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Social media use and emotional and behavioural outcomes in adolescence: Evidence from British longitudinal data

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ABSTRACT

We investigate the relationship between social media use and emotional and behavioural outcomes in adolescence using data from a large and detailed longitudinal study of teenagers from the UK. We use individual fixed effects, propensity score matching and treatment effects with Inverse Probability Weighted Regression Adjustment, controlling for a rich set of children's and family's characteristics and using comprehensive sensitivity analyses and tests to assess the potential role of unobserved variables. Our results show that prolonged use of social media (more than 4 hours per day) is significantly associated with poor emotional health and increased behavioural difficulties, and in particular decreased perception of self-value and increased incidence of hyperactivity, inattention and conduct problems. However, limited use of social media (less than 3 h per day) compared to no use has some moderate association with positive peer relationships.

1. Introduction

Social media are an important part of teenagers' lives throughout the world, with young people being extensive users of social media sites, such as Youtube, Facebook, Instagram, Whatsup and Snapchat. For example, almost 95 % of British 15 years old used social media outside school hours (OECD, 2016) and the proportion of young people spending extended hours on social media on school days has dramatically increased in the last 5 years (ONS, 2017, 2018; Frith, 2017; Royal Sociey for Public Health, 2018). Further, children and young people are likely to access the internet and use social media privately, using mobile devices from their bedrooms, without any form of adult supervision (Frith, 2017).

Poor emotional well-being in adolescence has several long lasting consequences and economic implications. Young people with mental health conditions are more likely to experience difficulties in their education (through increased chances of suspensions, exclusions, etc), poor engagement in the labour market (increases chances of unemployment and dependence on welfare), and are more likely to engage in criminal activities (see for example Currie and Stabile, 2006; Goodman et al., 2011; Lundborg et al., 2014; Anderson et al., 2015; Khan et al., 2015; Knapp et al., 2016; among many others, for discussion of the impact of mental health conditions in childhood and adolescence on later life outcomes).

The widespread use of internet and social media could constitute an opportunity for innovation, socialization and learning, through interaction with peers with similar interests, sharing information on sensitive topics, and can be a vehicle of collaboration and involvement with the community. On the other hand however, it can also facilitate transmission of harmful content, such as the spreading of cyber bullying and peer pressure, which can affect sleep patterns, perception of body image, and ultimately can result in increased stress and anxiety (House of Commons, 2019). For these reasons, policy makers and researchers in public health have voiced serious concerns about the potential implications for young people's mental well-being (Royal Society for Public Health, 2018). Evidence of social media addiction affecting around 5 % of young people has emerged (Centre for Mental Health, 2018), and concerns surrounding social media and young people have been debated in multiple domains (see for example, Parliamentary discussion in Britain in 2016; House of Commons, 2019).

The analysis of teenagers' and young adults' mental well-being is especially relevant for the UK and most likely many other countries. Several studies in the UK show that mood disorders in young people have increased dramatically in recent years,

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particularly among girls and young women (see Collishaw, 2015; Knapp et al., 2016; and Gunnell et al., 2018, among many others). Recent evidence has suggested that one in ten children and young people has some form of diagnosed mental health disorder, with 6 % of British children having conduct disorder, 3 % having anxiety, 1 % having depression, and between 1 and 3 % with other disorders (Department of Health, 2017). Self-harm among adolescents has steadily increased over the last decade (for example Morgan et al., 2017 describe a 68 % increase in cases of hospital self-harm presentations in teenage girls between 2011 and 2014). Further, over three quarters of mental illness in adult life starts in adolescence (Knapp et al., 2016).

Evidence on the possible causal relationship between social media exposure and adolescents' well-being is still relatively scarce and most of the existing literature uses cross-sectional data, without necessarily considering the importance of unobserved individual characteristics. For this reason, several studies have pointed out that more research is needed in order to fully understand the potential impact of social media use on young people's lives (Gunnell, 2018; Frith, 2017; Royal Society for Public Health, 2018; House of Commons, 2019 provide comprehensive reviews of existing descriptive evidence).

Identifying the causal pathways that make up the transmission mechanism through which high levels of social media use operate on mental well-being is however a very complex task. There are a variety of channels through which social media use can affect adolescents' well-being and mental health.

In the health psychology literature, a number of theories have been advanced to explain the associations and potential causal pathways between time spent on social media and mental health issues during adolescence. Coyne et al. (2020) describe two widely used theories. The first, *the displacement hypothesis* (Lin, 1993) suggests that time spent engaging with social media might displace other health behaviours that might boost mental health, or protect against reductions in mental health, such as sleep (Scott and Woods, 2018), face-to-face time with friends (Twenge, 2017), or other productive activities (Wallsten, 2013). This hypothesis is usually taken to suggest that greater social media use could be a causal factor in the development of later mental health problems. However, viewed more broadly, it is a specific example of the *opportunity cost* concept within economics, with the implication that social media use may also displace activities that are also harmful to mental health, e.g. crime, drug use and excessive alcohol intake.

The second hypothesis builds on *uses and gratifications theory* and suggests that social media use amongst people with poor mental health use might be a utility maximising strategy (Quan-Haase and Young, 2010). The assumption is that each individual chooses to engage in certain types of media to fulfil certain needs, motivated in part to escape other problems in life (Coyne et al., 2013). The prediction is that individuals experiencing depression and other mental health conditions may be more likely to make greater use of social media as a self-management strategy, aiming to manage their symptoms and improve well-being. However, whether such use is harmful or helpful for mental health outcomes is left unresolved, and is ultimately an empirical question. The conventional wisdom to date has been that long hours of social media exposure may do more harm than good, as it may disrupt sleeping patterns, increase the risk of online bullying, and contribute to increased peer pressure, fear of missing out and feelings of inadequacy (Fardouly et al., 2015; Woods and Scott, 2016; Nesi et al., 2017; Booker et al., 2018; Kelly et al., 2018; Viner et al., 2019).

More recently developed is an alternative theory that suggests a potentially positive role for social media use. This is built around the "everything in moderation" argument and has been named the *Goldilocks Hypothesis* (Przybylski and Weinstein, 2017). This suggests that modest screen use can be positive for mental health where screen use is common within society, or more specifically, amongst peers. However, over-engagement can be problematic and harmful, due to displacement of health-promoting behavioural activities such as sleep, as can under-engagement, as it may reduce time spent in the production and maintenance of social relationships (see Przybylski and Weinstein, 2017). This suggests a potential non-linear relationship could exist between the likelihood of experiencing mental health problems and the amount of social media use.

Addressing the above hypotheses, we build on the developing evidence examining the existence of non-linear associations, and assess the extent to which different levels of exposure to various forms of social media are related to changes in emotional and behavioural outcomes.

More specifically, we contribute to the existing literature on social media and adolescents' well-being in several ways. First, we focus on the intensity of social media use, and compare the different effects of various levels of exposure on well-being, captured by number of hours spent on social media each day.

Second, we extend the existing literature from epidemiology, public health and social sciences by analysing the relationship between social media use at age 11–14 and mental well-being at age 16–20 years old using rigorous estimation techniques that account for individual unobserved heterogeneity. Many existing studies analyse contemporaneous correlations between social media use and outcomes, and do not take into account the existence of unobserved time invariant characteristics (see for example Kelly et al., 2018, among many others). Further, cross sectional estimates can be biased because of the existence of omitted variables (Wooldridge, 2010), with unobserved characteristics such as personality traits, attitudes, or family values affecting both social media use and outcomes (Suzidelyte, 2015). We explicitly consider this possibility and estimate models using individual fixed effects.

Third, we take advantage of the richness of the longitudinal data available in Understanding Society and expand the analysis of the effect of social media by considering new outcomes, in particular focusing on the relationship between social media use and emotional and behavioural difficulties.

Fourth, we analyse the heterogeneity of the effect of social media, by studying the impact by gender, age, and socio-economic background of the child, and therefore shed some light on the possible policy implications of our findings, by identifying the most vulnerable groups.

Lastly, we test the robustness of our findings by using propensity score matching and treatment-effects with inverse-probability-weighted regression-adjustment (IPWRA) (Imbens and Wooldridge, 2009; Cattaneo et al. (2013), which allow robust comparisons of individuals who are similar based on observable characteristics but differ in their social media use.

The rest of the paper is organised as follows. Section 2 provides a brief review of the most relevant existing work. Section 3 describes our data, Section 4 outlines our estimation methods, Section 5 presents results, and Section 6 discusses the results.

2. Review of existing literature

Several studies in public health and epidemiology have analysed the relationship between social media use and indicators of mental health and well-being, producing mixed results (Royal Society for Public Health, 2018; Booker et al., 2018). The main drawback with many of these studies is that they do not directly take into account the possibility that unobserved characteristics or other confounders (such as, for example, personality traits, ability, family values and beliefs, etc.) could explain the relationship between social media use and well-being. These characteristics could make an individual more likely to use social media and have poor mental well-being. This is a major limitation and substantially reduces the possibility to draw causal inferences from the existing literature.

Recent evidence from experimental psychology highlights the importance of longitudinal data to analyse these issues, and has showed that results change substantially (more specifically, the relationship between technology use and well-being is lower) when longitudinal data are used (Orben et al., 2019; Orben, 2020). It is argued therefore that large scale data and more complex data analysis is needed to derive clearer results and conclusions (Orben and Przybylski, 2019a).

