Specification analysis for technology use and teenager well-being

Online Supplement

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This document contains supplementary information for our paper "Analysis of multiple specifications: statistical validity and a Bayesian proposal". Section S1 is a an introduction to Bayesian regression. In Section S2 we describe how BMS and BMA are used to produce a Bayesian Specification Curve Analysis (BSCA) and how to replicate our main results on teenager well-being using R. Section S3 contains supplementary data analyses that assess the robustness of our main findings for the Youth Risk Behavior Survey (YBRS) and Millenium Cohort Study (MCS) datasets. These robustness analyses include comparing linear to non-linear treatment effects and considering other well-being outcomes than those presented in the main paper. Section S4 describes certain aspects in which our analysis differs from that of Orben and Przybylski (2019). One motivation for these differences was to consider the inclusion of further control covariates, which as discussed in the main paper, is necessary to reduce biases in parameter estimates. We also adjusted the definition of some of the variables – e.g. expressing them on a common scale to facilitate interpretation and comparability, using validated psychometric scales as opposed to (unvalidated) individual outcome variables, fixing minor errors related to variable codes and including unemployed parents in the analysis.

S1 Introduction to Bayesian regression

This section provides a short introduction to Bayesian regression. It is designed to allow readers who are unfamiliar with Bayesian statistics to follow the main text. We recommend anyone who wants to use BSCA to first get a deeper understanding of the Bayesian framework. Two excellent introductions are 'Statistical Rethinking' by McElreath (2020) and 'Bayesian Data Analysis' by Gelman et al. (2013). Two more applied texts are Hoeting et al.'s (1999) BMA tutorial and the open textbook (and course) 'An Introduction to Bayesian Thinking' by Clyde et al. (2020).

Bayesian statistics is based on a law of probability, known as Bayes theorem (or Bayes rule). It states that for two events A and B with non-zero probability, the probability of A occurring given that B occurred is

$$p(A \mid B) = \frac{p(B \mid A)p(A)}{p(B)}$$

where $p(A)$ and $p(B)$ are the marginal (or unconditional) probabilities of A and B occurring, respectively.

To apply Bayes' rule to regression models, consider the standard linear regression model $y_i = \beta^T x_i + \alpha^T z_i + \epsilon_i$, where y_i is the value of the dependent variable, x_i contains one or more treatment variables of interest, z_i are adjustment covariates, and $\epsilon_i \sim N(0, \sigma^2)$ are independent errors for observations $i = 1, \ldots, n$. The parameters $(\beta, \alpha, \sigma^2)$ describe the probabilistic dependence of the outcome y_i on the treatment(s) x_i, after accounting for the effect of control covariates z_i. Specifically, β is a vector with one or more parameters that captures the association between the outcome and the treatment(s) of interest. α is a parameter vector capturing the association with control covariates which, despite not being of immediate interest, is needed to reduce biases and variance when estimating β. Although

we describe the linear regression setting for simplicity, an analogous construction applies to any other regression model, including the logistic regression model used in the main paper.

Applying Bayes rule, the information about $(\beta, \alpha, \sigma^2)$ after observing the data is contained in a posterior probability distribution that is described by the density function

$$\overbrace{p(\beta, \alpha, \sigma^2 \mid \text{data})}^{\text{posterior prob.}} = \frac{\overbrace{p(\text{data} \mid \beta, \alpha, \sigma^2)}^{\text{likelihood}} \overbrace{p(\beta, \alpha, \sigma^2)}^{\text{prior prob.}}}{p(\text{data})}$$

where 'data' denotes the observed data $y_1, x_1, z_1, ..., y_n, x_n, z_n$. Values of $(\beta, \alpha, \sigma^2)$ receiving higher $p(\beta, \alpha, \sigma^2 \mid \text{data})$ are more supported, *a posteriori* after observing the data, than values receiving lower $p(\beta, \alpha, \sigma^2 \mid \text{data})$.

Two important quantities in the above equation are the likelihood function $p(\text{data} \mid \beta, \alpha, \sigma^2)$ and the prior distribution on the parameters $p(\beta, \alpha, \sigma^2)$. The likelihood is the probability (or probability density, for continuous data) that we would observe our actual data, given the parameters. The denominator $p(\text{data})$ does not depend on β, α, σ^2, it is a normalizing constant that we do not need to calculate directly and follows from the fact that (like all probability density functions) $p(\beta, \alpha, \sigma^2 \mid \text{data})$ integrates to 1.

The posterior information about our treatment effect coefficient(s) of interest β given the data is contained in $p(\beta \mid \text{data})$, which can be obtained by integrating the posterior distribution with respect to α and σ^2, that is

$$p(\beta \mid \text{data}) = \int p(\beta, \alpha, \sigma^2 \mid \text{data}) d\alpha d\sigma^2.$$

The posterior $p(\beta \mid \text{data})$ contains all the probabilistic information needed in a Bayesian analysis to make inference on the treatment effect(s) β. In particular, one may obtain a point estimate by taking the posterior mean of $p(\beta \mid \text{data})$, and quantify uncertainty via a 95% posterior interval (an interval that is assigned 95% probability by $p(\beta \mid \text{data})$). Of particular importance for BSCA, $p(\beta \mid \text{data})$ can be expressed via BMA as a weighted average across models, as we outline next.

S2 Reproducing the BSCA results for the teenager well-being datasets

We explain how to obtain BMA and BSCA results in R by reproducing our findings in the two teenager well-being datasets. Subsection 1 loads R packages and functions needed for the analysis, as well as the Youth Risk Behavior Survey (YBRS) and Millenium Cohort Study (MCS) datasets on adolescent mental well-being and technology use. Subsection 2 applies Bayesian model selection and averaging to both datasets. Finally, Subsections 3 and 4 produce Figs. 1 (single-outcome BSCA) and 2 (multiple-outcome BSCA) presented in the manuscript, respectively.

S2.1 Setup

We start by loading the required R packages. For the statistical analysis we use `mombf` and `BAS`, whereas `tidyverse` offers some convenient functions for treating the data. We source file `functions.R`, which contains auxiliary functions to produce the BSCA plots, and load the pre-processed version of the YBRS and MCS datasets in files `yrbs.Rdata` and `mcs.Rdata`, respectively. We cannot provide these pre-processed data due to copyright issues, but you can run the code provided in the replication file `bsca_preanalysis.Rmd` to create the processed data from the raw data and code provided by Orben and Przybylski (2019). See also `bsca_preanalysis.html` for a compiled version displaying the R code and output.

```
library(mombf); nn=NULL
library(BAS)
library(tidyverse)
options(scipen=999)  # turn off scientific notation
```

```
source('code/functions.R')
yrbs = new.env(); mcs = new.env()
load('data/export/yrbs.Rdata', yrbs)
load('data/export/mcs.Rdata', mcs)
```

S2.2 Bayesian model selection

S2.2.1 YRBS data

We begin by analyzing the YRBS data. The data frame `y` stores several outcomes, whereas `x` stores treatment variables and `data` stores other recorded variables. We specify that we wish to use the outcome variable *thought about suicide* (the second column in `y`) by setting `idy=2`. We also specify that we wish to use TV and electronic device use (first and second column in `x`) as treatment variables to be jointly included in all regression models by setting `idx=c(1,2)`. Finally we specify to use race, age, gender, school grade, survey year and body mass index as potential control variables (saved in `cvars` and `cvarsplus`).

```
attach(yrbs)
names(y)
```

```
## [1] "loneliness"     "think suicide"  "plan suicide"   "commit suicide"
## [5] "doctor suicide"
```

```
names(x)
```

```
## [1] "TV Use"                "Electronic Device Use"
```

```
c_names
```

```
## [1] "Race"    "Aged 12" "Aged 13" "Age"     "Male"    "Grade"   "Year"
## [8] "BMI"
```

We obtain the number of observations and prepare the data for regression.

```
idy = 2; idx = c(1,2)
datareg = data.frame(y[,idy], x[,idx], data[,c(cvars,cvarsplus)])
dim(datareg)[1]
```

```
## [1] 75083
```

```
names(datareg) = c('y', names(x)[idx], c_names)  # set names
datareg = datareg[rowSums(is.na(datareg))==0, ]  # remove NAs
detach(yrbs)
```

The data.frame `datareg` contains the outcome, treatment and control variables. For illustration, its first few rows are displayed below. These variables have been conveniently coded so they can be entered directly into the usual R regression equation. For instance, `Aged 12` and `Aged 13` are indicators for an individual's age being 12 and 13 years, whereas `Age` contains the age in years, using these 3 columns to code the effect of age allows to capture non-linear effects detected in preliminary exploratory data analyses (see reproduction file `bsca_preanalysis.Rmd`).

```
head(datareg %>% rename('ED Use' = 'Electronic Device Use'))
```

	y	TV Use	ED Use	Race	Aged 12	Aged 13	Age	Male	Grade	Year	BMI
45	0	medium	0.333	0	1	0	12	1	11	2007	20.85
46	0	low	0.000	0	1	0	12	1	12	2007	23.85
47	0	medium	0.500	0	1	0	12	1	9	2007	18.04
50	1	high	1.000	0	1	0	12	1	12	2007	29.47
54	0	low	0.167	0	1	0	12	1	11	2007	26.36
55	0	high	0.000	0	0	1	13	1	9	2007	21.19

A first step in BSCA is to run Bayesian model selection (BMS), which will assign a score (posterior probability) to each model (possible set of control variables). Next, we use Bayesian model averging (BMA) to combine these estimates. Since the outcome variable is binary we use logistic regression models, setting a uniform prior on the model size (`modelbbprior(1,1)`). The function `mombf::modelSelectionGLM` computes scores for all 1024 possible models, and may take a while to run.

```
yrbs_ms = mombf:::modelSelectionGLM(
  y ~ ., data=datareg,
  includevars=1, familyglm=binomial(link='logit'),
  priorDelta=modelbbprior(1,1)
)
```

```
## Enumerating 1024 models.........
```

The BMA treatment effect estimates, 95% posterior intervals and marginal posterior probability that the variable has an effect on the outcome are stored in `yrbs_coef`. The output indicates a strong evidence that both treatments have an effect, albeit with opposing signs, and that age, gender, grade and BMI are control covariates that one should include in the model to avoid biases in the treatment effect estimates (driven by under-selection of truly relevant controls).

```
yrbs_coef = coef(yrbs_ms)
yrbs_coef
```

	estimate	2.5%	97.5%	margpp
(Intercept)	-1.344	-1.768	-1.080	1.000
‘TV Use‘medium	-0.233	-0.280	-0.184	1.000
‘TV Use‘high	-0.048	-0.119	0.027	1.000
‘Electronic Device Use‘	0.629	0.565	0.692	1.000
Race	0.001	0.000	0.025	0.036
‘Aged 12‘	1.157	0.000	2.180	0.790
‘Aged 13‘	-0.002	0.000	0.000	0.009
Age	0.011	0.000	0.072	0.221
Male	-0.789	-0.833	-0.745	1.000
Grade	-0.086	-0.147	-0.058	1.000
Year2009	0.000	0.000	0.000	0.006
Year2011	0.000	0.000	0.000	0.006
Year2013	0.000	0.000	0.000	0.006
Year2015	0.001	0.000	0.000	0.006
BMI	0.025	0.021	0.029	1.000

