: Brandon Davidson

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. “Related” means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author’s relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UKRI Medical Research Council	Paid to the department for the project led by Dr. Amy Orben. Core funding, code SUAG/091.
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date:	5/1/2025
Your Name:	Dr Oliver Davis
Manuscript Title:	Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People
Manuscript Number (if known):	N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Consulting payment to the University of Bristol
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: David A. Ellis

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Consulting payments made to me.
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		ESPRC 'Co-designing technological solutions to loneliness with at-risk Populations' - additional funds allocated from LEAP.	Payments made to my institution
		EPSRC 'LEAP (Leadership Engagement Acceleration & Partnership) - an EPSRC Digital Health Hub'	Payments made to my institution
		EPSRC 'Data donation for digital citizens' – extension of REPHRAIN	Payments made to my institution
		EPSRC 'Footprints to emissions: Exploring near-future digital vulnerabilities with creative methodologies'	Payments made to my institution
		EPSRC 'REPHRAIN: Research center on Privacy, Harm Reduction and Adversarial Influence online'	Payments made to my institution
3	Royalties or licenses	☐ **None**	
		Cambridge University Press	Royalty payments made to me
		ALCS	Royalty payments made to me
4	Consulting fees	☐ **None**	
		We Adapt	Consultancy fees paid to me
		Duco	Consultancy fees paid to me
		Plexal	Consultancy fees paid to me
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☐ **None**	
		BBC	Contribution payments made to me
		Girton College Cambridge	Reviewer payments made to me
		UKRI	Interdisciplinary Assessment College (IAC) payments made to me

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☐ **None** External Advisory Board: Wellcome-funded project at Lancaster University ’Reimagining research practices: toward a sustainable, ethical and inclusive future’	Honoraria payments made to me
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☐ **None** Chair	Social Sciences Research Ethics Committee (University of Bath)
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs,	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
	medical writing, gifts or other services		
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

☒ I certify that I have answered every question and have not altered the wording of any of the questions on this form.

Victoria Goodyear

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: Victoria Goodyear

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	All funding was paid to The University of Birmingham
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		NIHR	NIHR Public Health Research Programme funding was received for the reported work (NIHR131396). All funding is paid to The University of Birmingham.
		Alumni / Daro Funding	Philanthropic funding from David and Vicky Gill for the School Phone Policies and Practices Study (SPPP). All funding is paid to The University of Birmingham.
		ESRC/ Centre-UB	Starting School Study. All funding is paid to The University of Birmingham.
		ESRC	Project Safety Net. All funding is paid to The University of Birmingham.
		Research England	SMS Study. All funding is paid to The University of Birmingham.
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☐ **None**	
		DfE	TAG Member Growing up in the 2020s. Unpaid.
		ukactive	Advisory role and panel speaker; Active Uprising Event, Anxious Generation. Unpaid.
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
	writing, gifts or other services		
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

☒ I certify that I have answered every question and have not altered the wording of any of the questions on this form.

Claire Haworth

ICMJE DISCLOSURE FORM

Date: 5/1/2025

Your Name: Professor Claire Haworth

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

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		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Consulting payment to the University of Bristol
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 5/1/2025

Your Name: Professor Chris Hollis

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

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		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	CONSULTING PAYMENT MADE TO ME PERSONALLY BY CAMBRIDGE UNIVERSITY TECHNICAL SERVICES LTD
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		National Institute of Health Research (NIHR)	HealthTech Research Centre (HRC) for Mental Health (MindTech) - Director
		UKRI/Medical Research Council	Adolescent Mental Health and the Developing mind: Digital Youth Programme – Co-lead
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☐ **None**	
		UKRI Mindset XR Support Programme Advisory Board (Managed by Health Innovation Network – South London)	Advisory Board Co-Chair (unpaid)
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☐ **None**	
		NHS England – Digital Mental Health Innovation Group	Committee member (unpaid)
		National Institute of Health and Clinical Excellence (NICE) – Expert Advisor on digital mental health	Early Value Assessment (EVA) expert committee member (unpaid)
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 5/8/2025

Your Name: Adam Joinson

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Consulting payment to personal company
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		UKRI REPHRAIN	University of Bath
		UKRI Discribe Hub+	University of Bath
		UKRI / DSTL Cyber statecraft	University of Bath
		HMG Trust project	University of Bath
		UKRI CRANE Network Plus	University of Bath
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 5/4/2025

Your Name: Srinivasa Vittal Katikireddi

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	
		Medical Research Council	To institution: MC_UU_00022/2
		Scottish Government Chief Scientist Office	To institution: SPHSU17
		European Research Council	To institution: 949582
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☐ **None**	
		Obesity Action Scotland	Member of steering committee; provide unpaid advice on evidence for effective actions to address obesity
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an “X” next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 5/2/2025

Your Name: Sonia Livingstone

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

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		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	I believe I will receive £1250
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		MRC (DIORA) grant for Digital Youth	Payment to my institution
		ESRC grant for PlatFAMs project (via CHANSE)	Payment to my institution
		Digital Futures for Children grant from 5Rights Foundation	Payment to my institution
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☐ **None**	
		Advisory board for European Digital Media Observatory	Payment to me as consultant (I believe £4000)
		Wavestone (advising their consultancy for the European Commission)	Payment to me as consultant (I believe £3000)
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None** none	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 4/30/2025

Your Name: Margarita Panayiotou

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

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The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

In item #1 below, report all support for the work reported in this manuscript without time limit. For all other items, the time frame for disclosure is the past 36 months.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
		Time frame: Since the initial planning of the work	
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Payments were made to me
			Click the tab key to add additional rows.
		Time frame: past 36 months	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☒ **None**	
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