However, evidence from longitudinal data is now beginning to emerge. For example, a recent comprehensive systematic literature review assessed the relationship between different forms of social media use and mental health and well-being among adolescents (Schønning et al., 2020). Amongst the 79 studies that were identified and reviewed, 17 reported results using longitudinal data. Amongst these, three studies assessed the relationship between social media use and at least one of the specified health and well-being outcomes considered in this paper. First, Frison and Eggermont (2017) assessed the relationship between different types of Instagram use (i.e., browsing, posting, and liking) and adolescents' depressed mood (using the CES-D scale) amongst 671 participants. They found a higher probability of developing greater depressed mood occurred amongst users with more frequent Instagram browsing, and that adolescents were more likely to post more on Instagram when they had higher depressed mood. Second, Houghton et al. (2018) evaluated whether there were associations between screen media use (social networking platforms and internet gaming) and subsequent depressive symptomatology, and vice versa. Using six waves of data from Western Australia over 2 years, collected among 1749 adolescents aged between 10–17 years of age, a Random Intercept Cross Lagged Panel Model revealed statistically significant, but small, cross-lagged effects for total screen time and symptoms of depression, suggesting at best a modest causal association between screen use and depression. More specifically, assuming linearity, an increase in screen time of approximately 13 h per day would be required to move an average respondent (in terms of current screen time use) into a symptom score range suggestive of depression. Third, Booker et al. (2018) assessed the association between frequency of social media use and behavioural responses using the SDQ from five waves of the youth questionnaire. Respondents were aged between 10–15 years from Understanding Society, the UK Household Longitudinal Study. A pooled analysis sample of 9859 respondents was used, and therefore the estimates are not calculated from individual level changes in social media use and SDQ variation. They found significant correlations between interacting on social media and SDQ, as well as vice versa. Additionally, higher social media interaction at age 10 was associated with statistically significant higher levels of behavioural problems thereafter for females, with no association found for males.

In addition to these studies, three further studies have been published more recently. Coyne et al. (2020) examined the association between time spent using social media and depression (CES-DC) and anxiety (Spence Child Anxiety Inventory) in an 8 year longitudinal study. Participants included 500 adolescents who completed once-yearly questionnaires between the ages of 13 and 20. Modelling within-person changes, they found that increased time spent on social media was not associated with significant changes in mental health. Puukko et al. (2020) investigated the within-person effects between active social media use and depressive symptoms (using the Depression Scale, 'DEPS') from a five-wave longitudinal dataset gathered from 2891 Finnish adolescents. Depressive symptoms predicted small increases in active social media use during both early and late adolescence, whereas no evidence of the reverse relationship was found. However, the associations were very small, statistically weak, and somewhat inconsistent over time. Finally, Thorisdottir et al. (2019) examined in a longitudinal cohort design whether social media use among adolescents was related to symptoms of anxiety (using the Multidimensional Anxiety Scale for Children (MASC) and depressed mood (Original Symptom Checklist) over time. Employing three waves of school-based surveys from approximately 2,000 adolescents born in Iceland in 2004, the results showed that more time spent on social media was weakly but significantly associated with increased symptoms of depressed mood, social anxiety and symptoms of physical anxiety over time. However, the effect size of these relationships was judged likely to be too small to be of clinical relevance. The relationship between time spent on social media and all outcomes of psychological distress were stronger for girls than boys.

Overall, the take away message from the above longitudinal studies is that there is evidence of limited association between levels of social media and mental health outcomes, with only a minority of studies finding evidence of small, potentially clinically insignificant associations between higher levels of social media use and greater likelihood of poorer mental health outcomes. Recent studies now recommend a need to move the evidence base forward through better measurement of the intensity, frequency and type of social media use, as negative effects are more likely to be found for prolonged hours only under some circumstances (see for example Przybylski et al., 2020; Odgers and Jensen, 2020).

In term of the economics literature, on the whole different questions have been addressed to those described above, with focus on the relationship between internet use and income comparisons (Clark and Senik, 2010; Lohman, 2015), the impact of social image on economic behaviours (Holm and Samahita, 2018), or, more broadly, the impact of technology devices on young people's development (Suziedelyte, 2015). Most relevant to our focus is a study by Wallsten (2013), who analyses the crowdout effect of time spent online, and shows that increasing online leisure time decreases time for other activities, such as socialising, attending cultural events, working and sleeping. More recently, McDool et al. (2019) uses the UK Household Longitudinal Study to analyse the relationship between internet use and life satisfaction for adolescents. They use quasi-random assignment of broadband (BB) speed to identify the effect; and show that an increase in BB speed reduces life satisfaction in several domains, including school work, appearance, family and life as a whole. They suggest that the negative effect is driven by reduced time spent in other activities and by negative effect of social media use. The validity of these estimates however relies on the assumption that BB speed was quasi-randomly assigned and not related to time-varying local area characteristics, which may also affect life satisfaction (however there is some evidence to the contrary, e.g. Department for Communities and Local Government, 2013, who report an association between well-being and regional area).

Our work complements and extends the limited evidence from economics by specifically analysing the association between social media use (rather than internet access) and emotional and behavioural outcomes, by comparing the effect of different levels of engagement with social media (and in particular on the effect of prolonged exposure vs. limited number of hours online per day vs. zero hours). Further, we extend the methodology by including estimation with individual fixed effects, and through use of matching methods and treatment effects to limit the risk of selection on observable characteristics. Finally, we analyse longer lasting effects on mental well-being, by considering outcomes in later teenager years and early adulthood.

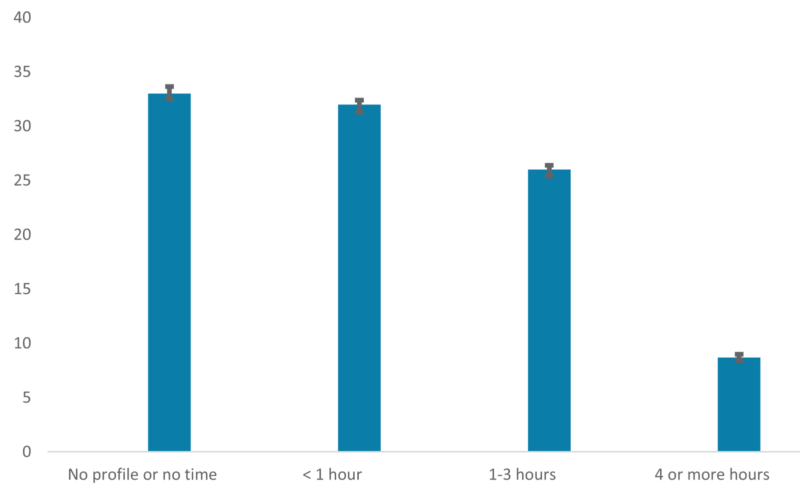


Fig. 1. Social media use in the estimation sample.
N = 26,667 observations (NxT). Confidence intervals are reported for each bar.

3. Data and descriptive statistics

We use data from the UK Household Longitudinal Study (UKHLS), known as *Understanding Society*. UKHLS surveyed approximately 40,000 households living in the United Kingdom in wave 1, and included a wide range of questions on social, economic and behavioural issues. Data collection started in 2009–2010 for wave 1 and eight waves of data are currently available. All adult household members were interviewed at each successive wave and all household members aged 10−15 years also completed a short self-completion youth questionnaire each year, until they were eligible to answer the adult survey at age 16. We use information about the children from the youth questionnaire and combine it with information about the parents derived from the adult survey. The final estimation sample includes over 23,000 observations from over 8,000 children.

Social media use is derived from two questions asked at every wave. First, children are asked whether they belong to a social media website (such as Bebo, Facebook, Myspace, etc.) and, if they answer positively to this question, they are also asked how long they spend chatting or interacting with friends through a social web-site on a normal school day.[1] The response options are: none, less than an hour, 1–3 hours, 4–6 hours, and 7 or more hours.

3.1. Outcomes

We first assess answers to eight questions included in the UKHLS youth survey covering mental well-being. These questions are partially derived from the Rosenberg Self-Esteem Scale[2] and are very similar to the General Health Questionnaire items included in the adult survey. These questions are asked every second wave starting at wave 2 and are:

- I feel I have a number of good qualities
- I feel that I do not have much to be proud of
- I certainly feel useless at times
- I am able to do things as well as most other people
- I am a likeable person
- I can usually solve my own problems
- All in all, I am inclined to feel I am a failure
- At times, I feel I am no good at all

Responses to each question range from 1 to 4, from “Strongly agree” to “Strongly disagree”. We follow the literature (e.g. Ermisch et al., 2001) and construct a mental health index by summing up the number of times individuals place themselves in the most distressed category. The mental health index ranges from 0 to 8, where 0 indicates no problems at all and 8 indicates maximum mental distress. The estimation sample for this model includes 12,961 observations from individuals with non-missing values for the mental health questions and all independent variables[3] .

Second, we analyse the relationship between social media activity and the Strengths and Difficulties Questionnaire (SDQ), which is a behavioural screening questionnaire for children and young people. The SDQ includes 25 questions (see Appendix for details) covering five areas, including hyperactivity/inattention, emotional symptoms, conduct problems, peer relationship, and pro-social behaviour. Children are presented with the 25 statements and choose one option between: ‘not true’, ‘somewhat true’ and ‘certainly true’. Twenty of these items (excluding the ones related to prosocial behaviour) are summed to create a total difficulties score ranging from 0 to 40 (see Goodman, 1997 for a detailed analysis of SDQ; and Goodman et al., 2003 for consistency of the self-reported SDQ). The UKHLS youth questionnaires includes SDQ every second wave (starting at wave 1). The estimation sample for this model includes 13,796 observations from individuals with non-missing values for the SDQ questions and all independent variables[4] .

[1] A limitation of this study is that, unfortunately, Understanding Society does not include information on social media use on weekends. Most of the existing literature using similar data also has this problem, as several datasets only include questions on social media use on weekdays (see for example Booker et al., 2018; Kelly et al., 2018; McDool et al., 2019; Orben et al., 2019; Orben, 2019b; among others).

