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Associations between social media use and cognitive abilities: Results from a large-scale study of adolescents

Stefan Stieger [a,*], Sabine Wunderl [b]

[a] Department of Psychology and Psychodynamics, Karl Landsteiner University of Health Sciences, Krems an der Donau, Austria
[b] WKNÖ-Educational Information Centre, St. Pölten, Austria

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ABSTRACT

In adolescence, smartphone use in general and social media use in particular has often been associated with negative effects, such as higher anxiety levels and body dissatisfaction. Other outcomes – such as fundamental cognitive abilities and skills (e.g., intelligence, information processing, spatial perception) – have rarely been the focus of research. Here, we analysed data from a large sample of adolescents (12–16 years; $N > 12{,}000$) who performed a series of psychometric tests ranging from intelligence, spatial perception, and information processing, to practical numeracy, and compared their test results with their social media usage (average active and passive time per day, problematic social media use). We additionally applied a random-forest model approach, useful for designs with many predictors and expected small effect sizes. Almost all associations did not outperform known age- and sex-differences on social media use; that is, effect sizes were small-to-tiny and had low importance in the random-forest analyses compared to dominant demographic effects. Negative effects of social media use may have been overstated in past research, at least in samples with adolescents.

1. Introduction

In the early days of the Internet, communication was typically unidirectional and often time-staggered, that is, real-time communication was rarely possible. Since then, however, Internet-mediated communication has become so fast that it is possible to communicate with people worldwide with only very small time delays, so much so that we do not truly see much difference compared with face-to-face communication. This transformation from unidirectional, time-staggered communication to bidirectional, almost real-time communication has often been termed Web 2.0 or social media (Ellison & boyd, 2013). Since then, research has analysed what impact this transformation may have had on people, especially adolescents as frequent users, and how this could be explained.

One example is the transformation framework (Nesi et al., 2018), which focuses on the impact of social media-based communication on adolescents' peer experiences (i.e., experiences typically occurring between two or more individuals). It is assumed that this impact is based on seven key differences between face-to-face and online communication via social media. Specifically, social media is mostly asynchronous (i.e., there is time lapse due to the time taken to construct messages, though videoconferencing is an exception), permanent (i.e., texts and other content is stored or can be recorded), public (i.e., usually accessible by large audiences), almost universally available (i.e., can be shared regardless of physical location), lacks certain cues (i.e., physical cues such as gesture may be absent), quantifiable (i.e., use of social metrics, such as likes), and visual (i.e., use of photographs and videos). According to proponents of the transformation framework, these aspects of social media communication can have an impact in five key ways: changing the frequency and/or immediacy of experiences (e.g., frequency may be higher, leading to increased friendship quality and well-being; e.g., Burke & Kraut, 2016); amplifying experiences and demands (e.g., being available all the time elicits feelings of pressure or guilt to be available online and to respond to communication; Fox & Moreland, 2015); altering the qualitative nature of interactions (e.g., misinterpretation of information in online conversations leading to higher levels of social anxiety; Kingsbury & Coplan, 2016); facilitating new opportunities for compensatory behaviours (e.g., higher self-esteem in shy or introverted adolescents interacting with exclusively online friends; van Zalk et al., 2014), and; creating entirely novel behaviours (e.g., adolescents adjusting their offline behaviours to avoid a negative self-image presentation to their online audience through statements,

* Corresponding author. Department of Psychology and Psychodynamics, Karl Landsteiner University of Health Sciences, Dr.-Karl-Dorrek-Straße 30, A-3500, Krems an der Donau, Austria.
E-mail address: stefan.stieger@kl.ac.at (S. Stieger).

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pictures, or videos; Marder et al., 2016).

These changes in the forms of communication raise important questions, especially for children and adolescents who intensively use Internet-based social media applications, such as Twitter, Facebook, Instagram, or YouTube (e.g., O'Keeffe & Clarke-Pearson, 2011; Wiederhold, 2019). These issues have been compounded by the introduction of the smartphone (Andreassen & Pallesen, 2014) – now owned by more than 80% of the world's population (2021: 6.4 billion users) – offering possibilities to be permanently online in everyday life.[1] For example, cyberbullying, sexting, online harassment, and extensive use of social media platforms have been described as increasingly prevalent (Kennedy, 2021). In 2017, 98% of all children in the U.S. under the age of 8 years had access to mobile devices in their homes (a 23% increase from 2013; Rideout, 2017). Meanwhile, a third of these children's screen time is mobile (an increase of 31% compared to 2011; Rideout, 2017; the rest is TV, computers, etc.). Furthermore, children of that age use mobile devices for 48 min per day on average, a substantial increase compared to data from 2013 (15 min) and 2011 (5 min; Rideout, 2017). Therefore, it is likely that the peak of potential problematic use has been reached as yet (e.g., Twenge et al., 2018).