Given these coefficients, we use the function `getOR` to obtain odds ratios for increasing the TV use from low to medium/high, and for increasing the electronic device use from 0 to >= 5 hours (coded as EDU=1 in our dataset, leading to setting `treatvals=1` below). The function exponentiates the coefficient estimates and formats the result.

```
getOR(yrbs_coef, treat='TV Use', digits=2)
```

	OR	CI.low	CI.up
‘TV Use‘medium	0.79	0.76	0.83
‘TV Use‘high	0.95	0.89	1.03

```
getOR(yrbs_coef, treat='Electronic Device Use', treatvals=1, digits=2)
```

	OR	CI.low	CI.up
Electronic Device Use 1	1.88	1.76	2

Note that the regression models include simultaneously the two treatment variables, TV and electronic device (ED) usage, which is necessary to avoid biased estimates when treatments are correlated. In these data the correlation is mild, for instance Pearson's correlation between the number of hours of TV use and ED use (columns `q81` and `q82` in `data`) is 0.21.

```
round(cor(na.omit(yrbs$data[c('q81', 'q82')]), method='pearson')[1,2],
      digits=2)
```

```
## [1] 0.21
```

The control variables that were omitted by Orben and Przybylski (2019) have important associations.

```
getOR(yrbs_coef, treat='Male', treatvals=1, digits=2)
```

	OR	CI.low	CI.up
Male 1	0.45	0.43	0.47

```
getOR(yrbs_coef, treat='Grade', treatvals=1, digits=2)
```

	OR	CI.low	CI.up
Grade 1	0.92	0.86	0.94

S2.2.2 MCS data

Next, we load the MCS dataset and run Bayesian model selection and averaging, analogously to the above analysis of the YRBS data. As described in the main manuscript, for illustration in our analysis we considered 4 outcome variables, 5 treatments and 14 potential control variables (results for other outcome variables are shown in Fig. S1). We display the names of these variables, which have been stored in the `mcs` workspace, as well as the number of observations.

```
attach(mcs)
names(yvars)
```

```
## [1] "Depressed (adolescent)"
## [2] "Low self-esteem (adolescent)"
## [3] "High total difficulties (parent)"
## [4] "High emotional problems (parent)"
## [5] "High conduct problems (parent)"
## [6] "High hyperactivity/inattention (parent)"
## [7] "High peer problems (parent)"
## [8] "Low pro-sociality (parent)"
```

```
x_names
```

```
## [1] "TV"               "Electronic games" "Social media"     "Other internet"
## [5] "Own computer"
```

```
names(cvars)
```

```
##  [1] "Male"       "Age"        "BMI"        "Motivation" "Ethnicity"
##  [6] "Closeness"  "Father"     "Score"      "Employed"   "Illness"
## [11] "Time"       "Distress"   "Siblings"   "Income"
```

```
nrow(data)
```

```
## [1] 11884
```

```
detach(mcs)
```

The code below runs BMA for all 5 outcome variables.

```r
attach(mcs)
mcs_coef = list(); mcs_ms = list()
for (idy in 1:length(yvars)) {
  # select data
  yvar = yvars[idy]; yname = names(yvars)[idy]
  datareg = na.omit(data[c(yvar, x_vars, cvars)])
  names(datareg) = c('y', x_names, names(cvars))

  # BMA
  message(yname)
  mcs_ms[[yname]] = mombf:::modelSelection(
    y ~ ., data=datareg, includevars=1, family="binomial",
    priorDelta=modelbbprior(1,1), priorCoef=bicprior(), priorGroup=bicprior(),
    niter=50
  ); cat('\n')

  mcs_coef[[yname]] = coef(mcs_ms[[yname]])
}
```

```
## Depressed (adolescent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Low self-esteem (adolescent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## High total difficulties (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## High emotional problems (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## High conduct problems (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## High hyperactivity/inattention (parent)
```

```
## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## High peer problems (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Low pro-sociality (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.
```

```
detach(mcs)
```

We can inspect the BMA results for the four outcomes. For brevity here we focus on *parent-assessed* high total difficulties and *adolescent-assessed* depression (see Subsection 3 below for a plot summarizing the BMA results for the two other outcomes). The analysis provides strong evidence that, according to parents, social media decrease the odds of total difficulties (marginal posterior probability=1, up to rounding), whereas electronic games increase those odds. We also find strong evidence that BMI, educational motivation, closeness to parents, the primary caregiver's word ability score and psychological distress, presence of a longstanding illness and the household income are necessary control covariates, as well as strong evidence that other covariates are not needed.

```
mcs_coef[["High total difficulties (parent)"]]
```

	estimate	2.5%	97.5%	margpp
(Intercept)	1.877	1.068	2.649	0.000
TV	-0.015	-0.306	0.000	0.066
'Electronic games'	0.573	0.353	0.795	1.000
'Social media'	-0.715	-0.956	-0.469	1.000
'Other internet'	0.000	0.000	0.000	0.015
'Own computer'	0.000	0.000	0.000	0.013
Male	0.000	0.000	0.000	0.015
Age	0.000	0.000	0.000	0.028
BMI	0.043	0.027	0.058	1.000
Motivation	-0.793	-0.941	-0.644	1.000
Ethnicity	0.000	0.000	0.000	0.014
Closeness	-0.537	-0.651	-0.426	1.000
Father	0.039	0.000	0.292	0.224
Score	-0.055	-0.074	-0.037	1.000
Employed	-0.002	0.000	0.000	0.029
Illness	1.037	0.881	1.194	1.000
Time	-0.008	-0.111	0.000	0.137
Distress	0.113	0.098	0.128	1.000
Siblings	-0.001	0.000	0.000	0.034
Income	-0.001	-0.002	-0.001	0.998

The output for adolescent-assessed depression can be interpreted analogously. Briefly, here there is strong evidence that social media and other internet use increase the odds of depression, in contrast with the results of the earlier parent-assessed outcome. Some of the needed control covariates are also different, for instance males self-report lower odds of depression than females, whereas gender did not play a role in the parental assessment.

```
mcs_coef[["Depressed (adolescent)"]]
```

	estimate	2.5%	97.5%	margpp
(Intercept)	4.138	3.262	5.011	0.000
TV	0.000	0.000	0.000	0.011
'Electronic games'	0.000	0.000	0.000	0.038
'Social media'	0.996	0.652	1.345	1.000
'Other internet'	1.039	0.654	1.407	1.000
'Own computer'	0.000	0.000	0.000	0.016
Male	-1.111	-1.266	-0.960	1.000
Age	0.000	0.000	0.000	0.019
BMI	0.045	0.028	0.061	1.000
Motivation	-1.609	-1.766	-1.452	1.000
Ethnicity	0.000	0.000	0.000	0.023
Closeness	-0.783	-0.894	-0.668	1.000
Father	0.000	0.000	0.000	0.011
Score	0.013	0.000	0.040	0.495
Employed	0.000	0.000	0.000	0.012
Illness	0.512	0.335	0.687	1.000
Time	0.000	0.000	0.000	0.011
Distress	0.002	0.000	0.024	0.107
Siblings	-0.009	-0.108	0.000	0.116
Income	0.000	0.000	0.001	0.101

To summarize the treatment effects of interest we again use the auxiliary function `getOR`. These correspond to odds ratios for increasing the use of social media from 0 (no usage) to >7 hours (coded as 1 in our dataset, hence we set `treatvals=1`). We first obtain odds-ratios and 95% posterior intervals for social media and electronic games on parent-assessed total difficulties.

```
getOR(mcs_coef$`High total difficulties (parent)`, treat='Social media',
      treatvals=1, digits=2)
```

	OR	CI.low	CI.up
Social media 1	0.49	0.38	0.63

Next we report the odds ratios for adolescent self-assessed depression and low self-esteem.

```
getOR(mcs_coef$`Depressed (adolescent)`, treat='Social media',
      treatvals=1, digits=2)
```

	OR	CI.low	CI.up
Social media 1	2.71	1.92	3.84

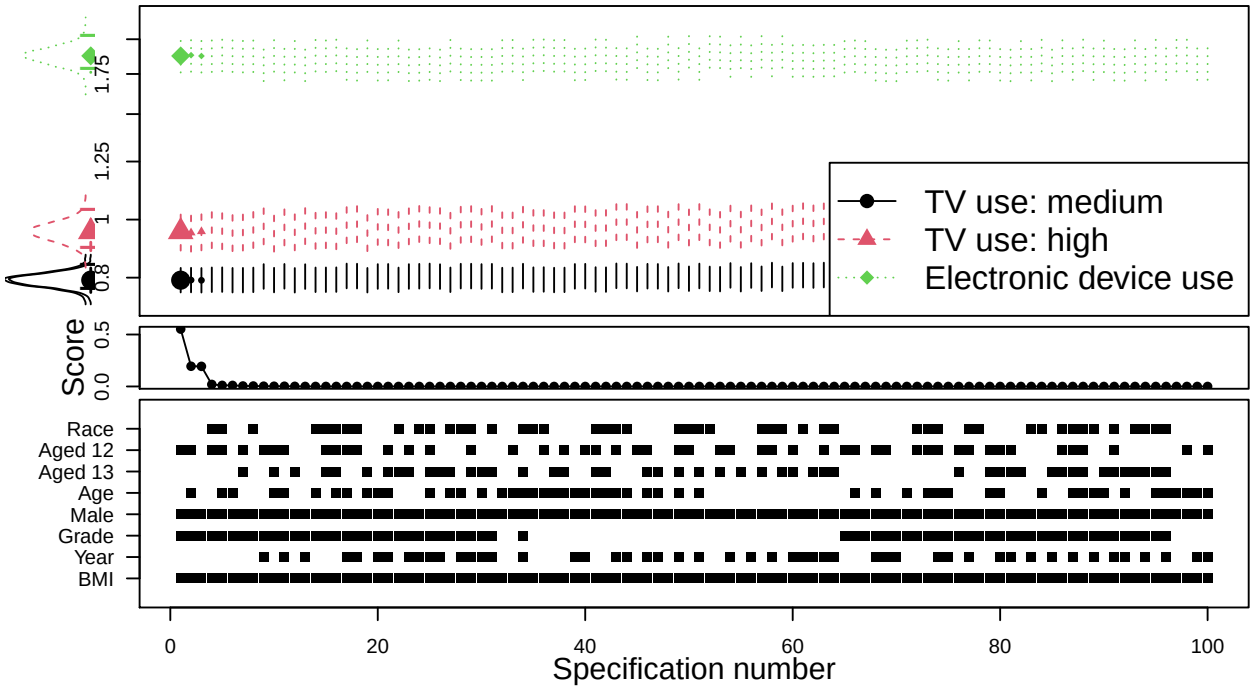
```
getOR(mcs_coef$`Low self-esteem (adolescent)`, treat='Social media',
      treatvals=1, digits=2)
```

S2.3 Single-outcome BSCA

S2.3.1 YRBS data

We use function `single_bsca` to plot the single-outcome BSCA for the YRBS data and the outcome *thought about suicide*. The argument `coefidx` specifies the names of the treatment variables that should be plotted. The function also allows specifying optional arguments such as the treatment names to be displayed in the legend (argument `x.labels`), variable names to be displayed in the bottom panel displaying variable configurations (argument `var.labels`), and omitting variables from that panel (argument `omitvars`, useful when there are many variables or when several columns code for the non-linear effect of a single variable and are always included together, such as year in the YRBS data). The labels on the y axis are stored in an array whose names (optionally) are the original values (argument `y.labels`). Here, we turn the estimated coefficient into the odds ratio by exponentiating it.