[2] The Rosenberg self-esteem scale (RSES) (Rosenberg, 1965) includes the following 10 questions: On the whole, I am satisfied with myself; At times I think I am no good at all; I feel that I have a number of qualities; I am able to do things as well as most other people; I feel I do not have much to be proud of; I certainly feel useless at times; I feel that I'm a person of worth, at least on an equal plane with others; I wish I could have more respect for myself; All in all, I am inclined to feel that I am a failure; I take a positive attitude toward myself. The internal consistency of the RSES for the British population has been discussed in Bagley and Mallick (2001).

[3] This estimation sample includes 4,168 observations from wave 2; 3,346 observations from wave 4; 2,775 observations from wave 6; 2,672 observations from wave 8.

[4] This estimation sample includes 3,794 observations from wave 1; 3751 observations from wave 3; 3,048 observations from wave 5; 3,113 observations from wave 7.

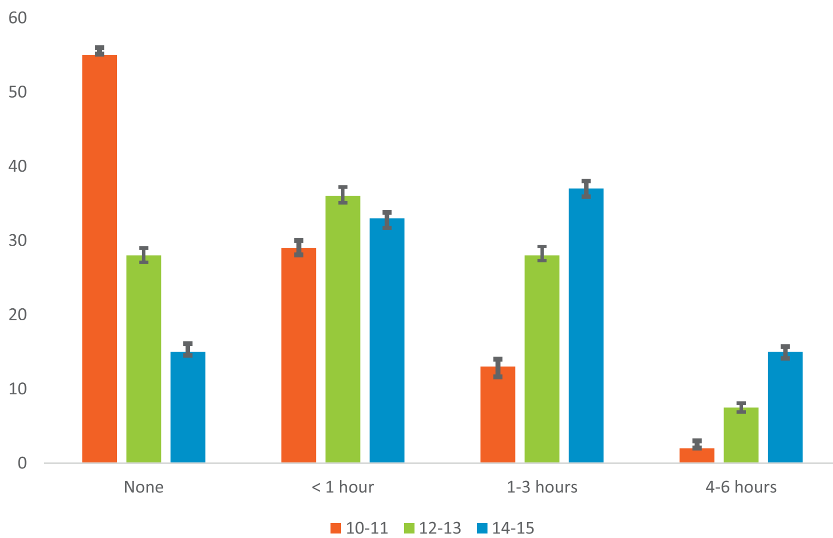


Fig. 2. Social media use by age.
N = 26,667 observations (NxT).). Confidence intervals are reported for each bar.

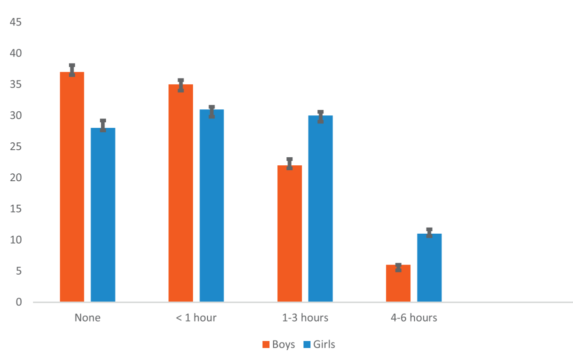


Fig. 3. Social media use by gender.
N = 26,667 observations (NxT).). Confidence intervals are reported for each bar.

Lastly, when young people turn 16, they are interviewed in the adult survey, which includes the General Health Questionnaire (GHQ) Caseness score (Goldberg, 1972, 1992). Previous literature refers to the GHQ as one of the most reliable indicators of psychological distress or "disutility" (Argyle, 1989; Clark and oswald, 1994). The GHQ Caseness score is constructed from responses to 12 questions covering feelings of strain, depression, inability to cope, anxiety-based insomnia and lack of confidence. The twelve answers are combined into a total GHQ score that indicates the level of mental distress, giving a scale from 0 (the least distressed) to 12 (the most distressed).

3.2. Descriptive statistics

Around a third of children in the estimation sample do not spend any time chatting and interacting with friends online (or do not have a social media profile), a similar proportion spends less than an hour online on a school day, just over a quarter are online between 1 and 3 h per day, and around 8 % spend over 4 h chatting online (see Fig. 1). A minority of respondents have a social media profile but do not spend any time online interacting with friends (around 7 % of the overall sample), and are similar in descriptive characteristics and outcomes to children without a social media profile. Therefore, we decide to combine these two groups in the main analysis.[5]

Figs. 2 and 3 show that the number of children who spend very long hours on social media on a regular school day dramatically increases by age (2 % of children age 10–11 are online for 4 or more hours, and this increases to 16 % for children age 14–15). Girls are also more likely to interact online for longer periods of time.

Table 1 presents descriptive statistics for relevant control variables by social media use, for the sample pooled across all waves and treated as a cross-section. The first column relates to all observations, while subsequent ones relate to subsets defined by various level of social media use (e.g., the sample includes 26,667 observations of individuals overall, 8,583 observations of individuals who spend less than 1 h on social media, and so on). Children who use social media for 4 or more hours on a school day are less likely to have highly educated mothers, more likely to have mothers who are separated or single, and who work, and less likely to come from families with high monthly income. They are also less likely to be from ethnic minorities and more likely to live in urban areas. Given these observable differences, we use a model with individual fixed effects to analyse the impact of social media use on children from different socio-economic groups.

Descriptive statistics of emotional and behavioural outcomes are presented in Table 2.

Fig. 4 reports outcomes by social media use. The number of observations is different from the one in Table 1 because questions about mental well-being and the SDQ are asked every second wave. There is a strong descriptive association between long hours spent on social media and worst outcomes in all the areas we consider. Children who spend 4 or more hours chatting with friends on social media on a school day have on average lower scores in most domains in the SDQ (excluding peer problems). They are also more likely to experience negative feelings about themselves (e.g. feeling useless, not proud, not likeable, failure, etc.).

[5] Results from the estimation where all groups are separate are presented in the Appendix (Table A2).

Table 1
Means (Std Devs) of independent variables for sub-groups of estimation sample, by social media use.

	Whole sample	Does not belong to a social media website	Spends no time online	Spends less than 1 hour online	Spends 1−3 h online	Spends 4 hours or more online
Mother has a degree (%)	25	30	26	26	20	19
Mother has other HE (%)	15	14	15	16	16	16
Mother is senior high school graduate– Age 18 (%)	19	18	18	19	19	18
Mother is junior high school graduate– Age 16 (%)	26	24	26	26	28	27
Mother has other qual. (%)	8	7	7	7	9	10
Mother has no education (%)	7	7	7	7	8	11
Mother is married (%)	67	67	70	68	63	55
Single mother (%)	16	13	14	16	18	21
Mother is divorced or separated (%)	17	14	16	16	19	23
Mother is employed (%)	70	67	66	70	72	70
Mother is unemployed (%)	4	4	4	4	5	5
Mother is out of labour force (%)	26	29	29	26	24	25
Family Monthly Income < £ 2,272 (%)	24	23	24	23	26	28
Family Monthly Income £ 2,272- £ 3,439 (%)	25	25	24	24	26	25
Family Monthly Income £ 3,439-£ 5,114 (%)	25	26	26	26	24	26
Family Monthly Income > £ 5,114 (%)	26	26	26	28	25	20
Living in an urban area (%)	76	76	76	75	77	80
Living in a rural area (%)	24	24	24	25	23	20
Female (%)	50	45	39	47	57	67
Male (%)	50	55	61	53	43	33
Age – Mean (SD)	12.5 (1.69)	11.47 (1.48)	12.22 (1.69)	12.62 (1.61)	13.2 (1.49)	13.6 (1.36)
White (%)	80	75	79	80	84	83
Black (%)	4	5	11	4	4	5
Other ethnic group (%)	5	5	5	5	5	5
Asian (%)	10	14	5	11	7	7
Has ever smoked (%)	7	2	5	6	11	19
Has ever drunk alcohol	31	10	35	30	45	59
Has 5 or more close friends	58	48	52	60	24	62
N	26,667	6,891	1,904	8,583	6,965	2,324

Table 2
Means (Std Devs) of SDQ Scores and Mental Health components.

SDQ Scores	Mean (SD)
Emotional Symptoms (0-10)	2.82 (2.23)
Conduct Problems (0-10)	2.15 (1.78)
Hyperactivity/Inattention (0-10)	3.92 (2.31)
Peer Relationship Problems (0-10)	1.76 (1.65)
Prosocial (0-10)	7.75 (1.82)
Total Difficulties (0-35)	10.65 (5.67)
Mental health index (0-8)	1.23 (1.52)
Mental health Index components (= 1 if in the most distressed group)	
SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree	
I feel I have a number of good qualities (D or SD)	0.05 (0.21)
I don't have much to be proud of (A or SA)	0.18 (0.38)
I certainly feel useless at times (A or SA)	0.39 (0.49)
I am able to do things as well as most other people (D or SD)	0.09 (0.29)
I am a likeable person (D or SD)	0.05 (0.21)
I can usually solve my own problems (D or SD)	0.11 (0.31)
All in all, I am inclined to feel I am a failure (A or SA)	0.10 (0.30)
At times, I feel I am no good at all (A or SA)	0.27 (0.44)

4. Methodology

We begin by estimating[6] a linear panel data model to control for observable confounders:

$$Y_{it} = \alpha + \beta sm_{it} + \boldsymbol{\delta}^{'}\mathbf{x}_{it} + u_i + \varepsilon_{it},$$

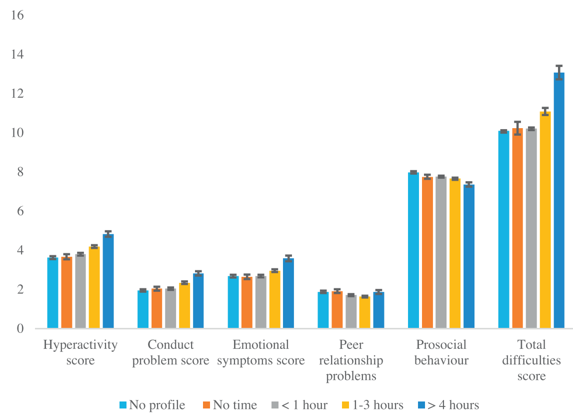
where Y_{it} represents an outcome for individual i at time t; sm_{it} is an individual's reported social media activity; $\mathbf{x}_{it}$ is a vector of child and family characteristics; u_i is an individual fixed effect; and ε_{it} is the unobservable determinant of the outcomes that varies across i and t.