Although a plethora of articles have highlighted possible negative effects of excessive use of smartphones and social media (e.g., Ellison, 2012; O'Keeffe & Clarke-Pearson, 2011), recent research has questioned the overall (negative) picture that has developed about overuse (George & Odgers, 2015; Mills, 2016). For example, a large-scale, nationally representative (U.K.) panel study with adolescents found that, although the amount of time adolescents devoted to social media negatively affected their satisfaction with life (Orben et al., 2019a; N = 12,672, 8 waves), effect sizes were very small. In another large study (N = 355, 358), the authors found only weak evidence that digital technology use, in general, was associated with well-being (explained variance 0.4%; Orben & Przybylski, 2019). To put these small effects into context, other behaviours had larger effects on well-being than technology use *per se*; these other behaviours included being bullied and having asthma, but also seemingly trivial factors, such as wearing glasses or the amount of sleep. Even a large 8-year longitudinal study with yearly assessments of 500 participants between the ages of 13 and 20 years did not find substantial associations between time spent using social media and mental health issues, such as symptoms of depression and anxiety (Coyne et al., 2020).

In short, although there is a raft of studies about the impact of social media usage (and smartphone usage in general) with sometimes contradictory results, recent studies suggest that negative effects presented in the past are perhaps exaggerated and that the 'real' effect sizes are probably small and likely not of clinical and practical relevance (e.g., Coyne et al., 2020; Orben & Przybylski, 2019). Nevertheless, past research is also restricted in several aspects. For example, many studies have focused on well-being, satisfaction with life, loneliness, and depression, but not other constructs, such as fundamental cognitive abilities and skills (e.g., intelligence, information processing, spatial perception, etc.; for exceptions, see Barr et al., 2015; Minear et al., 2013; Takeuchi et al., 2018; Walsh et al., 2020).

Furthermore, previous research has often used statistical procedures, such as multiple linear regressions, that can be biased when prerequisites are not met (which is often not clear in these studies). For example, multicollinearity (i.e., substantial intercorrelation between predictors) can make it difficult to assess the individual importance of predictors and increase the standard errors of coefficients, making them unreliable (e.g., Lavery et al., 2019). This is especially problematic if small effect sizes are expected. Another concern is that many social media usage variables (e.g., average usage per week in hours) show an exponential distribution, which again can be problematic (for a similar methodological discussion, see Foster & Jackson, 2019; but see Orben et al., 2019b).

To overcome some of these restrictions, we present the results of a study with a large sample of adolescents (12–16 years; $N > 12{,}000$) who were tested at a vocational information centre to support the vocational choice of adolescents during the final years of secondary school. At this centre, cognitive abilities and skills – such as intelligence, spatial orientation, and information processing – are routinely assessed using validated psychometric tests and procedures. We added several measures of social media usage in this test battery, i.e., a problematic social media use (PSMU) questionnaire adapted from the Young Diagnostic Questionnaire (YDQ; Young, 1998). Additionally, two questions about average active and passive social media use per day were included, both of which have been frequently used in past research (e.g., Chen et al., 2016).

The analysis of large datasets raises particular issues that require consideration. First, even tiny effects may become significant. Therefore, the focus should not be on whether or not the result is significant, but rather on how large the effect is and whether it is of practical relevance (for a discussion, see Götz et al., 2021). Second, past research has almost exclusively focused on correlational methods (e.g., zero-order correlations, regressions; for exceptions, see Coyne et al., 2020, who used a latent-trajectory model using longitudinal data), but this can be problematic especially if expected effect sizes are small. Here, slight changes in a model (e.g., removing or adding predictors to a model) could lead to different conclusions (for a similar reasoning, see Orben & Przybylski, 2019) due to a multitude of reasons (e.g., multicollinearity, violations of assumption of the used statistical procedure, suppression effects). To account for this possibility, we additionally used a random-forest (RF) model approach (i.e., machine learning algorithm).