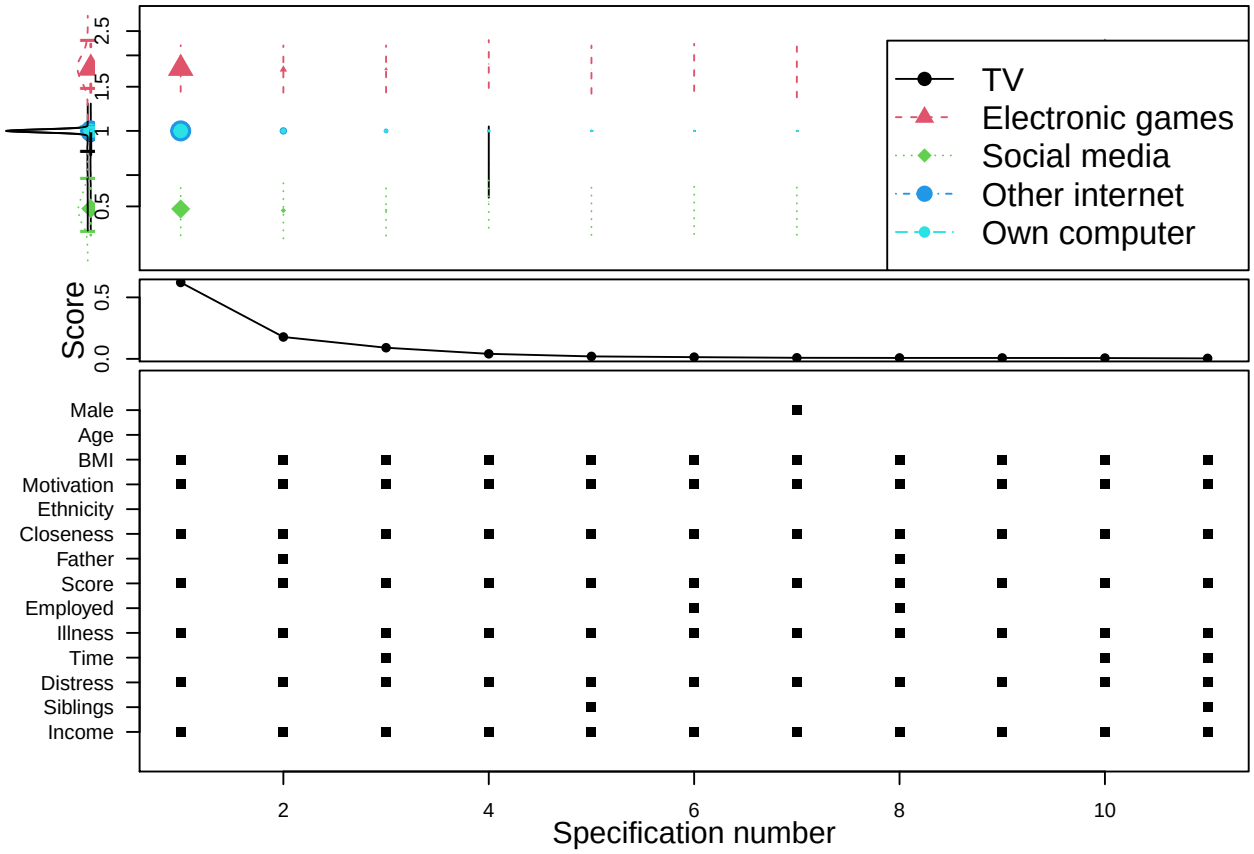
```
idx_fit = c(2:4)
id_years = c(12:14)
y_labels = c(0.8, 1, 1.25, 1.5, 1.75, 2)
names(y_labels) = log(y_labels)  # y scale as odds ratio

single_bsca(
  yrbs_ms, coefidx=idx_fit, omitvars=c(1, idx_fit, id_years),
  x.labels=yrbs$x_labels, var.labels=yrbs$c_names, y.labels=y_labels
)
```



S2.3.2 MCS data

Alternatively, we can plot the single-outcome BSCA for the MCS data and the parent-assessed outcome *high total difficulties*.

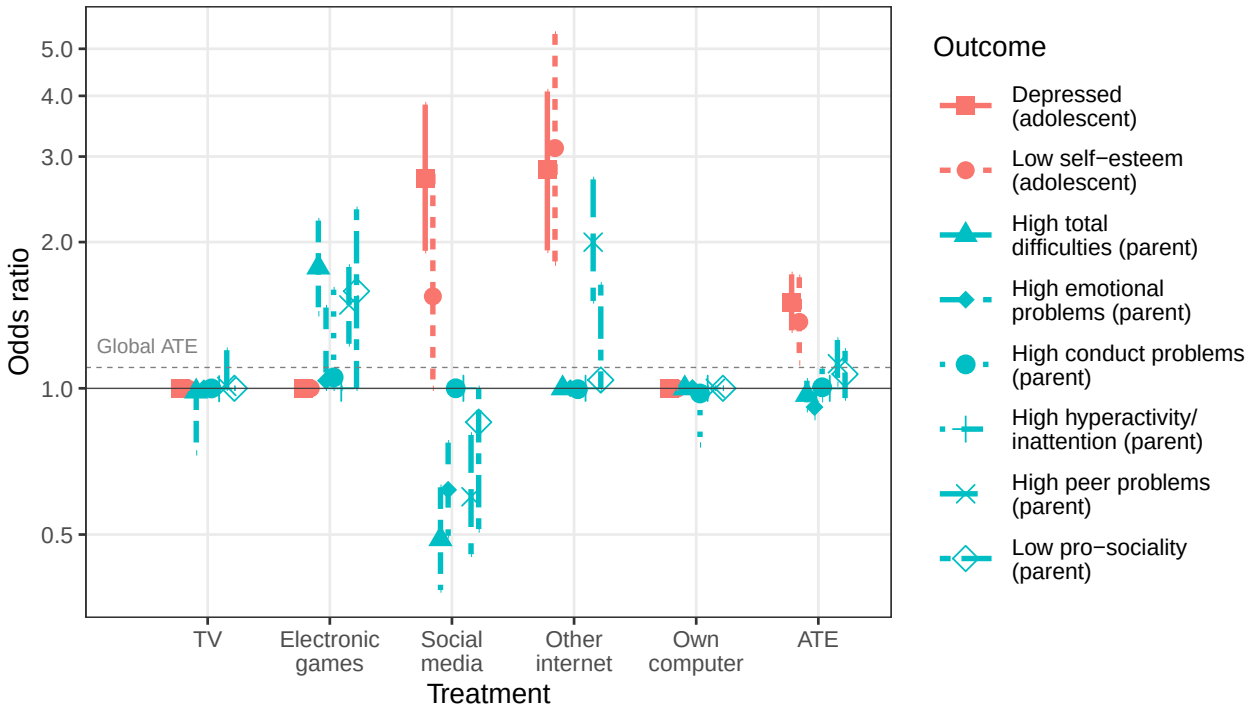
```
y_labels = c(1/2, 1/1.5, 1, 1.5, 2, 2.5)
names(y_labels) = log(y_labels)  # y scale as odds ratio

single_bsca(
  mcs_ms$`High total difficulties (parent)`, coefidx=2:6,
  x.labels=mcs$x_names, var.labels=names(mcs$cvars), y.labels=y_labels,
  height.vars=0.55
)
```



S2.4 Multiple-outcome BSCA

Our MCS data analysis included eight outcomes and five treatments of interest, for a total of 40 treatment-outcome combinations. To reduce the burden associated with producing a single BSCA plot for each outcome, the function `multi_bsca` summarizes the BMA results in a single plot. This plot allows one to easily evaluate and compare effects of several treatments on several outcomes. For instance, below all treatments have a similar effect on adolescent-assessed depression and on self-stem. However, these effects are non-comparable to those on parent-assessed total difficulties and emotional problems. We also add the ATE across treatments (`add.ate=TRUE`) and the simple average across outcomes (`add.avg=TRUE`). The average of the ATE estimates is the global ATE.

```
source('functions.R')
g = multi_bsca(mcs_coef, ms=mcs_ms, conversion=exp,  y.scale='Odds ratio',
               treatments=c('TV', '`Electronic games`', '`Social media`',
                            '`Other internet`',  '`Own computer`'),
               add.ate=TRUE, add.global.ate=TRUE,
               extract.color=TRUE) +
  scale_y_continuous(trans='log', breaks=c(1/2,1:5), minor_breaks=NULL)
g + geom_hline(yintercept=1, lwd=0.2, colour=g$theme$panel.border$colour)
```