We take advantage of the richness of *Understanding Society* by including an extended list of control variables. The basic vector of covariates includes observables child's and family's characteristics such as: child's age, ethnic group, gender, mother's mental health[7],

[6] Estimates are calculated using the *xtreg* routine in Stata (StataCorp, 2017)

[7] Maternal mental health is potentially endogenous, as it could be affected by children's social media use. However, we believe it is an essential control in the analysis of children mental health as there is evidence of important transmission in mental health status across generations. For this reason, we test the stability of our model by omitting mother's mental health from the analysis. Main results are unchanged

A - Strengths and Difficulties Questionnaire scores by social media use



B – Mental health score by social media use

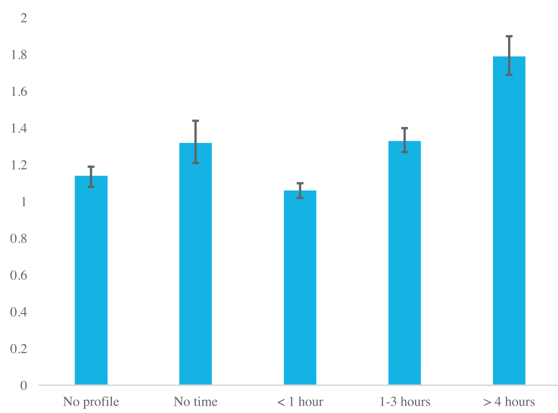


Fig. 4. Outcomes by social media use.
A - Strengths and Difficulties Questionnaire scores by social media use.
N = 13,706 observations (NxT).). Confidence intervals are reported for each bar.
B - Mental health score by social media use.
N = 12,961 observations (NxT) Confidence intervals are reported for each bar. Mental health score ranges from 0 to 8, where 8 represents the most distressed category.

education, labour market activity and marital status, family income, region of residence, year and urbanization[8] . The set of control variables follows the relevant literature and in particular Booker et al. (2018) and McDool et al. (2019), who use the same dataset to investigate the relationship between internet use and life satisfaction.

We progressively extend the set of independent variables included in the model by also controlling for additional observable characteristics, including: child's risky behaviours (smoking and drinking), whether the child has at least five close friends[9], and number of children by age group in the family.

We use recently developed tests (see Oster, 2019, and Krauth, 2016, which extend the method proposed by Altonji et al., 2005) in order to investigate the stability of the coefficient(s) of interest when increasing the number of independent variables. In particular, we report estimates of the parameter δ, developed in Oster (2019), which indicates the level of selection on unobserved variables, proportional to the level of selection on observed variables, required to drive the treatment effect to zero.

The assumptions behind the calculation of δ can be varied. In particular, it is possible to vary the assumed value of *R-max*, defined as the *R*-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls. We follow Oster (2019) and set *R-max* equal to 1.3 times the *R*-squared from a regression of the outcome on the treatment and observed control variables. Results from this test are reported in the relevant section and confirm the credibility of our main estimates.

Pooled OLS estimates[10] (without fixed effects) could be biased because of unobserved time-invariant characteristics that simultaneously affect social media use and mental health and behavioural outcomes (e.g. individual personality, attitudes, etc). To address this issue, we use the "within" (i.e., person-specific) variation in the levels of social media use and within person variation of outcomes by estimating an individual fixed-effects model.

The causal interpretation of β in the fixed-effects model relies on the assumption that the time-dependent error term ε_{it} is independent of changes in social media use and mental health, conditional on the regressors $\boldsymbol{x}_{it}$, and the individual fixed effect. This assumption fails if there are unobserved random events that affect both mental well-being and social media use (e.g. an accident; job loss; sudden illness; death in the family; divorce, etc, or any other unexpected event that can affect the individual mental health and her/his propensity to use social media at the same time).

For this reason, we include several independent variables that may capture random events (such as maternal mental health, employment, marital status, and child's risky behaviours and friendships), and we use propensity score matching (PSM) and inverse probability weighted regression adjustment (IPWRA) treatment effects estimation[11] to show the stability of the main results from the OLS fixed effects estimates.

PSM does not rely on the same functional form assumptions of OLS and restricts inference to samples where we can find overlap in the distribution of covariates across the treatment (i.e. children who spend long hours on social media are compared with children who have very similar observable characteristics but do not spend long hours on social media) (Dehejia and Wahba, 2002, Dehejia, 2005, and Smith and Todd, 2004). Matching attaches appropriate weights to the observations in the control group, so that the distribution of their observable characteristics is realigned to the treatment group (Berger et al., 2005; Goodman and Sianesi, 2005; Ruhm, 2008; Caliendo et al., 2015).

More specifically, we first estimate the conditional probability of spending long hours on social media, called the propensity score, given our covariates. Then, estimated propensity scores are used to create a matched control group and for each treated child we find the comparison member with the closest propensity score. Non-matched individuals are dropped from the analysis[12] .

We also examine the role of various levels of social media exposure and mental health using IPWRA treatment effects estimation based on the implementation in Cattaneo et al. (2013). This allows comparison of outcomes for children with

[8] Time-invariant variables, such as child's gender and ethnic group cannot be included in the individual fixed effects model. Results from OLS models including all these variables are included in the Appendix.

[9] The threshold of five close friends has been set as it because it represents the median number of close friends derived from answers to the question "How many close friends do you have". We have tested the results by choosing a threshold of 2 or more friends and main results are unchanged.

[10] Basic results from pooled OLS model (without FE) are presented in the Appendix (Table A3).

[11] Estimates are calculated using the *teffects* routine in Stata (StataCorp, 2017).

[12] Our analysis is performed using *teffects psmatch* and appropriate tests have been run, in order to compare covariate distributions across our matched groups to ensure that adequate balance has been obtained (results available in the Appendix Tables).

Table 3
Social media usage and mental health. Estimation by Linear Panel Data model with FE.

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Specification 1									
Less than 1 hour	−0.014	0.011	−0.021	0.015	0.002	−0.014	−0.004	−0.003	−0.025
	(0.008)	(0.014)	(0.017)	(0.011)	(0.008)	(0.012)	(0.011)	(0.016)	(0.052)
1−3 hours	0.006	0.014	0.033	0.018	0.002	−0.013	0.026	0.026	0.119
	(0.010)	(0.016)	(0.020)*	(0.013)	(0.009)	(0.014)	(0.013)**	(0.019)*	(0.061)*
4 or more hours	0.052	0.080	0.135	0.031	0.034	−0.004	0.090	0.130	0.550
	(0.013)***	(0.023)***	(0.029)***	(0.018)*	(0.014)**	(0.019)	(0.018)***	(0.027)***	(0.085)***
p-value test1	0.0001	0.0003	0.0002	0.4205	0.0206	0.7909	0.0004	0.0000	0.0000
p-value test2	0.0000	0.0008	0.0000	0.1365	0.0185	0.4101	0.0000	0.0000	0.0000
N	12,961	12,961	12,961	12,961	12,961	12,961	12,961	12,961	12,961
Specification 2									
Less than 1 hour	−0.012	0.018	−0.013	0.019	0.005	−0.012	−0.003	0.001	0.007
	(0.008)	(0.015)	(0.017)	(0.011)*	(0.008)	(0.012)	(0.011)	(0.016)	(0.053)
1−3 hours	0.006	0.016	0.041	0.022	0.004	−0.007	0.026	0.030	0.146
	(0.010)	(0.017)	(0.021)**	(0.013)*	(0.010)	(0.014)	(0.013)**	(0.019)	(0.062)**
4 or more hours	0.052	0.074	0.130	0.025	0.031	−0.008	0.086	0.120	0.515
	(0.014)***	(0.024)***	(0.029)***	(0.019)	(0.014)**	(0.020)	(0.019)***	(0.027)***	(0.086)***
p-value test1	0.0002	0.0019	0.0016	0.8717	0.0602	0.8352	0.0008	0.0004	0.0000
p-value test2	0.0000	0.0086	0.0000	0.4416	0.0625	0.6728	0.0000	0.0000	0.0000
N	12,625	12,625	12,625	12,625	12,625	12,625	12,625	12,625	12,625

Note: Specification 1 includes child's age binary variables, mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked); n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above). The outcomes are binary variables equal to 1 if the child has placed herself/himself in the most distressed category (e.g. has answered "agree" or "strongly agree" to the statement "I am inclined to feel I am a failure"; or has answered "disagree" or "strongly disagree" to the statement "I feel like I have a number of good qualities", and so on). Therefore, a positive sign of the estimate represents increased distress. Highest mental health score represents worse mental health. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave). Test1: test (4 or more hours ≠ 1−3 h); Test2: (4 or more hours ≠<1 h).

Table 4
Social media usage and mental health. Estimation by Treatment effects IPWRA (Spec. 1).