RF models are especially useful for designs with many predictors and where small effect sizes are expected. Through a process called "recursive partitioning" (IJzerman et al., 2018), RF models draw random subsets of predictors and participants, and examine the predictive power of each available predictor within the respective subset. The method then repeats this technique over hundreds of bootstrap samples and averages the predictive power of each variable across all iterations to determine its overall importance. As a non-parametric, data-driven ensemble learning method, RFs are robust to overfitting, non-linearity, higher-order interactions, correlated predictors, or heterogeneity (Joel et al., 2020), and are consequently highly accurate in identifying meaningful predictors of the outcome variable. For these reasons, RF models have been frequently used in, for example, genetics (e.g., Li et al., 2016) and geographical psychology (e.g., Götz et al., 2020; Stieger et al., 2021). Because RF models are non-parametric, this has a further advantage that skewed distributions and outliers are not a concern. Furthermore, with RF the focus is not on the significance of the statistical test, but rather on comparing predictors against each other to determine which one is more or less relevant (i.e., relative importance). This supports conclusions about the practical relevance of certain predictors by comparing them with, for example, well-known effects such as sex- or age-differences (Orben & Przybylski, 2019).

Although the design of the present study was exploratory in nature, we expected that, if smartphone use generally and social media use in particular has a substantial negative effect on adolescents' cognitive abilities and skills, then we should see significant negative associations between test scores and social media usage variables (problematic social media use; average active and passive social media usage per day), which outperform the effect size of other known predictors such as sex- or age-differences (e.g., being older, greater usage; girls' higher social media use compared to boys: e.g., Coyne et al., 2020). For example, if social media use really leads to a reduction in both short- and long-term memory (e.g., Aharony & Zion, 2019), then we should see a substantial association between social media use variables and the subscale *long-term memory* of the intelligence measure (INSBAT) utilised in the present study.

[1] https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/.

2. Method

2.1. Participants

The sample consisted of adolescents mainly from the Austrian district of Lower Austria (N = 12,043; 49.1% female). Analysed data were collected between January 2019 and August 2020. Adolescents were on average 13.1 years old (SD = 0.62; range 12–16).

Adolescents' parents gave written informed consent in accordance with the Declaration of Helsinki. The ethics committee of the first author's research institution approved the study (EK Nr: 1031/2020).

2.2. Measures

2.2.1. Problematic social media use (PSMU)

We adapted the German 8-item version of the Young Diagnostic Questionnaire (YDQ), which assesses pathological Internet use (Wartberg et al., 2017), by replacing the word 'Internet' with 'Social Media'. In instructions to participants, we asked them to use the previous 6 months as the relevant time frame. Because it is still not clear if a binary (e.g., Wartberg et al., 2017) or Likert-type scale (e.g., Andreassen et al., 2013) is optimal for answering these questions, we used an experimental design by randomly assigning participants either to a binary condition (*No* vs. *Yes*; Cronbach α = 0.48; McDonald ω = 0.50) or a Likert-type scale condition (1 = *never or very seldom*, 6 = *very often or always*; Cronbach α = 0.73; McDonald ω = 0.74). For the binary version, we calculated a sum-score and for the Likert-type version a mean score.

2.2.2. Social media usage behaviour

We asked two questions about how much time (in minutes) social media was used on average each day. We differentiated between active and passive use ["**On average per day**, how much time do you typically spend **actively** on social media (e.g., creating a Facebook post, writing a Twitter message, sending a WhatsApp message)?"; "**On average per day**, how much time do you typically spend **passively** on social media (e.g., watching YouTube videos, reading Facebook posts, viewing Snapchat pictures)?" (bold script appeared in original)].