S2.5 Subgroup analysis

We perform subgroup analyses for males using the continuous MCS outcomes, normalized to 1-10. After selecting the right data, we parameterize the variables as described in the paper. Interaction terms are included only if the corresponding main variable is included. We then perform BMA using `mombf:::modelSelection`.

```
attach(mcs)

idg="Male"; NITER_MCS = 10
{
  options(na.action='na.pass')
  x.reg = model.matrix(~ ., data[,x_vars])[, -1]
  colnames(x.reg) = x_names
}

ms_inter = list(); coef_inter = list()
for (idy in 1:length(y_cont)) {
  yname = names(y_cont)[idy]
  message(yname)

  datareg = na.omit(data[c(y_cont[idy], x_vars, cvars)])
  names(datareg) = c('y', x_names, names(cvars))

  # treatments
```

```
  idt = colnames(x.reg)
  datareg[idt] = datareg[idt] - 1/2
  # group
  g = datareg[[idg]]; rho = sum(g == 1)/length(g)
  datareg[[idg]] = ifelse(g == 1, 1-rho, -rho)
  # interaction
  inter = datareg[idt]*datareg[[idg]]
  colnames(inter) = paste0(colnames(inter), " × male")

  d = mombf:::createDesign(y ~ ., cbind(datareg, inter))
  p=length(d$constraints); pi=ncol(inter)
  d$constraints[(p-pi+1):p] = 1:pi+1
  ms_inter[[yname]] = mombf:::modelSelection(
    d$y, d$x, includevars=1, priorDelta=modelbbprior(1,1),
    priorCoef=bicprior(), priorGroup=bicprior(),
    niter=NITER_MCS, groups=d$groups, constraints=d$constraints,
  )
  coef_inter[[yname]] = coef(ms_inter[[yname]])
}
```

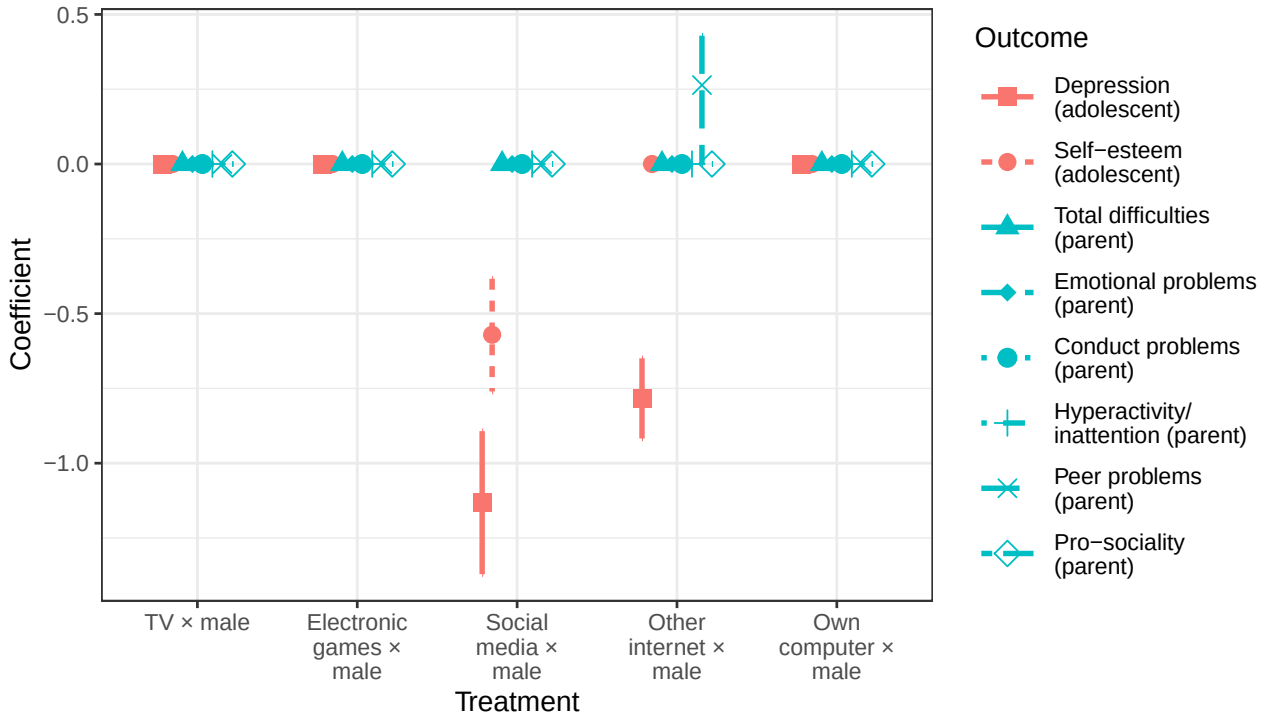
```
## Depression (adolescent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Self-esteem (adolescent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Total difficulties (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Emotional problems (parent)
```

```
## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Conduct problems (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Hyperactivity/inattention (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Peer problems (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead

## Pro-sociality (parent)

## Greedy searching posterior mode... Done.
## Running Gibbs sampler.......... Done.

## Warning in hasPostSampling(object): Exact posterior sampling not implemented,
## using Normal approx instead
```

```
detach(mcs)
```

We show the results in a multiple-outcome BSCA.

```
multi_bsca(
  coef_inter, ms=ms_inter, treatments=paste0("`", colnames(inter), "`"),
  extract.color=TRUE
)
```



The interaction coefficients for self-reported depression are:

```
print(coef_inter$`Depression (adolescent)`[paste0("`", colnames(inter), "`"), ])
```

```
##                              estimate       2.5%      97.5%      margpp
## `TV × male`                 0.0000000  0.0000000  0.0000000 0.000000000
## `Electronic games × male`   0.0000000  0.0000000  0.0000000 0.001116968
## `Social media × male`      -1.1312392 -1.3709710 -0.8929189 0.999999991
## `Other internet × male`    -0.7846076 -0.9174801 -0.6495155 0.983863396
## `Own computer × male`       0.0000000  0.0000000  0.0000000 0.000000000
```

The interaction coefficients for self-reported self-esteem are:

```
print(coef_inter$`Self-esteem (adolescent)`[paste0("`", colnames(inter), "`"), ])
```

```
##                              estimate       2.5%      97.5%      margpp
## `TV × male`                 0.0000000  0.0000000  0.0000000 0.000000000
## `Electronic games × male`   0.0000000  0.0000000  0.0000000 0.009004628
## `Social media × male`      -0.5707064 -0.7604759 -0.3836722 0.998087804
## `Other internet × male`     0.0000000  0.0000000  0.0000000 0.007465021
## `Own computer × male`       0.0000000  0.0000000  0.0000000 0.000000000
```

S3 Robustness checks

In this section, we provide robustness checks for the results presented in the main paper.

S3.1 YRBS: alternative outcomes

In their analysis of the YRBS data, besides 'thought about suicide', Orben and Przybylski (2019) used several well-being measures to study the effect of technology use: loneliness, planned suicide, attempted to commit suicide and saw a doctor about suicide. We have reproduced Fig. 1 for these outcomes in Fig. S1. All associations are qualitatively similar, although the magnitudes vary.

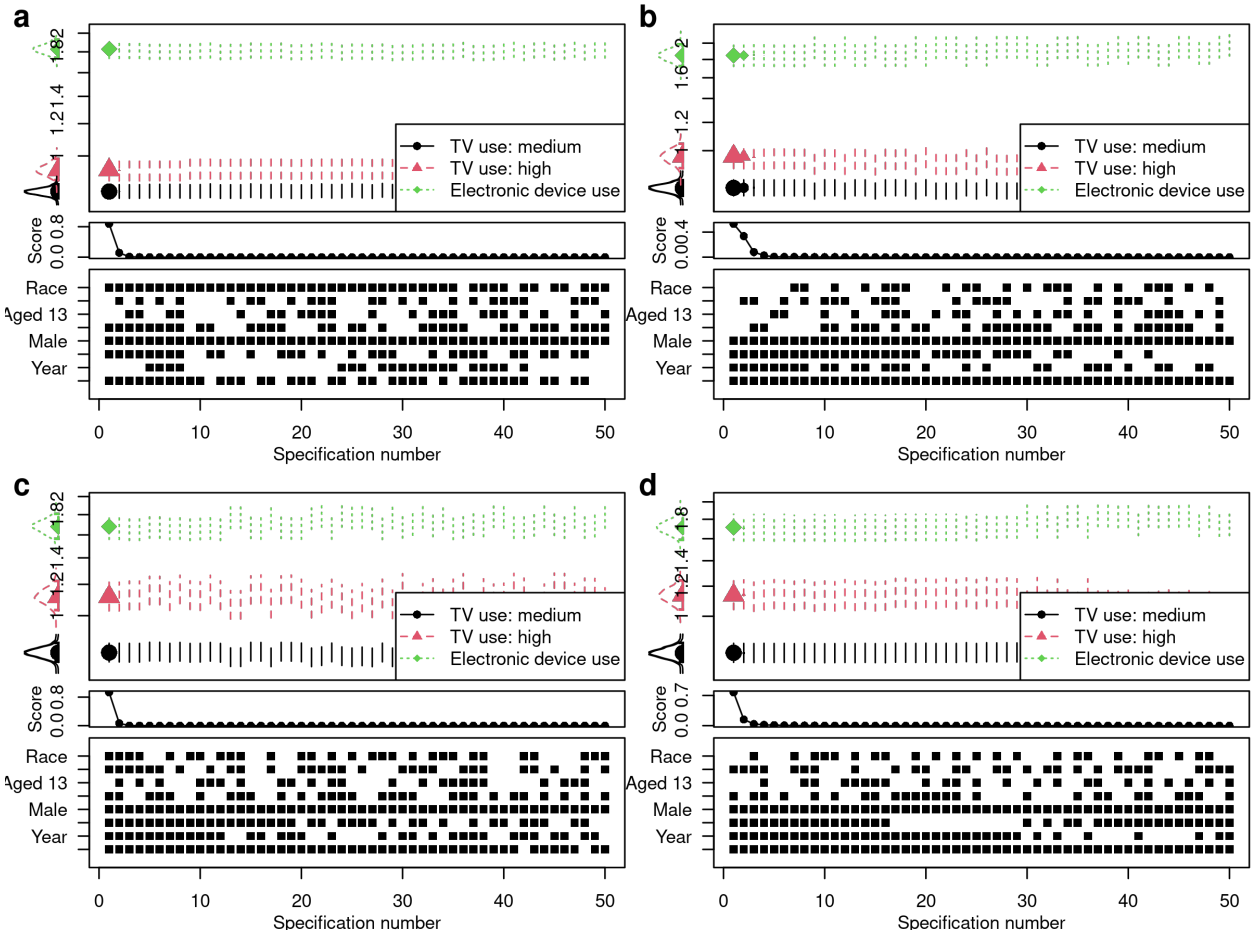


Figure S1: BSCA for other outcomes using YRBS data: (a) loneliness, (b) planned suicide, (c) attempted to commit suicide and (d) saw a doctor about suicide. Otherwise, everything – including the order of control variables in the bottom panel – is as in Fig. 1 of the main text.

S3.2 YRBS: linear regression

All outcome variables in the YRBS are binary (e.g. 0 = did not think about suicide, 1 = thought about suicide). Orben and Przybylski (2019) used linear regression, which is unsuitable for binary outcomes. Instead, we used logistic regression to model the probability

of the outcome being one. The logistic regression coefficient is easily interpretable; it is the log odds-ratio associated of said probability relative to the reference group, for example the log odds-ratio of the probability that a teenager who watches a moderate amount of TV thinking about suicide relative to a teenager who does not watch TV.