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Less than 1 hour	−0.019	−0.001	−0.011	−0.013	−0.023	−0.033	−0.009	−0.009	−0.120
	(0.005)***	(0.009)	(0.012)	(0.007)	(0.006)**	(0.007)**	(0.007)	(0.011)	(0.038)***
1−3 hours	−0.006	0.027	0.047	−0.002	−0.019	−0.026	0.019	0.040	0.081
	(0.006)	(0.011)**	(0.014)***	(0.008)	(0.006)***	(0.009)**	(0.009)***	(0.013)***	(0.044)*
4 or more hours	0.021	0.079	0.130	0.006	0.006	0.004	0.058	0.104	0.406
	(0.008)***	(0.018)***	(0.022)***	(0.013)	(0.012)	(0.016)	(0.014)***	(0.020***	(0.073)***
N	12,961	12,961	12,961	12,961	12,961	12,961	12,961	12,961	12,961

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence.). Highest mental health score represents worst mental health. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

different levels of social media use to those of children who do not use social media at all (in this, IPWRA treatment effects is different from PSM, which only allows to examine the effect of a binary outcome).

Specifically, the probability of "treatment" (in this context, using social media for different number of hours) is estimated using a multinomial logit specification. The inverse of these predicted probabilities are used as weights in a second-stage regression (Wooldridge, 2007, 2010; Imbens and Wooldridge, 2009)[13] .

[13] The IPWRA estimator has the "double robustness property" (Wooldridge, 2007, 2010) in that only one of the two equations in the model must be correctly specified to consistently estimate the parameters of interest. In practice, estimates in the second stage (the mental health equation) are robust to misspecification of the first stage (the multinomial logit model of treatment propensities) provided that the second stage is correctly specified. Similarly, estimates from the first stage are robust to the second step, provided the weighting is correctly specified

5. Results

Table 3 shows the relationship between social media use and mental health outcomes using individual-level fixed effects. The outcomes are binary variables representing increased distress for all outcomes[14] .

There is a clear association between extended social media use and mental health. Compared to children who do not spend any time on social media on a school day, adolescents who spend very long hours (more than 4 h each day) on social media are more likely to experience several negative feelings about themselves, including feeling that they don't have any qualities or much to be proud of (+ 8 percentage points, p.p.), feeling useless (+ 14 p.p.), not likeable (+3 p.p.), not good at all (+13 p.p), and feeling a failure (+9 p.p.). The coefficients of the variable capturing long hours on social media

[14] We tested results using the complete scale 1 to 4 ("strongly agree" to "strongly disagree") for all outcomes and the pattern of the main results is unchanged. Results are available on request.

are significantly different from the other coefficients (representing lower exposure). Short hours of interaction on social media (less than 1 h per day or 1–3 h per day) have a much smaller association with mental well-being (+ 2 p.p and only for some indicators). The association of extensive use of social media with overall mental health index is also sizeable (+0.55 on a scale 0–8), equivalent to over 30 % of a standard deviation. This suggests that the potential impact of long hours on social media on youths' mental health is higher than the effect of other important socio-economic characteristics, such as maternal education, marital status, and risky behaviours (see Appendix Table A1 for a comparison).

In order to understand the clinical significance of this result, we analyse the proportion of youth with poor mental health (a score in the worst 25 % of the distribution, or greater or equal to 2) by looking at the distribution of the predicted mental health score in each subsample by social media use. Over 45 % of children who spend 4 or more hours on social media show a predicted score in poor mental health category. This proportion is around 25 % on average and for the sample of youths who do not spend any time online (or don't have a social media account).

In Table 4, results from the treatment effects model with IPWRA estimator are presented. Results confirm findings from the estimation with individual fixed effects. The use of social media for prolonged hours has a detrimental effect on young people's mental well-being and the size of the effects is large. Interestingly, short exposure to social media (less than 3 h per day) seems to have some beneficial effects on individuals' perceptions of their likeability and ability to solve problems (even if the coefficients of short hours are not significantly different from the others). However, the effect of long hours clearly have the opposite effect on the majority of mental health questions (6 out of 9 indicators) and the size of the effects is nontrivial. Results from balance tests for the model with treatment effects are reported in the Appendix (Table A4 and Table A5) and show that the weighting reduces differences between treatment and controls groups (for the vast majority of covariates, weighted standardized differences are closer to zero and the variance ratios are closer to one).

Results for the SDQ scores are presented in Tables 5 and 6 and confirm previous findings. Children who spend very long hours (4 or more per day) on social media have higher scores (more difficulties) in the areas of hyperactivity and attention deficit (+0.85 points or over 20 % of a standard deviation); emotional symptoms (+0.40 points or 18 % of a standard deviation); and conduct problems (+0.53 points or 27 % of a standard deviation). However, limited or moderate use of social media (less than 1 h or 1–3 h per day), presents an association with worse scores for hyperactivity and conduct problems (8–13 % of a standard deviation), but is also associated with a slight decrease in peer relationship problems (around 10 % of a standard deviation), although this is not statistically significant.

The total difficulties score is significantly higher for children who spend very long hours on social media (+2.022 points or 35 % of a standard deviation). This shows that the impact of long hours spent on social media on the SDQ score is higher than the effect of many other important variables, such as maternal mental health, maternal education and marital status; and individual age and risky behaviours (see Table A1 in the Appendix).

To put this result in context, we compare the distribution of the predicted SDQ scores with values from Goodman (2001) and Goodman et al. (2003), showing that, in an average sample, roughly 80 % of children have a normal score (below the 80th percentile, or 0–16), 10 % have a borderline score (80th-90th percentile, or 16–19) and 10 % have abnormal score (above the 90th percentile, or above 19). In the estimation sample of children using social media for 4 or more hours each day, the predicted SDQ score distribution shows that over 24 % of children are in the borderline or abnormal group, while this percentage is around 9 % for youths without social media profile or never using social media on a school day (see Hayes, 2007 for a similar comparison).

Results from the treatment effects model with IPWRA estimator presented in Table 6 are higher in magnitude than the ones from the model including individual fixed effects, but confirm the overall associations. Long hours of social media are associated with worst scores in all areas (and the size of the effects ranges from 15 %

Table 5
Social media usage and Strengths and Difficulties Questionnaire (SDQ) Scores. Estimation by Linear Panel Data model with FE.

SDQ Items	Emotional Symptoms (0–10)	Conduct Problems (0–10)	Hyperactivity/ Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Specification 1						
Less than 1	0.016	0.075	0.208	−0.070	0.060	0.228
hour	(0.070)	(0.053)	(0.068)***	(0.053)	(0.058)	(0.161)
1–3 h	0.181	0.275	0.398	−0.104	−0.022	0.750
	(0.082)**	(0.062)***	(0.079)***	(0.061)*	(0.068)	(0.188)***
4 or more hours	0.706	0.531	0.853	−0.068	−0.135	2.022
	(0.116)***	(0.088)***	(0.112)***	(0.087)	(0.096)	(0.266)***
N	13,706	13,706	13,706	13,706	13,706	13,706
p-value test1	0.0000	0.0008	0.0000	0.6421	0.1754	0.0000
p-value test2	0.0000	0.0000	0.0000	0.9402	0.0245	0.0000
Specification 2						
Less than 1	0.038	0.083	0.196	−0.043	0.046	0.275
hour	(0.073)	(0.055)	(0.070)***	(0.054)	(0.060)	(0.166)*
1–3 h	0.179	0.273	0.370	−0.098	−0.038	0.725
	(0.086)**	(0.064)***	(0.082)***	(0.064)	(0.070)	(0.194)***
4 or more hours	0.715	0.519	0.828	−0.006	−0.124	2.057
	(0.122)***	(0.091)***	(0.117)***	(0.091)	(0.099)	(0.276)***
N	13,038	13,038	13,038	13,038	13,037	13,038
p-value test1	0.0000	0.0019	0.0000	0.2443	0.3160	0.0003
p-value test2	0.0000	0.0000	0.0000	0.6503	0.0586	0.0000

Note: Specification 1 includes child's age binary variables, ethnicity, and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked); n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above).* indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave). Test1: test (4 or more hours $\neq$ 1–3 h); Test2: (4 or more hours $\neq$<1 h).

Table 6
Social media usage and Strengths and Difficulties Questionnaire (SDQ) Scores. Estimation by Treatment effects IPWRA (Spec. 1).

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Less than 1 hour	−.004 (0.052)	0.118 (0.040)***	0.213 (0.053)***	−0.208 (0.042)***	0.002 (0.042)	0.118 (0.133)
1−3 h	0.086 (0.059)	0.528 (0.049)***	0.613 (0.061)***	−0.302 (0.046)***	−0.118 (0.048)**	0.926 (0.155)***
4 or more hours	0.435 (0.092)***	0.826 (0.083)***	1.102 (0.107)***	−0.148 (0.089)*	−0.471 (0.010)***	2.215 (0.256)***
N	13,706	13,706	13,706	13,706	13,706	13,706

Note: Specification 1 includes child's age binary variables, ethnicity, and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table 7
Long hours (4 or more hours per day) on social media and mental health. Estimation by Linear Panel Data model with FE and PSM.

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Specification 1									
OLS FE	0.055 (0.011)***	0.069 (0.019)***	0.127 (0.024)***	0.015 (0.015)	0.032 (0.011)**	0.008 (0.016)	0.078 (0.015)***	0.115 (0.022)***	0.501 (0.071)***
δ	2.96	3.13	3.83	15.52	2.74	−0.67	4.19	3.39	3.56
PSM	0.058 (0.012)***	0.079 (0.018)***	0.097 (0.022)***	0.0050 (0.014)	0.034 (0.009)	0.024 (0.014)	0.078 (0.015)***	0.120 (0.021)	0.488 (0.072)***
N	12,961	12,961	12,961	12,961	12,961	12,961	12,961	12,961	12,961
Specification 2									
OLS FE	0.053 (0.011)***	0.059 (0.020)***	0.114 (0.024)***	0.006 (0.015)	0.027 (0.012)**	0.001 (0.016)	0.075 (0.016)***	0.104 (0.023)***	0.438 (0.072)***
δ	2.57	2.36	3.05	2.43	1.93	−0.03	3.46	2.64	2.90
PSM	0.047 (0.013)***	0.047 (0.019)**	0.069 (0.022)***	0.018 (0.015)	0.022 (0.010)**	0.015 (0.014)	0.059 (0.016)***	0.087 (0.022)***	0.376 (0.076)***
N	12,625	12,625	12,625	12,625	12,625	12,625	12,625	12,625	12,625

Note: Specification 1 includes child's age binary variables, ethnicity, and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked); n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above). Highest mental health score represents worst mental health. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table 8
Long hours (4 or more hours per day) on social media and Strengths and Difficulties Questionnaire (SDQ) Scores. Estimation by Linear Panel Data model with FE and PSM.