2.2.3. Intelligence (IQ)

For the assessment of psychometric intelligence, the INSBAT (Arendasy et al., 2012) was used, which uses an adaptive testing design, is modular, and is frequently used in German-speaking countries. It measures the following ability factors: fluid intelligence, that is, the ability to recognise relations between stimuli, understand implications, and draw logical conclusions (subtests: Numerical-Inductive Reasoning, Figural-Inductive Reasoning, Verbal Deductive Thinking), crystallised intelligence, that is, the breadth and depth of the acquired cultural knowledge as well as word fluency and word comprehension (General Knowledge, Verbal fluency, Word Meaning), quantitative reasoning (Arithmetic estimation ability, Arithmetic competence, Arithmetic flexibility, Algebraic Reasoning), short-term memory (Visual short-term memory, Verbal short-term memory), long-term memory, and visual processing (Spatial awareness). Because of its modular design, the vocational information centre elected to assess only the following ability factors because of higher relevance for vocational decisions: fluid intelligence (Figural-Inductive Reasoning: α = 0.72; Verbal Deductive Thinking: α = 0.75), crystallised intelligence (Verbal fluency: α = 0.73), quantitative reasoning (Arithmetic competence: α = 0.75), and long-term memory (α = 0.75).

In the subtest *Figural-Inductive Reasoning*, respondents were presented with a 3 × 3 matrix, which has a symbol in eight of the nine boxes. The eight figures were ordered according to different rules. Participants were asked determined what these rules were and to complete the empty boxes of the 3 × 3 matrix appropriately. *Verbal deductive reasoning* is the ability to deal with verbal statements formally and logically. Individuals with a high level of verbal reasoning are able to grasp the content of verbal statements independent of their own background experience and are able to draw logical conclusions from them. *Verbal fluency* measures the ability to use words fluently and produce them with convergent goals. A high level of fluency therefore means that a person can access their mental lexicon quickly and efficiently. The subscale *Arithmetic competence* measures the ability to deal quickly and automatically with the simplest arithmetic operations. A high score can be seen as an indication of extensive arithmetic factual knowledge (e.g., one times one, etc.) and the availability of efficient mental arithmetic strategies.

2.2.4. Spatial perception

The 3D spatial orientation test from Bratfisch and Hagman (2004) was used. This test consists of 30 items using a multiple-choice format (i.e., one 3D object plus one correct answer and three distractors). It assesses spatial imagination, that is, the ability to mentally move objects in a three-dimensional space. The speeded version was used with a time restriction of 3 min, but participants could end the test whenever they had finished all items. Three scores are issued: the number of correct answers, the number of wrong answers, and the answering time.

2.2.5. Information processing

This assesses the ability to process information under complex stimulus conditions by eliciting a psycho-physical stress situation. Participants have to react as quickly as possible to different colours (through LEDs) and different sound signals (over a headset) by pressing certain buttons or a foot pedal. It is a speeded test where three scores are obtained: number of correct trials, number of incorrect trials, and number of correct but delayed trials.

2.2.6. Technical understanding

A short test was used with 10 multiple-choice items depicting technical tasks, such as the rotation of gear wheels, the lever law, mass inertia, behaviour of fluids, and so forth. For example, in one of these tasks, several numbered and connected gear wheels were depicted on a paper and adolescents had to solve the following problem: "In which direction does the large gear wheel move if gear wheel X moves clockwise? [A: clockwise, B: counter-clockwise, C: oscillating back and forth, D: does not move at all, E: no correct answer]". A maximum of 20 points could be attained.

2.2.7. Creativity

A creativity test was used with two different tasks. In the first task, participants were instructed to extend 10 half circles ('∩') with a pen however they liked. The half circles were depicted in matrix form (five rows, two columns) on a single page. In a second task, participants were instructed to write down everything that could be done with a certain thing (e.g., a piece of cloth, spoon, comb, ruler, or string). Trained psychologists rated pictures and words. A maximum of 20 points could be attained.

2.2.8. Practical numeracy

Numeracy was assessed using arithmetic problems based on the 'Neue Mittelschule (NMS)' [new secondary school] certificate test. It uses 10 items (example item: "How many m^2 of wooden floor are needed to cover an area 34 m long and 16 m wide?") and the procedure had a time restriction (15 min). Every correct answer was worth 0.8 points, and every correct calculation but wrong result was worth 0.4 points. A maximum of 8 points could be attained.

2.2.9. Spelling skills

Participants heard seven sentences where every sentence was repeated once. Participants were instructed to immediately write down the sentence on a sheet of paper (speeded test). After that, the number of errors was counted by trained psychologists.

2.2.10. Vocabulary test

Participants were instructed to draw a card out of a stack of five. On the cards were five different syllables (e.g., BU). Next, participants were instructed as follows: "What words come to your mind containing this syllable. Write down as many different words with this syllable as you can think of. The syllable does not have to be the beginning of the word! Geographical terms such as country names and Germanized English words also count here – but you don't get a point for brand or personal names and repetitions of the same words." Participants could attain a maximum of 10 points.