For robustness, Fig. S2 shows the single-outcome BSCA for a linear regression model. Our main results remain qualitatively unaltered: electronic device use is associated with an increase in the probability of thinking about suicide, whereas moderate TV use is associated with a decrease.

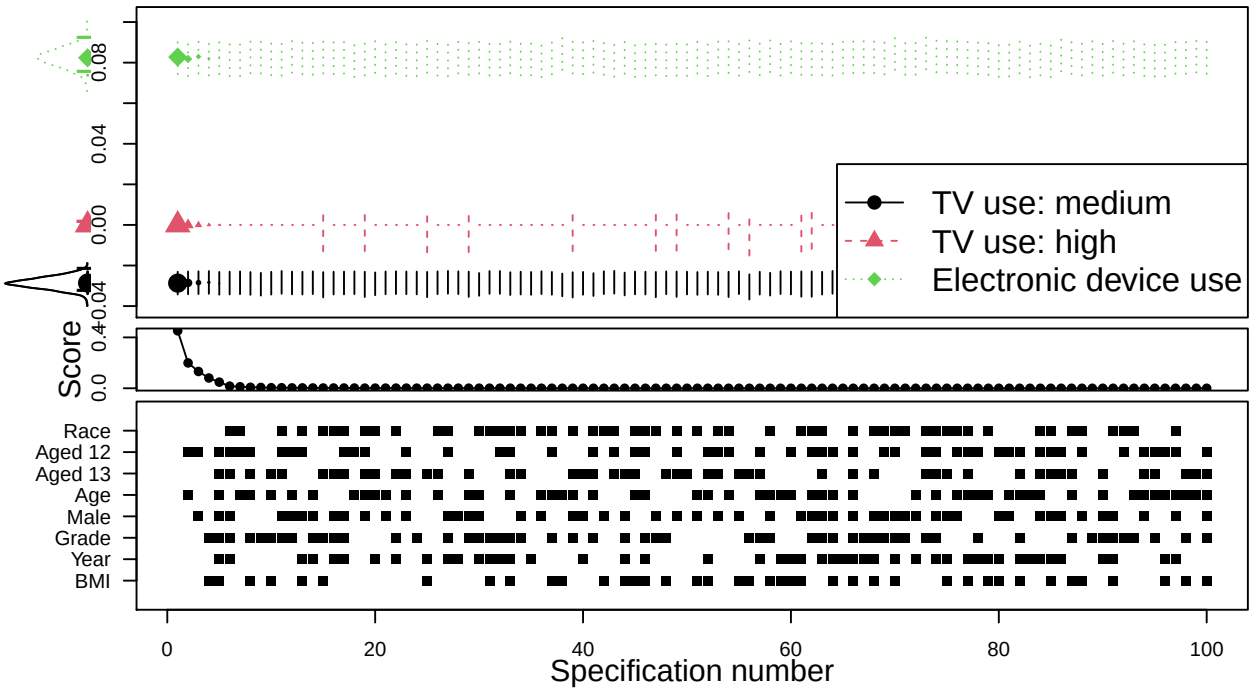


Figure S2: YRBS data. BSCA for the effect technology uses on thinking about suicide. Estimates are obtained using the linear probability model, by iterating over all possible models – including with only one TV coefficient removed. Otherwise, everything is specified as in Fig. 1 of the main text.

S3.3 YRBS: lineary of association with TV use

Preliminary exploratory data analyses (see the supplementary file `bsca_preanalysis.html`) revealed that in both the YRBRS and MCS datasets almost all treatments had a monotone, near-linear association. The only exception was TV usage in the YRBS data, which displayed a U-shaped association with adolescent well-being, see Fig. S3.

Therefore, we estimated separate coefficients for medium and high TV use based on coefficient similarity in Fig. S3 (see the main text for the exact coding). For completeness, we also performed a BSCA with an assumed linear TV effect. As expected, the association was in between that for medium and high usage, as shown in Fig. S4. Note that the estimate

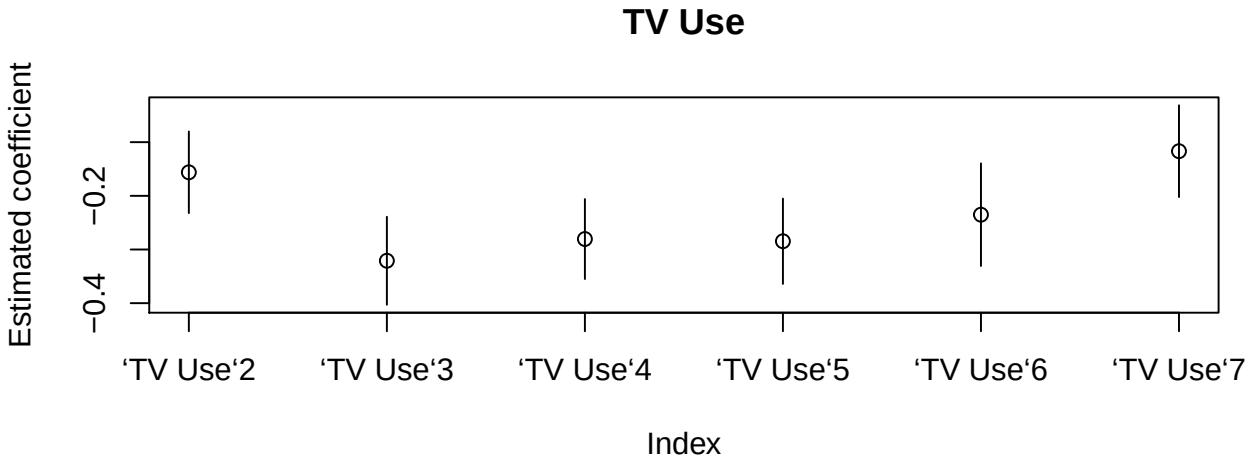


Figure S3: YRBS data. Estimated coefficient for different values of TV use on thinking about suicide. Coefficients were estimated by MLE for a model including all treatment and control variables. Estimated coefficients are qualitatively similar for other outcomes.

still suggests that higher TV use is associated with lower odds of thinking about suicide, as in our main analysis.

S3.4 MCS: full BSCAs

Fig. 2 of the main paper shows the summary of coefficients for different (parent- and self-assessed) outcomes. We showed the multiple-outcome BSCA for brevity. Fig. S5 shows the single-outcome BSCAs for those outcomes discussed in the text (self-assessed depression and low self-esteem, parent-assessed high total difficulities and emotional problems), whereas Fig. S6 shows those for the remaining parent-assessed outcomes.

S3.5 MCS: linear regression

Unlike in the YRBS dataset, which has binary outcomes, the outcomes in the MCS dataset are numerical. Parent assessments use the Strengths and Difficulties Questionnaire (SDQ), which provides a score for several well-being categories. Adolescent self-assessments come in three different forms: depressive symptoms according to the short version of the Mood and Feelings Questionnaire (SMFQ), self-esteem according to the Rosenberg scale, and a non-standardized "wellbeing grid" (with the prompt "On a scale of 1 to 7 where '1' means completely happy and '7' means not at all happy, how do you feel about the following parts of your life?" and various outcomes, e.g. 'Your life as a whole'). Individual questions use 3 item (SDQ and SMFQ), 4 item (Rosenberg) or 7 item (wellbeing grid) Likert scales and the aggregate scores (where available) also have different supports.

In our main analysis we converted the outcomes into a binary outcome where 1 codes for an abnormal outcome and 0 for a normal outcome. This conversion was done for two reasons. First, we could use logistic regression for both the YRBS and MCS data, making the results (i.e. odds ratios between low and high usage) comparable. Second, because the scales

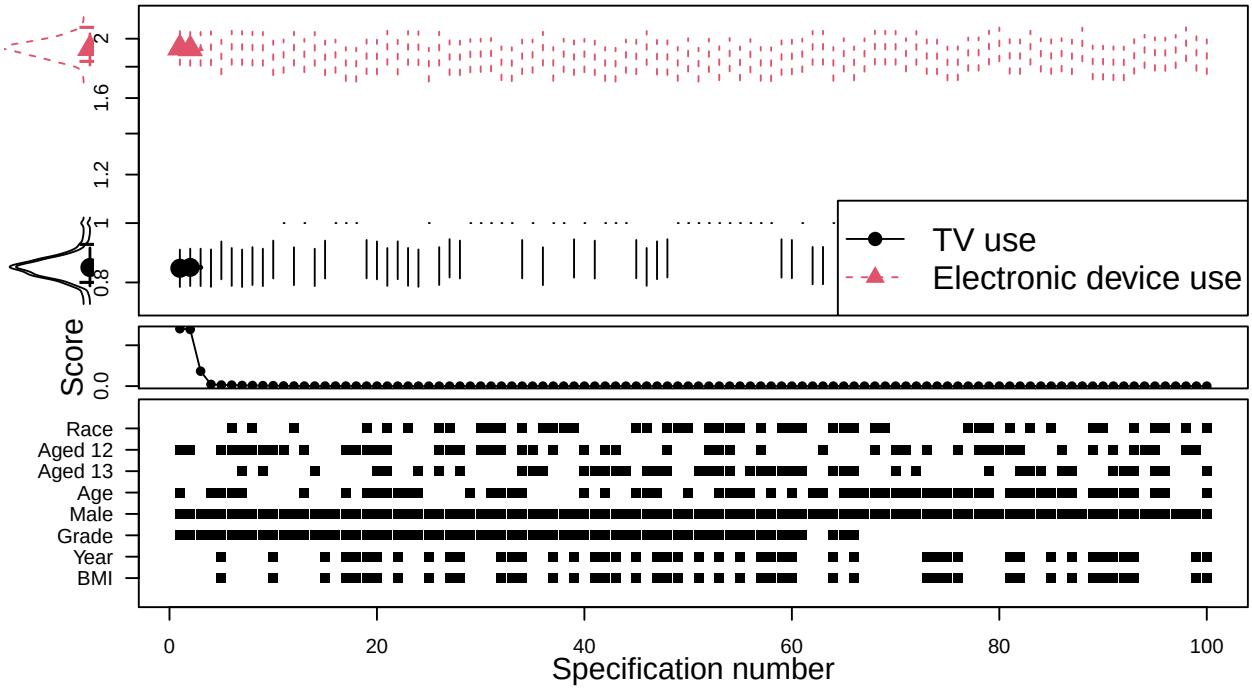


Figure S4: YRBS data. Bayesian SCA for the effect of technology uses on thinking about suicide. TV use is numeric, with 0 = no usage and 1 = 5 hours or more. Otherwise, everything is specified as in Fig. 1 of the main text.