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/ Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Specification 1						
OLS FE	0.598 (0.097)***	0.350 (0.074)***	0.556 (0.094)***	0.015 (0.072)	−0.144 (0.080)*	1.519 (0.222)***
δ	4.25	−7.38	38.85	0.99	1.26	9.99
PSM	0.464 (0.099)***	0.740 (0.080)***	0.934 (0.101)***	0.126 (0.071)	−0.422 (0.081)**	2.254 (0.241)***
N	13,706	13,706	13,706	13,706	13,706	13,706
Specification 2						
OLS FE	0.601 (0.102)***	0.336 (0.076)***	0.550 (0.098)***	0.065 (0.076)	−0.119 (0.083)	1.551 (0.231)***
δ	3.97	−11.17	21.88	4.60	0.98	9.27
PSM	0.411 (0.106)***	0.675 (0.081)***	0.805 (0.105)***	0.128 (0.07e)**	−0.368 (0.087)***	2.020 (0.252)***
N	13,038	13,038	13,038	13,038	13,038	13,038

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked) ; n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above).* indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table 9
Long hours (4 or more hours per day) on social media and mental health– By gender; age; maternal education; maternal marital status (Estimation by PSM, Specification 1).

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Girls	0.057 (0.017)***	0.036 (0.024)***	0.129 (0.027)***	0.033 (0.017)*	0.036 (0.012)**	0.028 (0.017)	0.067 (0.020)***	0.129 (0.026)***	0.513 (0.098)***
Boys	0.026 (0.014)*	0.085 (0.027)*	0.084 (0.038)*	−0.008 (0.020)	0.011 (0.015)**	0.029 (0.020)	0.063 (0.022)**	0.075 (0.033)***	0.336 (0.109)***
Age 10–12	0.037 (0.014)**	0.035 (0.034)	0.170 (0.045)**	0.029 (0.023)	0.008 (0.015)	0.037 (0.030)	0.050 (0.026)*	0.108 (0.041)***	0.495 (0.131)***
Age 13–15	0.069 (0.014)***	0.070 (0.021)***	0.130 (0.023)***	0.021 (0.015)	0.016 (0.013)	0.010 (0.016)	0.095 (0.016)***	0.112 (0.023)***	0.544 (0.085)***
Mother has degree or equivalent	0.052 (0.021)***	0.135 (0.027)*	0.102 (0.037)***	0.068 (0.021)**	0.012 (0.020)	0.008 (0.022)	0.109 (0.024)***	0.131 (0.033)***	0.578 (0.123)***
Mother has no degree or equivalent	0.048 (0.015)***	0.041 (0.023)*	0.121 (0.026)***	−0.002 (0.017)	0.010 (0.012)	0.023 (0.018)	0.061 (0.018)***	0.103 (0.026)***	0.416 (0.091)***
Mother is married	0.063 (0.013)***	0.081 (0.023)***	0.131 (0.027)***	0.012 (0.018)	0.036 (0.013)**	0.029 (0.017)	0.065 (0.018) ***	0.091 (0.027)***	0.509 (0.093)***
Mother is single or separated	0.056 (0.020)***	0.043 (0.029)	0.133 (0.031)***	0.032 (0.021)	0.013 (0.015)	0.032 (0.020)	0.093 (0.023) ***	0.111 (0.032)***	0.458 (0.129)***

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/ rural region of residence.). Highest mental health score represents worst mental health. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table 10
Long hours (4 or more hours per day) on social media and Strengths and Difficulties Questionnaire (SDQ) Scores – By gender; age; maternal education; maternal marital status (Estimation by PSM, Specification 1).

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Girls	0.591 (0.129)***	0.722 (0.103)***	1.048 (0.128)***	0.125 (0.091)***	−0.440 (0.092)***	2.486 (0.318)***
Boys	0.349 (0.145)	0.762 (0.133)***	0.642 (0.167)***	0.033 (0.128)	−0.475 (0.147)**	1.787 (0.396)***
Age 10–12	0.262 (0.214)	0.784 (0.168)***	0.966 (0.200)***	0.009 (0.165)	−0.933 (0.160)***	2.022 (0.525)***
Age 13–15	0.540 (0.112)***	0.759 (0.091)***	0.936 (0.118)**	0.036 (0.084)*	−0.319 (0.090)***	2.273 (0.277)***
Mother has degree or equivalent	0.734 (0.165)***	0.848 (0.132)***	1.244 (0.168)***	0.084 (0.124)**	−0.042 (0.138)	2.992 (0.406)***
Mother has no degree or equivalent	0.426 (0.124)***	0.675 (0.103)***	0.818 (0.126)***	0.063 (0.089)	−0.527 (0.105)***	1.983 (0.312)***
Mother is married	0.601 (0.123)***	0.867 (0.097)***	1.117 (0.132)***	0.077 (0.090)	−0.168 (0.107)	2.663 (0.292) ***
Mother is single or separated	0.475 (0.164)***	0.890 (0.126)***	1.126 (0.158)***	0.229 (0.116)	−0.464 (0.127) ***	2.532 (0.427) ***

Note: Specification 1 includes child's age binary variable, ethnicitys and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/ rural region of residence. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

to 50 % of a standard deviation) with the exception of a slight improvement in peer relationships. Results from balance tests for this model are reported in Table A6.

Results presented so far clearly show that children who spend more than 4 h per day on social media have significantly worse outcomes than all other groups. For this reason, in the next part of the analysis, we compare this group with average outcomes for all other youths, spending less than 4 h per day on social media, reporting an additional test for selection of unobservables (which cannot be performed when using categorical variables).

Tables 7 and 8 consider the relationship between long hours of interaction with peers on social media (4 h or more per day) and emotional and behavioural outcomes. In these tables, we also report the values of the parameter δ, proposed in Oster (2019). This value indicates the level of selection on unobserved variables, as a proportion of the level of selection on observed variables that would be required to drive the treatment effect to zero. Almost all estimates of the δ parameter associated with Specification 1 and 2 are above 1, consistent with an 'acceptable' level of selection based on the rule-of-thumb suggested in Oster (2019). These results provide evidence supporting the credibility of our main estimates, showing that it would take large, likely implausible, levels of selection bias to drive our results to zero and therefore selection on unobservable is unlikely to overturn our main conclusions.

Results are very consistent with the previous ones and confirm the strong and negative effect on all components of mental well-being, with the only exception of peer relationship problems.

In addition, in Tables 9 and 10, we further explore the heterogeneity of the main results with a series of sub-group analyses, focusing on children's gender, age and socio-economic status (following OECD, 2016; Booker et al., 2018; Kelly et al., 2018; McDool et al., 2019; Viner et al., 2019; Orben et al., 2019, who show important differences in impact of social media use across gender, age and socio-economic status).

First, considering two subsamples of age 10–12 years and 13−15 years, the results are very stable and consistent for both subgroups,

Table 11
Long hours (4 or more hours per day) on social media at age 14–15 and mental health at age 16–20 (Estimation by OLS and PSM).

	OLS			PSM		
	Whole sample	Age 16-17	Age 18-20	Whole sample	Age 16-17	Age 18-20
Mental health score from adult survey (0-12)	0.423 (0.102)***	0.441 (0.110)***	0.387 (0.149)**	0.475 (0.081)***	0.500 (0.104)***	0.415 (0.137)***
N	10,690	6,057	4,633	10,690	6,057	4,633

Note: Independent variables: gender; age binary variables; labour force status binary variables (employed, unemployed, out of the labour force; student-omitted group); GOR; higher educational qualification; * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave). OLS standard errors are clustered at individual level.

showing that high levels of exposure to social media are significantly associated with reduced mental well-being for both groups.

For gender, girls are more exposed to the negative effects of long hours on social media on self-esteem, but the overall effect on mental health is strong and significant for both groups (around +30 % of a standard deviation in the overall mental health score for both boys and girls).

Finally, for maternal education and different marital status, the results confirm the negative effect of long hours on social media, and the effect is slightly stronger for children with highly educated mothers (the impact on the mental health index is equivalent to 38 % of a standard deviation while it is around 28 % of a standard deviation for children whose mothers do not have a degree or equivalent).

Finally, in Table 11, we estimate the relationship between mental health age 16–20 and extensive social media use at age 14 or 15, using OLS and propensity score matching. This analysis only includes adolescents who are continuously observed in both the youth and adult survey. These results show that the negative effect of social media use persists for several years and is noticeable when the children move to the adult survey.

6. Conclusion

We estimate the relationship between social media use and emotional and behavioural outcomes for children aged 10–15 years old. We use information from the Youth Survey in the longitudinal study Understanding Society, and we control for individual-level heterogeneity. Our results indicate a mixed picture, where limited time on social media has no effect on most emotional and behavioural outcomes (and can actually positively impact social relationships), while there are strong negative associations between very long hours on social media and increased emotional distress and worse behavioural outcomes, which continue for several years. There is therefore some support for the *Goldilocks Hypothesis*, with the relationship between social media use and mental health and behavioural outcomes having both positive and negative associations, depending on the amount of social media use. This finding adds to the growing evidence regarding the impact of different levels of social media exposure on contemporaneous mental health, especially the negative consequences associated with larger exposures.