2.3. Procedure

Adolescents were recruited by the Austrian Institute for Economic Development with its vocational information centre (VIC; German: WKNÖ-BIZ) from a pool of almost all secondary school children in the federal state of Lower Austria, the second-largest populated federal state in Austria (1678 Mio – 2019 Eurostat) after the capital Vienna (1897 Mio – 2019 Eurostat). The VIC offers secondary schools the possibility of testing adolescents in order to support vocational choices when leaving secondary school. Annually in this institute about 12,000 to 15,000 adolescents aged between 12 and 16 years are tested, representing ~70% of all middle school and ~55% of all grammar school students in the particular school year, i.e., the full census.[2] Based on a sensitivity analysis, with such a large sample size ($N \sim 12{,}000$), even an effect size as small as $r = 0.026$ can be replicated with a probability of 80% (two-sided, ρ under $H_0 = 0$; 99% probability: $r = 0.039$). When using only half of the sample (e.g., for the experimental variation), similar low values are calculated: 80% probability: $r = 0.036$; 99% probability: $r = 0.055$.

At the VIC, many different psychological tests are used, from cognitive tests to finger dexterity tests, and from performance tests to speeded tests, all being self-assessed by the adolescents. Some of these are validated published tests and some have been self-developed by VIC. All self-developed tests underwent in-house validation and norm tables are available. Tests are frequently re-standardised as suggested by the DIN 33430 norm.[3] The administration of tests is not fixed throughout a typical test day, that is, different groups of adolescents start with different tests. Almost all questionnaire-based tests are administrated via computer. Trained employees at VIC are in charge of instructing adolescents, supervising test administration, and maintaining a quiet test setting. The entire test procedure is run in German and all tests had individual time restrictions (i.e., speeded tests).

2.4. Statistical analyses

In the test procedures at VIC, an apparatus to assess hand and finger dexterity is also used. Because hand and finger dexterity are not psychological concepts *per se* and all subscales from these measures did not reveal any substantial association with all measures of social media use (all adj. $R^2 < 0.3\%$), we excluded these measures. Furthermore, a practical skills test is used at VIC to assess understanding of instructions (e.g., using a calliper and a standardised instruction to measure different dimensions of a workpiece). Unfortunately, the distribution of test scores was irregular, probably due to coding problems. Therefore, we excluded this measure from further analyses. For all other measures, a very uniform distribution occurred, speaking to the quality of the data and coding schemas used by raters. Because active and passive social media use variables were highly skewed (skewness >3.5), we log-transformed these variables (1 + log) prior to analyses, which resulted in an acceptable range ($<|1.1|$) in relation to the recommendations of Bentler (2006; ±3) and Byrne (2010; ±5).

Because we adapted the wording of the PSMU scale by using the term 'Social Media' instead of 'Internet', we assessed test statistics. An exploratory factor analyses revealed a 1-factor solution (eigenvalue >1) for the binary condition (eigenvalue = 1.81, 22.6% explained variance) and the Likert-type scale condition (eigenvalue = 2.85, second factor close to 1 with 1.05; scree-plot criterion clear 1-factor solution; 48.7% explained variance). Furthermore, we used confirmatory factor analyses (CFA) to examine the fit of a 1-factor model with our PSMU scale in our dataset. For the CFAs, we used the *lavaan* package (Rosseel, 2012) with *R* (*R* Core Team, 2021). Parameter estimates were obtained using the robust maximum likelihood method with the Satorra-Bentler correction. To assess goodness-of-fit, we used the Steiger-Lind root mean square error of approximation (RMSEA) and its 90% confidence interval CI (values close to 0.06 are considered to be indicative of good fit and values of about 0.07–0.08 indicative of adequate fit; Steiger, 2007), the standardised root mean square residual (SRMR; values < 0.09 indicative of reasonable fit; Hu & Bentler, 1999), and the comparative fit index (CFI; values close to or > 0.95 indicative of adequate fit; Hu & Bentler, 1999). The 1-factor Likert-type PSMU scale showed acceptable fit: RMSEA = 0.058 (0.054, 0.062); SRMR = 0.042; CFI = 0.920, as did the binary-type PSMU-scale: RMSEA = 0.022 (0.017, 0.027); SRMR = 0.019; CFI = 0.958.