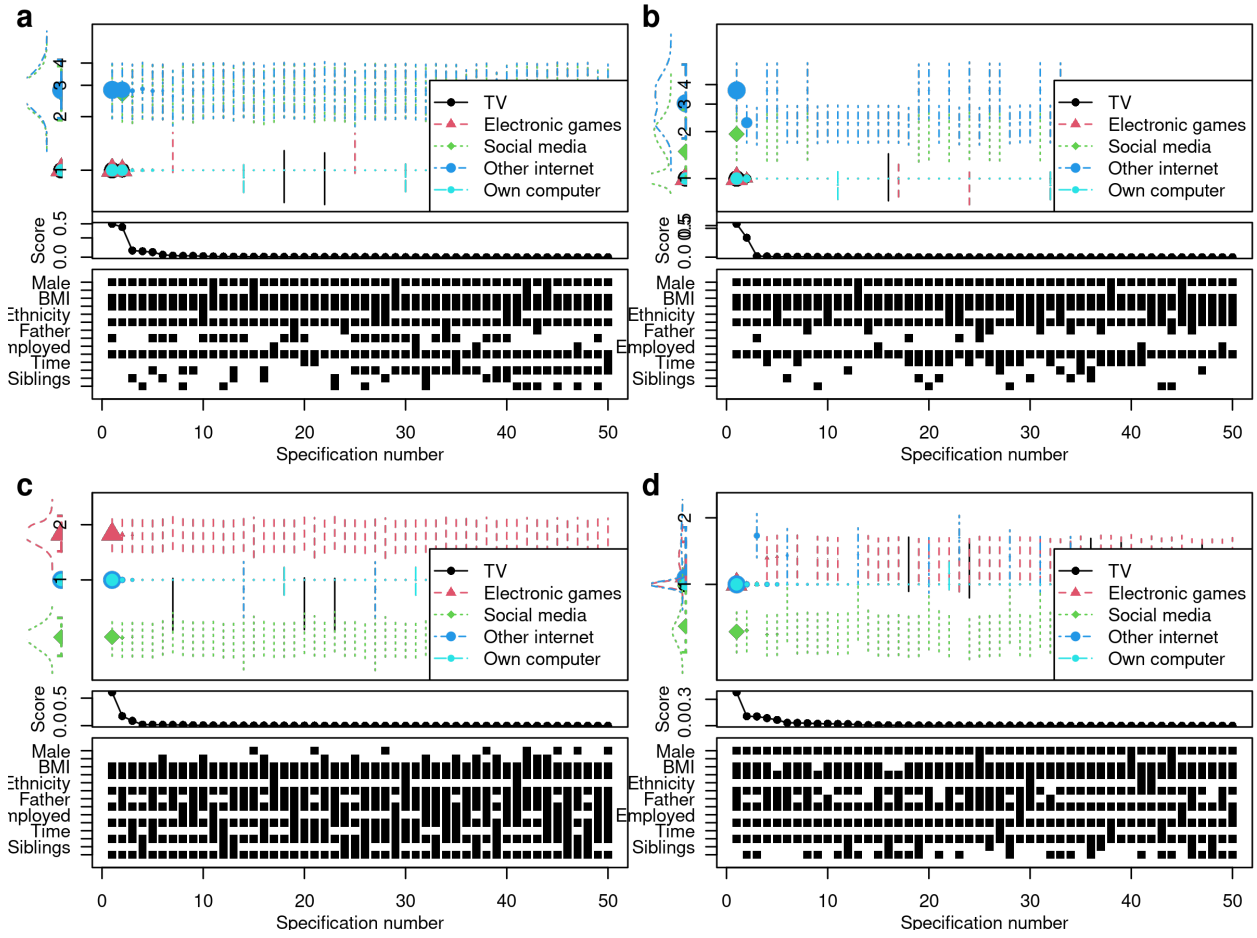


Figure S5: MCS data. BSCAs for outcomes: (a) adolescent-assessed depression, (b) adolescent-assessed low self-esteem, (c) parent-assessed high total difficulties and (d) parent-assessed high emotional problems. For variable codings and confounders, see Fig. 2 of the main text.

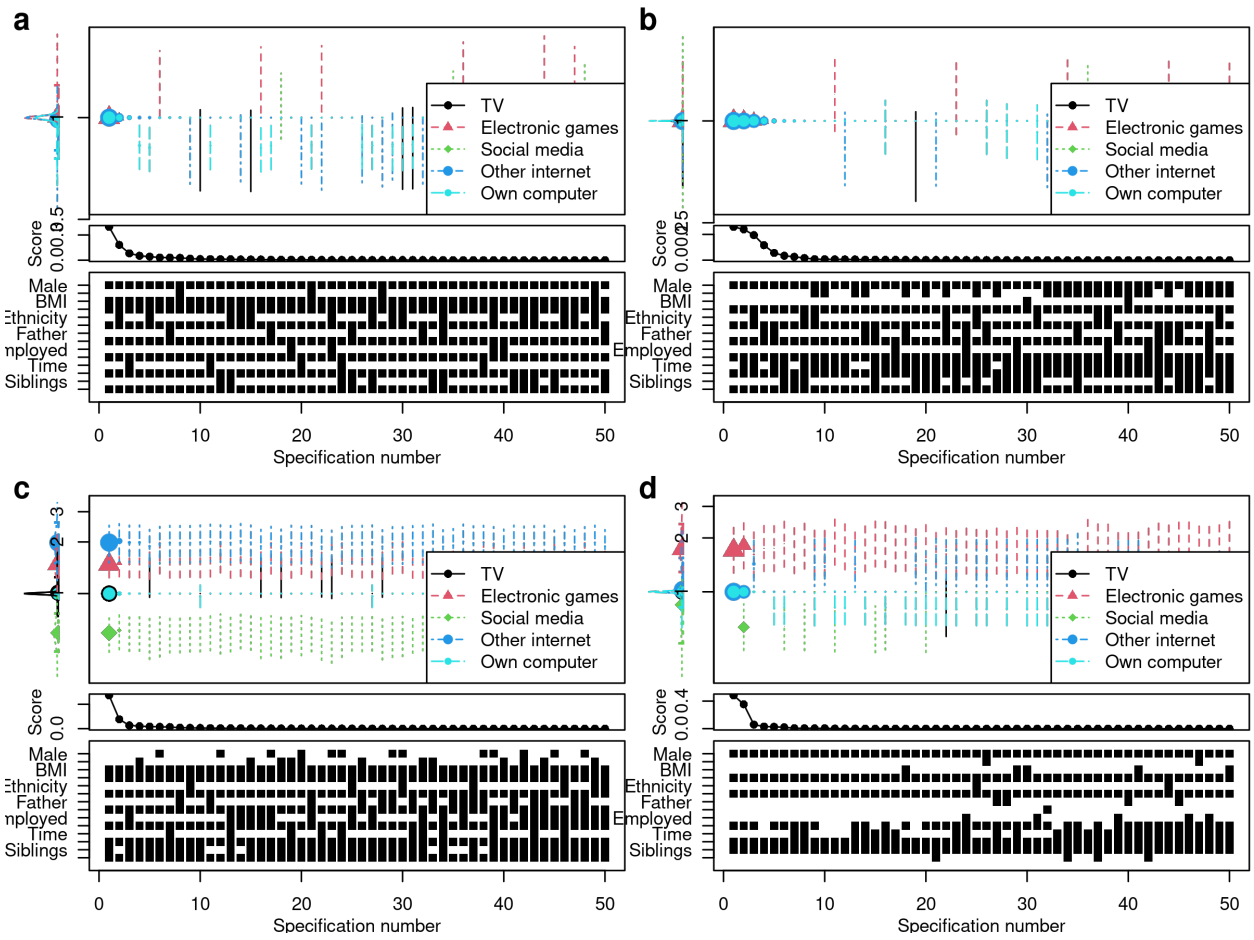


Figure S6: MCS data. BSCAs for parent-assessed outcomes (SDQ): (a) conduct problems (b) hyperactivity/inattention, (c) peer problems and (d) prosociality. For variable codings and confounders, see Fig. 2 of the main text.

are mostly standardized, there exist recommended cutoffs derived from population data to define our binary bad (abnormal) / good (normal) outcome. The cutoffs (given in Fig. 2 of the main text) come from Goodman (1997) and Goodman, Meltzer, and Bailey (1998) for the SDQ, Rosenberg (1965) and Nguyen et al. (2019) for the Rosenberg scale, and Thabrew et al. (2018) for the SMFQ. The 'well-being grid' outcomes are not included in Fig. 2, since they do not come from standardized scales and no population-based abnormality cutoffs are available, see next section.

For robustness, we also obtained results using the linear regression model on the original numerical outcomes. The linear regression results for the outcomes discussed in the main paper are shown in Fig. S7. One important difference is that social media is not included in the results for the self-esteem outcome. This is likely due to the high co-linearity with other internet (Pearson's correlation = -0.63). Otherwise, our main results retain their estimated signs.

In addition, Figs. S8 and S9 show the linear results for the remaining parent-assessed and adolescent-assessed outcomes, respectively. Notably, unlike in the logistical model, in Fig. S8 other (non-social media) internet usage and owning a computer are negatively and positively associated with parent-assessed prosociality. As shown in Fig. S9, technology use has very different estimated effects on different types of self-assessed happiness. Social media, for example, is positively associated with being happy with ones friends, but negatively with being happy with ones looks. In contrast, none of the technology uses considered are associated with happiness regarding school, school work or family.

S3.6 Subgroup analysis

Figures S10 and S11 replicate the subgroup analysis of the main paper using logistic regressions for the YRBS and MCS data, respectively. Variables are parameterized as described in Section 2. Thus, the estimated coefficient is a difference compared to the ATE. Besides the inclusion of the gender-treatment interaction variables, the models are specified as in Figures 2, S1 and 4.

There is less variation in the binary data. As a result, we cannot rule out that there is no gender effect for any of the treatments.

S4 Further differences with Orben and Przybylski (2019)

Our analysis is based on the YRBS and MCS datasets also used by Orben and Przybylski (2019) and largely followed their treatment of the data, which was facilitated by their commendable sharing of the R code used for the analysis. However, we deviated from their data treatment choices (in the MCS data) when we felt these were potentially problematic. We also enlarged the set of possible control variables in both datasets. In this section, we explain these differences.