These relationships are robust to the inclusion of several independent variables, including child's and family's characteristics, and to the use of different estimation techniques, including matching methods and the use of individual fixed effects. The results are also very consistent with McDool et al. (2019) showing that fast internet access increases the likelihood of long hours of internet use and this, in turn, decreases adolescents' life satisfaction with various domains by about 13 %–16 % of a standard deviation. In addition, they appear aligned with the main findings in the relevant literature from epidemiology and public health, such as, among others, Viner et al.(2018), showing that social media use is associated with worse mental health; Kelly et al. (2018), documenting how social media use is associated with increased depressive symptoms; and Booker et al.(2018), showing that social media use decrease adolescents' life satisfaction. Lastly, our findings are in line with recent results from the experimental psychology literature, showing that the influence of digital media engagement is more nuanced than expected, and that children show increased psychological difficulties after long hours of device-based activity (but not after more limited hours) (Przybylski et al., 2020).

The results suggest that high levels of exposure to social media have important negative effects on youths' mental well-being and behavioural difficulties, especially for girls and regardless of family's socio-economic status. This suggests that there is potentially a role for parents, teachers and educators to highlight the possible risks of extended hours of social media use, and also put forward the potential positive benefits of a balanced approach, i.e. reducing time on social media in order to create more time for other activities.

The results highlight that high intensity of use (rather than the use of social media *per se*) is strongly associated with adverse outcomes and therefore it seems important to address high levels of use, rather than stigmatise social media use as a completely negative phenomenon.

One of the major limitations of the analysis is the difficulty in providing strong causal evidence on the relationship between social media use and mental health, in the absence of an exogenous variation in social media use. Time varying confounders could affect estimates including individual fixed effects, and PSM and treatment effects rely on selection on observables.

A potential concern is that the results are driven by events which affect both the child's emotional and behavioral outcomes and the use of social media. These may not be properly accounted for in the fixed effects model and therefore different strategies and sensitivity tests were used to verify the stability of the main findings. The results were however robust to various specifications of the model and the main findings were consistent across different estimation techniques.

Further, we progressively increased the set of independent variables, adding covariates that may capture such random events (e.g. maternal employment, marital status, mental health, etc) and including additional control variables, such as individual risky behaviours; whether the individual has at least five close friends; whether there are other children of different ages in the family (specification 2). We also ran additional sensitivity tests including several variables which may capture time varying events, such as; health shocks; instances of bullying and family relationships. These results were also consistent with the main findings.

Although every effort has been made to minimize these risks (including an extensive list of covariates, and running several sensitivity tests), some caution is still needed when interpreting these results as causal effects. Further, the social media use variable is self-reported and therefore potentially problematic, as youths may incorrectly estimate the time spent in online activities.

Future research could explore possible mediators using data that allow these limitations to be addressed. In this context, it could be important to find exogenous variation in social media use, e.g. from cross-country estimates which exploit different mobile phone network speeds, which might then illuminate the existence of a causal relationship between social media use and mental health.

Author's statement

The authors have equally contributed to the development of the paper and its various components.

Appendix A.

Strengths and Difficulties Questionnaire – List of Items

"Now for some questions about how you see yourself as a person. For each item, please tick the box for Not True, Somewhat True or Certainly True. It would help us if you answered all items as best you can even if you aren't absolutely certain. Please give your answers on the basis of how things have been for you over the last six months."

Emotional Problems Scale

- I get a lot of headaches, stomach-aches or sickness
- I worry a lot
- I am often unhappy, down-hearted or tearful
- I am nervous in new situations. I easily lose confidence
- I have many fears, I am easily scared

Conduct problems Scale

- I get very angry and often lose my temper
- I usually do as I am told
- I fight a lot. I can make other people do what I want
- I am often accused of lying or cheating
- I take things that are not mine from home, school or elsewhere

Hyperactivity Scale

- I am restless, I cannot stay still for long
- I am constantly fidgeting or squirming
- I am easily distracted, I find it difficult to concentrate
- I think before I do things
- I finish the work I'm doing

Peer problems Scale

- I am usually on my own. I generally play alone or keep to myself
- I have one good friend or more
- Other people my age generally like me
- Other children or young people pick on me or bully me
- I get on better with adults than with people my own age

Prosocial Scale

- I try to be nice to other people. I care about their feelings
- I usually share with others (food, games, pens, etc.)
- I am helpful if someone is hurt, upset or feeling ill
- I am kind to young children
- I often volunteer to help others (parents, teachers, children)

See Table A4

Table A1
Association of other independent variables and youth mental health index (Specification 1 and 2 – See Tables 3 and 5).

	Mental health index		SDQ Total difficulties	
	Spec. 1	Spec.2	Spec. 1	Spec.2
Mother's mental health	0.012	0.014	0.058	0.054
	(0.008)	(0.008)*	(0.023)**	(0.024)**
Age 11	0.016	0.021	−0.856	−0.802
	(0.099)	(0.100)	(0.330)***	(0.339)**
Age 12	−0.064	0.025	−0.642	−0.349
	(0.057)	(0.082)	(0.164)***	(0.244)
Age 13	0.165	0.212	−1.040	−0.707
	(0.099)*	(0.118)*	(0.334)***	(0.391)*
Age 14	0.051	0.054	−0.605	−0.356
	(0.068)	(0.098)	(0.203)***	(0.296)
Age 15	0.374	0.300	−0.855	−0.670
	(0.103)***	(0.133)**	(0.346)**	(0.427)
Age 16	0.163	0.102	0.217	0.386
	(0.124)	(0.127)	(0.375)	(0.391)
Mother is unemployed	−0.030	−0.093	0.060	0.092
	(0.080)	(0.081)	(0.244)	(0.252)
Mother is out of the labour force	0.012	0.014	−0.283	−0.395
	(0.008)	(0.008)*	(0.544)	(0.563)
Single mother	−0.176	−0.158	0.739	0.743
	(0.159)	(0.159)	(0.404)*	(0.418)*
Mother is separated	0.043	0.022	0.128	0.094
	(0.120)	(0.123)	(0.169)	(0.171)
Log (Household Income)	0.002	−0.006	−0.594	−0.106
	(0.058)	(0.059)	(0.880)	(0.929)
Mother has other HE	−0.062	0.059	−0.282	0.177
	(0.326)	(0.330)	(0.921)	(0.958)
Mother is senior high school graduate	0.117	0.114	−1.902	−1.369
	(0.326)	(0.333)	(1.105)*	(1.144)
Mother is junior high school graduate	0.364	0.406	−2.361	−1.751
	(0.368)	(0.372)	(1.336)*	(1.404)
Mother has other qualification	0.332	0.335	−1.772	−1.434
	(0.462)	(0.467)	(1.479)	(1.624)
Mother has no education	0.534	0.518	0.058	0.054
	(0.490)	(0.498)	(0.023)**	(0.024)**
Living in urban area	−0.178	−0.173	1.284	1.176
	(0.238)	(0.241)	(0.849)	(0.853)
Ever smoked		0.217		0.995
		(0.093)**		(0.279)***
Ever drank alcohol		0.389		0.405
		(0.057)***		(0.141)***
N. children 0–2 y.o.		0.174		0.283
		(0.101)*		(0.303)
N. children 3–4 y.o.		0.151		0.406
		(0.098)		(0.288)
N. children 5–11 y.o.		0.173		0.218
		(0.071)**		(0.215)
N. children 12–15 y.o.		0.084		−0.047
		(0.051)*		(0.153)
Has at least 5 friends		−0.168		−0.738
		(0.042)***		(0.136)***
Constant	0.053	0.042		0.995
	(0.938)	(0.947)		(0.279)***
R^2	0.04	0.06	0.03	0.04
N	12,961	12,625	13,706	13,038

Note: GOR FE are omitted. Highest mental health score represents worst mental health. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table A2
Social media use and youth mental health index/SDQ score (distinguishing youths without social media profile – omitted group- and youths without any use of social media) (Spec. 1 – See Tables 3 and 5).

	Mental health Score	SDQ – Total difficulties score
No time	0.067	−0.054
	(0.091)	(0.217)
Less than 1 h	−0.008	0.210
	(0.057)	(0.177)
1–3 h	0.135	0.733
	(0.065)**	(0.201)***
4 or more hours	0.569	2.003
	(0.089)***	(0.277)***
N	12,961	13,706

Note: Specification 1 includes child's age binary variables, mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Mental health score ranges from 0 to 8, where 8 represents the most distressed category. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table A3
Social media use and youth mental health index/SDQ score (Pooled OLS model – No FE) (Spec. 1 – See Tables 3 and 5).

	Mental health Score	SDQ – Total difficulties score
Less than 1 h	−0.025	0.226
	(0.052)	(0.161)
1–3 h	0.119	0.748
	(0.061)*	(0.188)***
4 or more hours	0.548	2.018
	(0.085)***	(0.266)***
N	12,961	13,706

Note: Specification 1 includes child's age binary variables, child's gender, child's ethnicity, mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Mental health score ranges from 0 to 8, where 8 represents the most distressed category. * indicates significant at 10 % level, ** at 5 % and ***1 %. N represents number of observations (person × wave).

Table A4
Means and *t*-test for treated and control group.

	Treated	Control	T test (p value)
Age	13.575	13.603	0.634
Female	0.677	0.658	0.337
Mother's mental health (0-12)	2.62	2.70	0.447
Mother has other Higher Educational qualification (Degree is omitted)	0.157	0.183	0.101
Mother is senior high school graduate– Age 18	0.183	0.183	1.000
Mother is junior high school graduate– Age 16	0.286	0.265	0.250
Mother has other qualification	0.098	0.100	0.837
Mother has no education	0.088	0.088	0.942
Single mother	0.228	0.210	0.297
Mother is divorced or separated	0.211	0.218	0.689
Mother is unemployed	0.052	0.059	0.529
Mother is out of labour force	0.248	0.230	0.289
Log (Household income)	8.080	8.090	0.710
Living in an urban area	0.791	0.798	0.684
Black	0.054	0.061	0.480
Other ethnic group	0.059	0.058	0.930
Asian	0.046	0.051	0.568

Table A5
Covariate balance after teffects (outcome: mental health score – Spec. 1).