For the multiple linear regression analyses, we controlled for multicollinearity (i.e., inter-correlation between predictors) using variance inflation factors (VIFs). All VIFs were <3 (see Table 1), which represents an acceptable value following current practices and published recommendations (e.g., <10; O'Brien, 2007). Furthermore, we calculated a conditional RF model (Strobl et al., 2009). Conditional RFs assess the relative importance of each predictor by examining all possible relationships between predictors and the outcome through a process called recursive partitioning (IJzerman et al., 2018).

3. Results

Looking at Table 1 and Fig. 1, the results of the multiple linear regressions and RF models are clear. First, explained variance percentages were low (<7.1%), bearing in mind the number of predictors in the model ($k = 18$). Second, even the strongest predictors for each social media use indicator (e.g., PSMU, average social media use per day) revealed only low effect sizes, from $\beta = -0.071$ to 0.116 (PSMU binary: sex; PSMU likert: practical numeracy; time active per day: sex; time passive per day: practical numeracy; Table 1). Third, depending on the indicator of social media use (PSMU vs. average social media use per day), we see inconsistent patterns of rather tiny effect sizes. This suggests that PSMU might be different from social media use (zero-order correlations between these concepts: $r = 0.26$–0.28), which is perhaps surprising because usage duration should be one of the strongest indicators of problematic social media use. Fourth, if we compare the predictors for active and passive social media use, we do not see much difference except substantially lower explained variance for passive use (1.6% vs. 7.1% for active use respectively). In past research, passive use (in comparison to active use) was associated with negative aspects (e.g., stronger symptoms of anxiety and depressed mood: e.g., Escobar-Viera et al., 2018; Thorisdottir et al., 2019); therefore, we expected a more differentiated pattern of significant predictors between active and passive use, which is not apparent (see Table 1).

Fifth, because even small effect sizes can be of practical relevance, having a look at Fig. 1 depicting the results of the RF models, we see that for *active* social media use the strongest predictor was participant sex (girls more actively using social media compared to boys) followed by practical numeracy. All the other predictors had less than a third of the importance compared to participant sex. This means that, although some of these predictors were significant in the linear regression model, they were far less important when compared with each other and with the strongest predictor (i.e., participant sex) and thus likely of little practical relevance. For *passive* social media use, the predictor with the strongest importance was the number of correct responses in the

[2] https://www.talentecheck.at.

[3] https://de.wikipedia.org/wiki/DIN_33430.

Table 1
Predictors of several measures of social media usage.

	PSMU (Yes/No)	PSMU (Likert)	Time active per day (log)	Time passive per day (log)	Active vs. passive |Δ*r*|
	β (standardised *b*)				
Sex [1.male, 2. female]	.114***	.076***	.116***	-.053***	.169
Age [months]	.053***	.068***	.061***	.024*	.037
IQ – fluid intelligence - figural	-.037*	-.017	-.054***	-.014	.040
IQ – fluid intelligence - verbal	.003	-.029	-.056***	.026*	.082
IQ – crystallised intelligence	.006	-.016	-.008	.002	.010
IQ – quantitative reasoning	-.034*	-.008	.033**	.032**	.001
IQ – long-term memory	-.001	-.011	-.021*	-.002	.019
Spatial perception – correct	.029	.018	-.046***	.009	.055
Spatial perception – wrong	-.009	.001	-.020	-.039**	.019
Spatial perception – answering time	-.043**	-.018	-.046***	-.043***	.003
Information processing – correct	.003	.020	.034*	.067***	.033
Information processing – delayed	.037**	.036*	.015	-.015	.030
Information processing – errors	-.036	-.003	-.035**	.005	.040
Technical understanding	-.079***	-.048**	-.058***	-.055***	.003
Creativity	-.028	-.011	-.002	-.010	.008
Practical numeracy	-.084***	-.092***	-.113***	-.071***	.042
Spelling skills [errors]	.033*	.031*	-.050***	-.025*	.025
Vocabulary	.009	-.009	.008	-.002	.010
N	5,841	6,085	11,926	11,926	
adj. R^2	5.2%	4.3%	7.1%	1.6%	
VIF_{max}	3.0	2.9	2.9	2.9	

Note: ****p* < .001, ***p* < .01, **p* < .05.
PSMU = Problematic Social Media Use; IQ = Intelligence Quotient; VIF = Variance Inflation Factor.

information processing task, followed by the practical numeracy that was only half of the importance compared to information processing. However, we have to bear in mind that, in general, effects were all very low, reflected in the very low R^2 value of 1.6%.