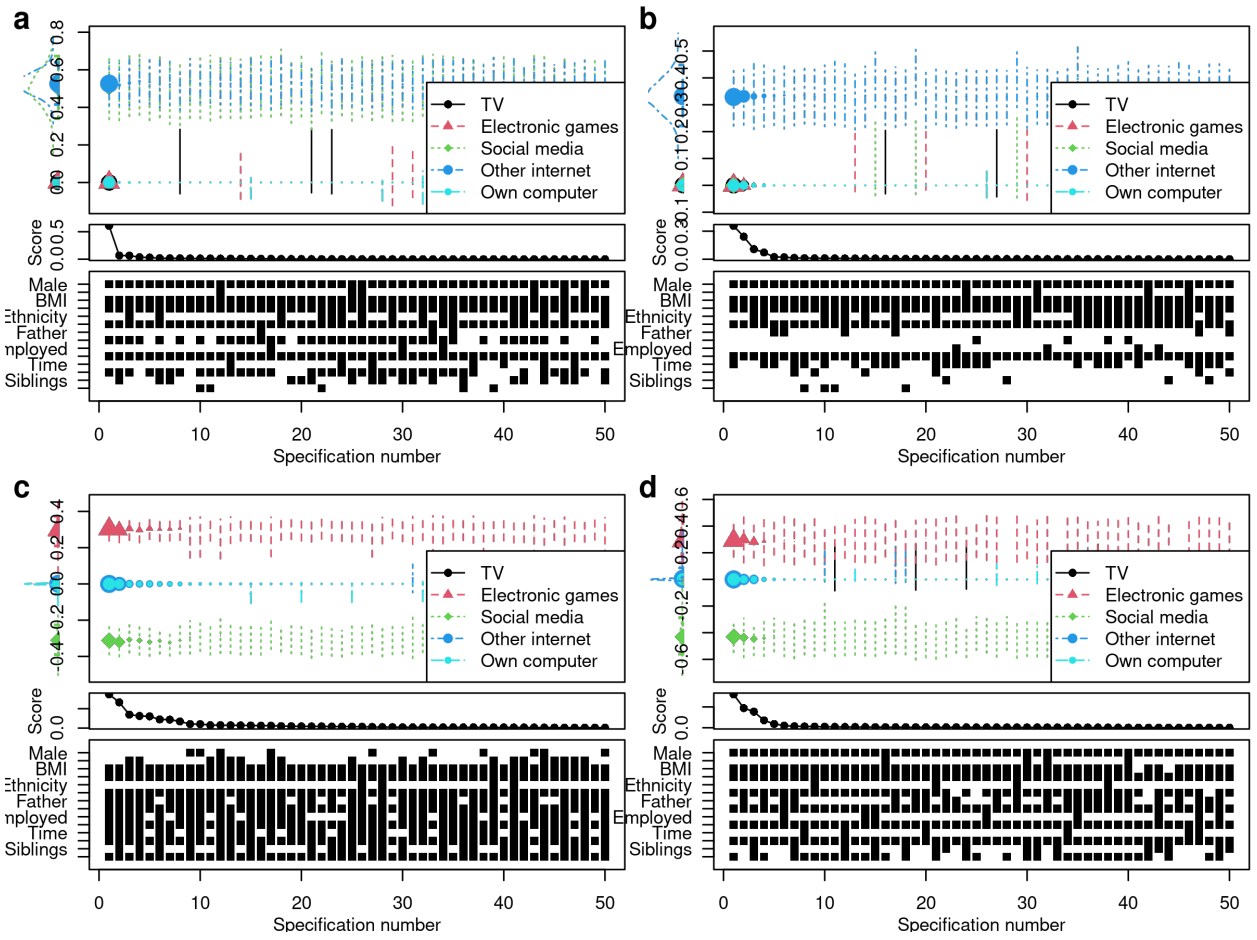


Figure S7: MCS data. Linear regression BSCA for main outcomes: (a) adolescent-assessed depression, (b) adolescent-assessed self-esteem (inverted), (c) parent-assessed total difficulties and (d) parent-assessed emotional problems.

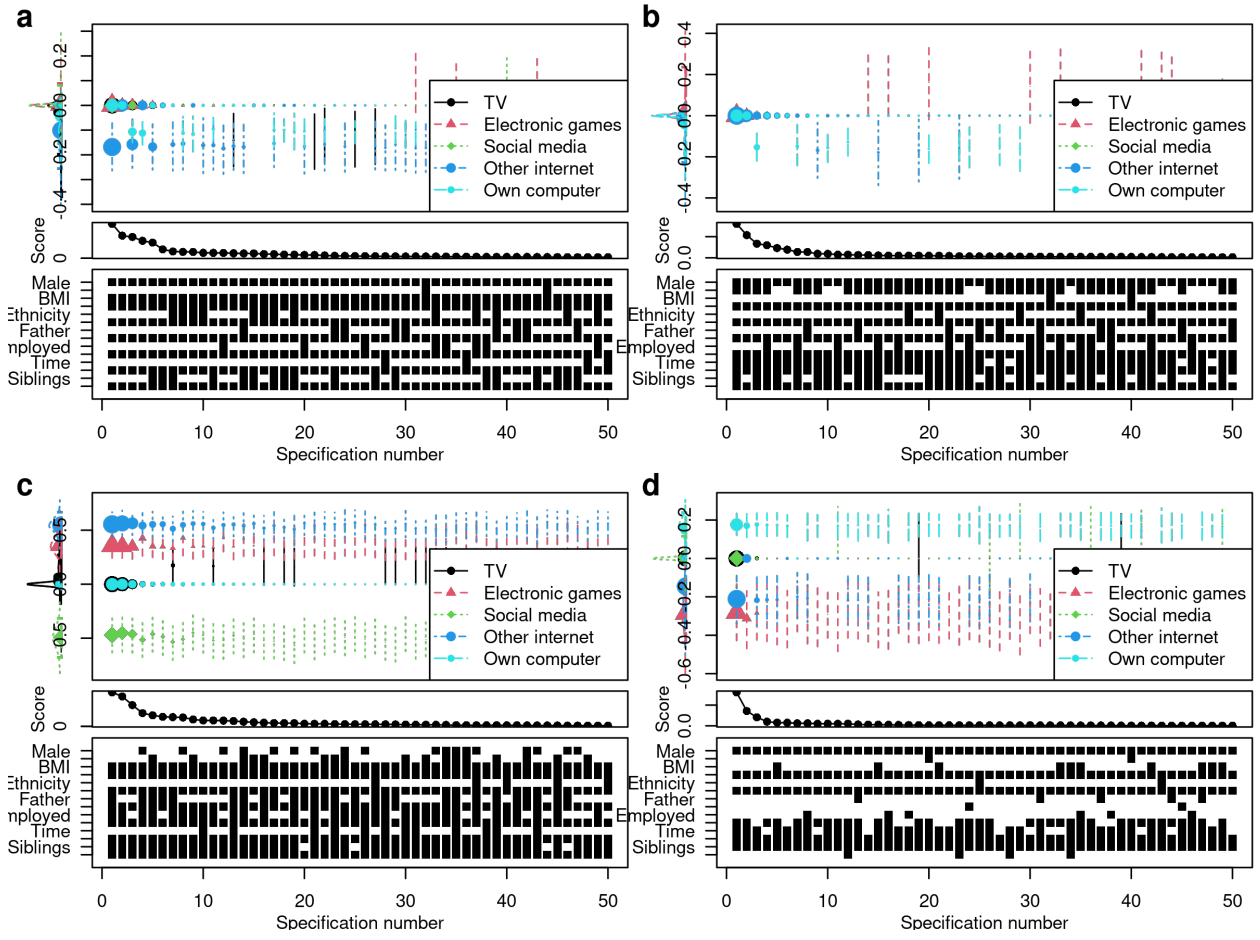


Figure S8: MCS data. Linear regression BSCA for parent-assessed outcomes (SDQ): (a) conduct problems (b) hyperactivity/inattention, (c) peer problems and (d) prosociality.

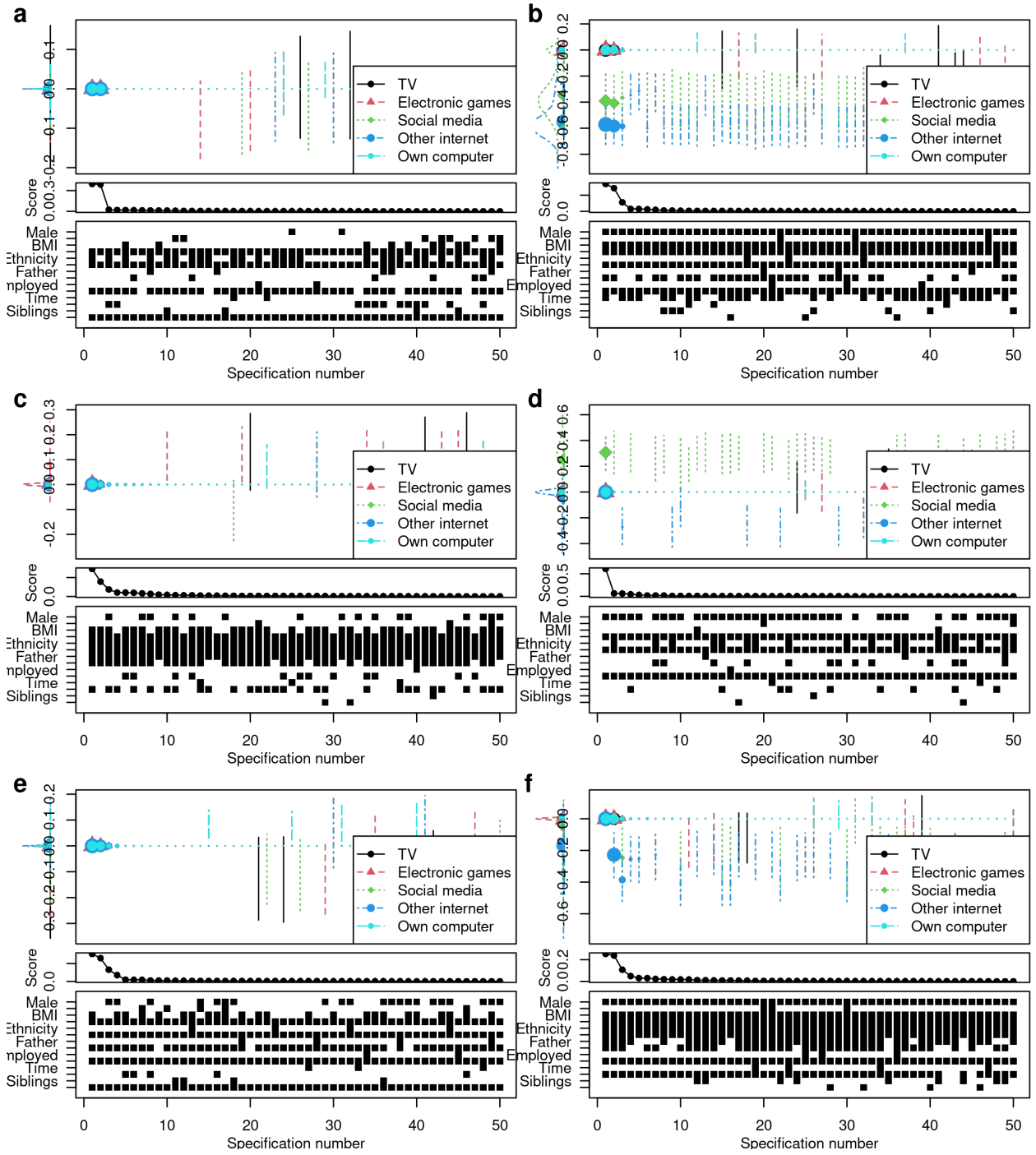


Figure S9: MCS data. Linear regression BSCA for adolescent-assessed outcomes (well being grid): happy with (a) school work (b) looks, (c) family, (d) friends, (e) school and (f) life as a whole.