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
<1 h				
Mother's mental health	0.006047	−0.01951	1.048998	1.004068
Female	0.053191	0.040505	1.011979	1.0019
Age = 11	−0.22708	0.001514	.7231426	1.002669
Age = 12	0.033602	0.006186	1.060371	1.011433
Age = 13	0.18605	0.01255	1.410975	1.021193
Age = 14	0.241488	−0.00629	1.752482	.988558
Age = 15	0.327754	−0.01004	2.285117	.9829484
Mother is unemployed	−0.01617	−0.01003	.9204558	.9549276
Mother is out of the labour force	−0.10511	−0.03996	.8985413	.9592668
Single Mother	0.069128	−0.0224	1.149043	.960057

Mother is separated	0.016998	−0.00657	1.034322	.9882136
Log income	0.042351	0.026795	.9996583	1.016404
Mother has other Higher Educational qualification (Degree is omitted)	0.05403	0.010656	1.112987	1.02129
Mother is senior high school graduate– Age 18	0.042462	−0.00353	1.070983	.9943874
Mother is junior high schoolgraduate – Age 16	0.020673	−0.00071	1.02488	.9992159
Mother has other qualification	0.02167	−0.01906	1.079143	.9410307
Mother has no education	−0.04337	−0.00657	.8585155	.9782854
Living in urban region1	−0.0276	0.007037	1.031986	.9917759
Asian	−0.10831	−0.01148	.7798858	.9710463
Black	0.006726	−0.03262	1.031126	.8650803
Other ethnic group	−0.00341	0.005454	.9863715	1.022269
1−3 h				
Mother's mental health	0.061136	0.013402	1.124769	1.02824
Female	0.279443	0.007629	.9996916	1.000603
Age = 11	−0.4092	−0.00797	.4865548	.9859252
Age = 12	−0.01539	−0.00669	.9722457	.9876209
Age = 13	0.234904	0.005331	1.514448	1.009009
Age = 14	0.37031	−0.00778	2.150275	.9858534
Age = 15	0.51756	−0.01446	3.013704	.9754219
Mother is unemployed	0.055383	0.000791	1.293208	1.003585
Mother is out of the labour force	−0.14523	−0.00477	.8562066	.9952545
Single Mother	0.109893	−0.02559	1.236633	.9543504
Mother is separated	0.106886	0.01206	1.21463	1.021598
Log income	−0.04377	−0.00015	.9526207	.9554491
Mother has other Higher Educational qualification (Degree is omitted)	0.052141	0.016356	1.109122	1.032671
Mother senior high school – Age 18	0.020172	0.001381	1.033948	1.002187
Mother junior high school – Age 16	0.073361	0.00123	1.085668	1.001357
Mother has other qualification	0.097821	−0.01351	1.372816	.9580908
Mother has no education	0.015374	0.00172	1.051853	1.005703
Living in urban region1	0.015596	0.011224	.9815212	.986849
Asian	−0.22343	0.01741	.5566982	1.04418
Black	−0.03909	−0.0129	.8267246	.9457463
Other ethnic group	−0.01256	−0.00225	.9503267	.9908605
4 or more hours				
Mother's mental health	0.21643	−0.07829	1.41832	.9298929
Female	0.510586	−0.1305	.8920023	.9718288
Age = 11	−0.59682	0.051664	.2552139	1.090331
Age = 12	−0.17422	−0.05236	.6861239	.9029146
Age = 13	0.191621	−0.05024	1.423875	.9143495
Age = 14	0.492485	−0.07566	2.490667	.8619838
Age = 15	0.693546	−0.08132	3.547075	.8607982
Mother is unemployed	0.081247	−0.00974	1.441877	.9561922
Mother is out of the labour force	−0.10919	0.000889	.8948417	1.000836
Single Mother	0.249125	−0.03968	1.524876	.9291071
Mother is separated	0.174788	−0.0708	1.34748	.8723742
Log income	−0.14808	0.021508	.9243028	.8234289
Mother has other Higher Educational qualification (Degree is omitted)	0.052056	0.038991	1.109561	1.077788
Mother is senior high school graduate– Age 18	0.014867	0.06841	1.025621	1.106572
Mother is junior high school graduate– Age 16	0.10394	−0.05244	1.119506	.9400407
Mother has other qualification	0.129894	−0.11151	1.503676	.6714081
Mother has no education	0.062603	−0.07131	1.216616	.7728668
Living in urban region1	0.091418	0.007642	.8879791	.9910236
Asian	−0.3312	0.106443	.3641337	1.273993
Black	0.063022	0.009758	1.307708	1.041773
Other ethnic group	0.027412	0.00118	1.112474	1.004756

Table A6
Covariate balance after teffects (outcome: SDQ Total Difficulties score – Spec. 1).

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
< 1 h				
Mother's mental health	0.011315	−0.03013	.9983798	.9354268
Female	0.082843	0.020009	1.015562	1.000145
Age = 11	−0.15447	0.005165	.7887469	1.009673
Age = 12	0.031144	0.012841	1.051634	1.022841
Age = 13	0.218723	−0.00612	1.541251	.9893731
Age = 14	0.293584	0.003686	1.939774	1.006487
Age = 15	0.242745	−0.01699	1.845536	.9702393
Mother is unemployed	0.01441	−0.04694	1.070281	.8171894
Mother is out of the labour force	−0.0491	−0.01572	.9512762	.9836003
Single Mother	0.075783	−0.02696	1.162582	.9524583
Mother is separated	0.072024	−0.01402	1.148076	.976437
Log income	0.02685	0.012448	.9972028	1.063775
Mother has otherHigher Educational qualification (Degree is omitted)	0.015446	0.009654	1.030353	1.018771

Table A6 (*Continued*)

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
Mother is senior high school graduate– Age 18	0.00807	−0.01188	1.013249	.9813977
Mother is junior high school graduate – Age 16	0.058925	0.010097	1.066836	1.010974
Mother has other qualification	0.024975	−0.01968	1.08564	.9429427
Mother has no education	0.002047	−0.02384	1.006957	.9285805
Living in urban region1	−0.02353	−0.01175	1.029321	1.015306
Asian	−0.08746	−0.00889	.8124586	.977367
Black	−0.01885	−0.00477	.922496	.9800979
Other ethnic group	−0.03117	0.007506	.8773525	1.032458
1–3 h				
Mother's mental health	0.07926	−0.04186	1.169009	.9542009
Female	0.290467	−0.01838	.9942443	.9991636
Age = 11	−0.36937	−0.00252	.4849294	.9952835
Age = 12	−0.05253	0.015358	.9117945	1.027306
Age = 13	0.26035	−0.01127	1.641134	.980411
Age = 14	0.417512	0.00336	2.322923	1.005911
Age = 15	0.497136	−0.01631	2.715885	.9714282
Mother is unemployed	0.036937	−0.04013	1.184138	.842844
Mother is out of the labour force	−0.11336	−0.02647	.8827458	.9721799
Single Mother	0.136822	−0.01775	1.292348	.9687226
Mother is separated	0.160137	−0.017	1.325676	.9714062
Log income	−0.04617	0.014825	.926292	.948757
Mother has other Higher Educational qualification (Degree is omitted)	0.049909	0.003918	1.097881	1.007619
Mother is senior high school graduate – Age 18	0.034361	0.002528	1.056051	1.003943
Mother is junior high school graduate– Age 16	0.080553	−0.00106	1.090084	.9988384
Mother has other qualification	0.080718	−0.01806	1.284445	.9475913
Mother has no education	0.031061	−0.03074	1.106901	.908188
Living in urban region1	0.022747	0.00085	.9711221	.9988865
Asian	−0.21234	0.012979	.5582777	1.033243
Black	−0.0154	−0.02946	.9365538	.8795958
Other ethnic group	−0.04292	0.014272	.8327176	1.062056
4 or more hours				
Mother's mental health	0.182591	−0.06069	1.322857	.8808362
Female	0.466328	−0.10719	.9158085	.9856627
Age = 11	−0.5283	0.03448	.2742025	1.064356
Age = 12	−0.24408	−0.06438	.5902746	.884738
Age = 13	0.298259	−0.04393	1.731336	.92334
Age = 14	0.584853	−0.06393	2.76266	.8868214
Age = 15	0.576834	−0.04362	2.947161	.9233664
Mother is unemployed	0.077148	−0.08281	1.400552	.6868401
Mother is out of the labour force	−0.11163	−0.00029	.8854689	.9996733
Single Mother	0.136945	−0.07144	1.293906	.8736037
Mother is separated	0.284351	−0.10046	1.560192	.8296177
Log income	−0.11392	0.13855	.9073555	.8201787
Mother has other Higher Educational qualification (Degree is omitted)	0.024851	0.06388	1.049863	1.123653
Mother is senior high school graduate– Age 18	−0.01558	−0.05352	.9753441	.9154656
Mother is junior high school graduate– Age 16	−0.00217	−0.05729	.9984667	.935161
Mother has other qualification	0.130757	−0.02105	1.472069	.9389759
Mother has no education	0.163442	−0.00735	1.596871	.9777743
Living in urban region1	0.110396	−0.07646	.8556159	1.096342
Asian	−0.28604	−0.04336	.4195364	.8905449
Black	0.007563	−0.08416	1.03284	.671812
Other ethnic group	0.075719	0.009755	1.323806	1.042227

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ehb.2021.100992.

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