ICMJE DISCLOSURE FORM

Date: 4/29/2025

Your Name: Andrew K. Przybylski

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

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		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	One time honorarium.
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		Huo Family Foundation Research Grant	Paid to institution, research support 2020-2025
		ESRC Understanding Video Game Play and Mental Health	Paid to institution, research support 2023-2025
		ESRC Capturing the Digital Footprints of Video Game Play	Paid to institution, research support 2024-2025
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☐ **None**	
		Scientific Advisor, Sync Digital Wellbeing Program	October 2022 to December 2024
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☐ **None**	
		Panelist, FOSI European Forum	Department reimbursement for travel and lodging to participate in panel in June 2023

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
		Editorial board member, Instagram data access pilot for well-being research	Unpaid role evaluating research proposals and projects linking independent researchers with industry data.
		Member of UK DCMS College of Experts	Unpaid role providing expert advice to DCMS CSA and dept civil servants.
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☒ **None**	
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)

☒ I certify that I have answered every question and have not altered the wording of any of the questions on this form.

ICMJE DISCLOSURE FORM

Date: 5/6/2006

Your Name: Professor Ellen Townsend

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

The author's relationships/activities/interests should be defined broadly. For example, if your manuscript pertains to the epidemiology of hypertension, you should declare all relationships with manufacturers of antihypertensive medication, even if that medication is not mentioned in the manuscript.

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		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☐ None	
		UK Department for Science, Innovation and Technology	Consultation fee to be claimed personally.
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☐ **None**	
		UKRI	Digital Youth Programme (co-PI)
		NIHR	MindTech (CI)
		Garfield Weston Foundation	Capital Award for Connect Nottingham (PI)
3	Royalties or licenses	☐ **None**	
		First Majorcan Symposium on self-harm in teenagers	Travel, subsistence and Honoria payment made directly to me.
4	Consulting fees	☐ **None**	
		West Sussex County Council	Paid to institution.
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☐ **None**	
		Honoraria for First Majorcan Symposium on self-harm in children and teenagers.	Travel, subsistence and Honoria payment made directly to me.
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☐ **None**	
		Honoraria for First Majorcan Symposium on self-harm in children and teenagers.	Travel, subsistence and Honoria payment made directly to me.

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☒ **None**	
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☐ **None**	
		Collateral Global	Unpaid
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☐ **None**	
		Storm skills Training donation to Self-Harm Research Group	My institution
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

	Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
☒	I certify that I have answered every question and have not altered the wording of any of the questions on this form.	

David Zendle

ICMJE DISCLOSURE FORM

Date: 5/1/2025

Your Name: David Zendle

Manuscript Title: Feasibility Study of Methods and Data to Understand the Impact of Smartphones and Social Media on Children and Young People

Manuscript Number (if known): N/A

In the interest of transparency, we ask you to disclose all relationships/activities/interests listed below that are related to the content of your manuscript. "Related" means any relation with for-profit or not-for-profit third parties whose interests may be affected by the content of the manuscript. Disclosure represents a commitment to transparency and does not necessarily indicate a bias. If you are in doubt about whether to list a relationship/activity/interest, it is preferable that you do so.

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		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
Time frame: Since the initial planning of the work			
1	All support for the present manuscript (e.g., funding, provision of study materials, medical writing, article processing charges, etc.) No time limit for this item.	☒ None	
		UK Department for Science, Innovation and Technology	Consulting payments will be given to myself (not my institution)
			Click the tab key to add additional rows.
Time frame: past 36 months			

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
2	Grants or contracts from any entity (if not indicated in item #1 above).	☒ **None**	
3	Royalties or licenses	☒ **None**	
4	Consulting fees	☐ **None**	
		Federal Trade Commission (USA)	Consulting payments for work on a regulatory enforcement matter in the digital sector (gaming). Matter is closed. Payments made to myself.
		PUBLIC / Department for Culture, Media, and Sport (UK)	Consulting payments from DCMS (via PUBLIC, a public sector consultancy) for consultancy relating to regulation in the video game sector. Consultancy is ongoing. Payments will be made to my institution (University of York), profit sharing with myself. I have not yet received any payments for this matter.
		Omidyar Network (USA)	Consulting payments for expert advice on the video game sector. Matter is closed. Payments made to myself.
5	Payment or honoraria for lectures, presentations, speakers bureaus, manuscript writing or educational events	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	Specifications/Comments (e.g., if payments were made to you or to your institution)
6	Payment for expert testimony	☒ **None**	
7	Support for attending meetings and/or travel	☒ **None**	
8	Patents planned, issued or pending	☒ **None**	
9	Participation on a Data Safety Monitoring Board or Advisory Board	☐ **None**	
		UK Gambling Commission	I am now interim chair (and formerly was an ordinary member of) the Advisory Board for Safer Gambling, the statutory body which provides independent advice to the Gambling Commission regarding safety. I am remunerated directly (i.e. payments are given to myself) for this role.
10	Leadership or fiduciary role in other board, society, committee or advocacy group, paid or unpaid	☒ **None**	

		Name all entities with whom you have this relationship or indicate none (add rows as needed)	**Specifications/Comments (e.g., if payments were made to you or to your institution)**
11	Stock or stock options	☒ **None**	
12	Receipt of equipment, materials, drugs, medical writing, gifts or other services	☐ **None**	
		Global Action Plan	I unexpectedly received a food hamper (approximate value £20-£50) as a thank you, following unpaid advice I gave to Global Action Plan regarding a campaign on online misogyny / the manosphere that they ran with Vodafone.
13	Other financial or non-financial interests	☒ **None**	

Please place an "X" next to the following statement to indicate your agreement:

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