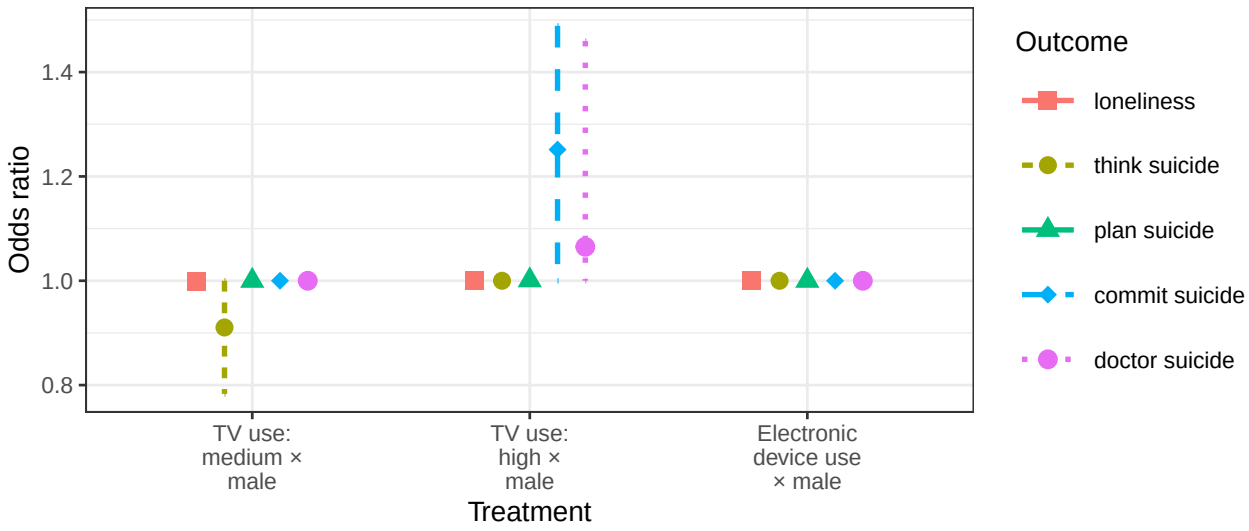


Figure S10: YRBS data. Multiple outcome BSCA for interactions between different treatments and male.

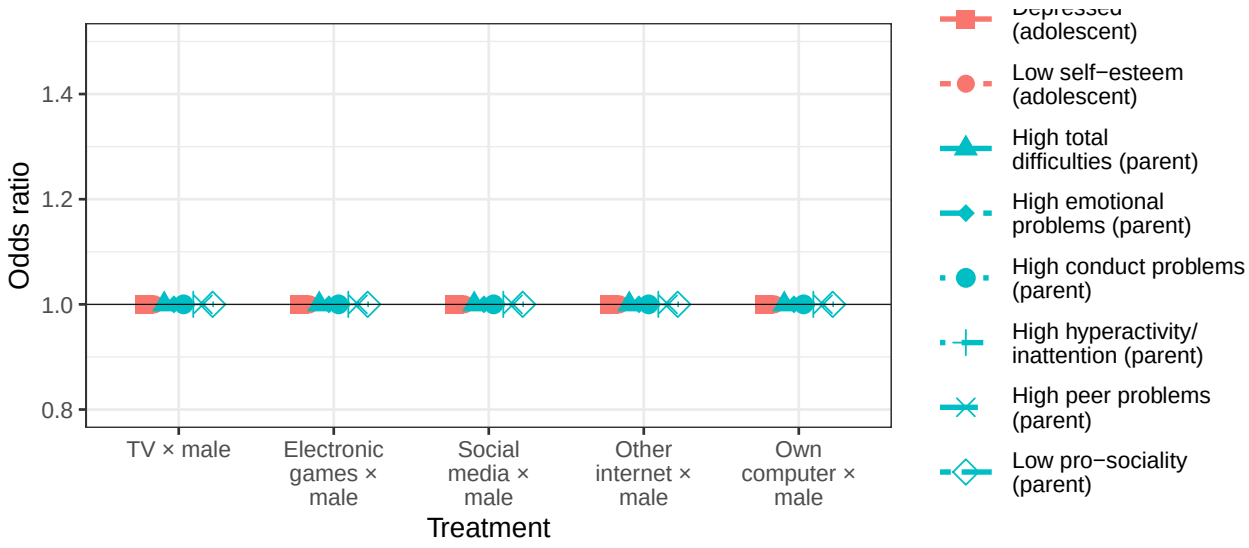


Figure S11: MCS data. Multiple outcome BSCA for interactions between different treatments and male.

Table S1: Summary statistics for parent-assessed MCS outcome variables used in Orben and Przybylski (2019)

	Obs.	Mean	S.D.	Min	25%	Median	75%	Max
fpsdro00	10265	0.53	0.68	-1	0	1	1	1
fpsdhs00	10214	0.54	0.65	-1	0	1	1	1
fpsdtt00	10242	0.42	0.71	-1	0	1	1	1
fpsdsp00	10234	0.48	0.68	-1	0	1	1	1
fpsdmw00	10242	0.50	0.66	-1	0	1	1	1
fpsdfs00	10198	0.67	0.60	-1	0	1	1	1
fpsdfb00	10255	0.92	0.32	-1	1	1	1	1
fpsdud00	10221	0.74	0.54	-1	1	1	1	1
fpsddc00	10228	0.32	0.72	-1	0	0	1	1
fpsdnc00	10240	0.52	0.66	-1	0	1	1	1
fpsdoa00	10240	0.80	0.46	-1	1	1	1	1
fpsdpb00	10220	0.71	0.57	-1	1	1	1	1
fpsdcs00	10249	0.94	0.29	-1	1	1	1	1
fpsdgb00	10249	0.46	0.67	-1	0	1	1	1
fpsdfe00	10271	0.68	0.57	-1	0	1	1	1
fconduct	11488	9.58	1.63	1	9	10	11	11
fhyper	11481	8.01	2.40	1	7	8	10	11
fprosoc	11489	8.31	1.85	0	7	9	10	10
fpeer	11491	9.26	1.82	1	8	10	11	11
femotion	11486	8.95	2.14	1	8	10	11	11
febdtot	11471	32.81	5.99	3	30	34	37	41

S4.1 Re-scaling of variables

Orben and Przybylski (2019) transformed all outcome variables into a common 1-10 point scale prior to their analysis, so that it is easier to compare outcome values, estimated treatment effects, and combining them across outcomes. Unfortunately, this pre-processing step was not coherently applied to all MCS outcomes (see `1_3_prep_mcs.R` in their replication files), which led to several outcomes not being in the 1-10 scale (some actually have negative values, whereas one outcome takes on values as large as 41, see Table S1). As a consequence, the estimated treatment effects for these outcomes are not really comparable to the outcomes that were in the 1-10 scale, leading to difficulties in interpreting their SCA plot.

S4.2 Outcomes: individual questions versus validated scales

The analysis by Orben and Przybylski (2019) used as outcomes individual questions that make up common scales (e.g. all the values ending in 00 in Table S1). This is done for the adolescent-assessed Mood and Feelings Questionnaire – short version (SMFQ), the adolescent-

assessed Rosenberg scale and the parent-assessed Strengths and Difficulties Questionnaire (SDQ). While we think it is generally useful to look at different outcomes, we do not recommend breaking up questions that make up established scales, unless there is a strong reason for doing so. This is because the combined scores have well-established psychometric properties, such as internal consistency, test-retest reliability and validity (see Stone et al. 2010; Sinclair et al. 2010; Thabrew et al. 2018 for the SDQ, Rosenberg scale and SMFQ, respectively). Hence, our analyses focused on the combined scores, rather than on individual questions. This point was also addressed by Orben and Przybylski (2020) themselves.

S4.3 Multiple treatment variables

As described in Section 1, in situations where there are multiple treatment variables it is statistically preferable to include them jointly in the model, to ameliorate the confounding between their estimated effects. The YRBS data has two treatments: TV and electronic devise use. The MCS data has five treatments: TV, electronic games, social media, other internet and own computer. In our analyses we always jointly included all treatments.

S4.4 Control variables

In our analysis, we included more control variables than Orben and Przybylski (2019). For the YRBS analysis, the only control variable they sometimes included is race. We added age, sex, grade, year of the survey and body-mass index (BMI), several of which were statistically significant (see Fig. 1 and Fig. S1). For the MCS analysis, Orben and Przybylski (2019) included a larger set of control variables (see Fig. 2), to which we added sex, age and BMI, which again turned out to be important. We also departed from their analysis in how we treated two MCS control covariates: primary caretaker's employment and education status.

Regarding employment, Orben and Przybylski (2019) used the NS-SEC 5 category for the current job (1="Manager" through 5="Routine"), meaning that all kids with unemployed primary caretakers (for which the variable is coded `NA`) are excluded from the analysis. This is actually a non-negligible proportion of the dataset, see Table S2. We believe that such exclusion may introduce biases, by restricting the scope of the inference to kids with employed parents caretakers. Instead, in our analysis we included a binary variable to control for employment status (1=employed or self-employed; 0 otherwise), which allows including kids with unemployed parents into the analysis.

Regarding education status, the covariate is also coded on a 1-5 scale, but there are two special values (95= "Overseas qualification" and 96="None of these"), see Table S3. Orben and Przybylski (2019) included the 95-96 values in their linear regression analysis, which is inappropriate: one cannot interpret the estimated coefficients as capturing the association between the outcome and the caretaker's education status. Possible alternative analyses are to either exclude individuals with these codes (excluding a non-negligible proportion of individuals), or use a non-linear coding for the covariate's effect. For simplicity, and given that we already included numerous other control covariates, in our analysis we excluded the education variable.

Table S2: Primary caretaker employment status (1-5). Number of individuals with each value

1	2	3	4	5	NA
3276	1832	696	273	2012	3795

Table S3: Primary caretaker education status (1-5). Number of individuals with each value

1	2	3	4	5	95	96	NA
660	2598	1496	3784	1170	331	1104	741

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