Finally, we may take a look at the PSMU score. Because the binary answering format revealed an unacceptably low scale reliability (≤0.50), we focus on the Likert-type response format. As shown in Fig. 1, practical numeracy was the strongest predictor, followed by participant sex and age, and technical understanding (importance of the last three about a third lower). All the other predictors had *less* than a third of importance than the strongest predictor in the model (i.e., practical numeracy). Again, we see that most predictors did not outperform demographic variables, except for practical numeracy.

4. Discussion

The results of the present study can be summarised and discussed as follows. The PSMU scale using a Likert-type response option revealed very good reliability, whereas the reliability was very low for the binary response format (see also Andreassen et al., 2013; Wartberg et al., 2017). Therefore, Likert-type scales should be given preference for the PSMU scale, at least when used with adolescent samples.

The correlation between PSMU scores and the average time using social media per day was low (~0.27; see also Wartberg et al., 2017, who also used adolescent samples and found $r = 0.34$ for pathological Internet use in general). This supports the assumption that adolescents of that age might miss an objective reference frame of which social media use behaviour is acceptable. As long as the core family (e.g., parents) does not provide negative feedback about adolescents' possible social media overuse (or even show similar social media behaviour themselves), adolescents will probably not state problems in the PSMU scale although they may use social media for a substantial amount of time on average each day. Additionally, using a parent-form of the PSMU scale or non-parametric measures of social media use (e.g., objectively assessed social media usage behaviour by smartphone apps; e.g., Ellis et al., 2019) might be a good approach for future research.

Past research has found evidence that it makes a difference whether one uses social media actively (e.g., chatting, sharing photos) or passively (e.g., browsing, reposting messages, looking at content; Escobar-Viera et al., 2018; Thorisdottir et al., 2019). In the present study, some support for this assumption was found, but differences were of very low effect size (see correlation differences in Table 1, sixth column). Girls were significantly more likely to be actively using social media compared to boys, whereas boys were significantly more likely to be passively using social media compared to girls. Furthermore, active social media users had slightly lower verbal intelligence, whereas passive social media users had slightly higher scores, which is rather counterintuitive. If adolescents' active use of social media by writing texts and so forth is associated with positive aspects, then we should not expect a negative association with verbal intelligence. Further, although past research found that social media use reduces working memory short-term (e.g., Aharony & Zion, 2019), it does not seem to have long-term effects because the association between active social media use and the long-term memory was, although in the expected direction, of tiny effect size (-0.021; see Table 1) and of marginal importance (third least important predictor in the RF model; see Fig. 1).

Although we cannot draw conclusions about the causal directions of the found effects, in general, the effects themselves were of very weak effect sizes and, compared with each other, the importance of effects mostly did not outperform known demographic differences, such as sex- or age-differences in social media usage (e.g., Coyne et al., 2020). For example, when it comes to the time social media is used *actively* per day, the association with fluid intelligence (figural) had only about a quarter of importance compared with the sex-difference between boys and girls (girls using social media more than boys). Or put differently, being a boy or a girl is by far more impactful on differences in active social media use than the effect found for figural fluid intelligence.

Furthermore, we found no evidence of any substantial association with adolescents' intelligence, spatial perception, information processing, technical understanding, creativity, spelling skills, and vocabulary. The only exception was practical numeracy, where we at least found effects similar in effect size to demographics, such as sex-differences (see Fig. 1). Adolescents with higher social media use or higher PSMU scores had lower practical numeracy ability and *vice versa*. Because of the cross-sectional design, it remains unclear whether adolescents with lower practical numeracy skills more actively search for social media communication or the other (more alarming) way round; that is, more social media usage leads to reduced numeracy abilities, i.e., reduced ability to solve simple text-based mathematical problems (e.g., calculation of areas). Although we also found an association between social media *passive* use and information processing outperforming demographics, the overall explained variance was very low (1.6%); therefore, we did not interpret this result in detail.

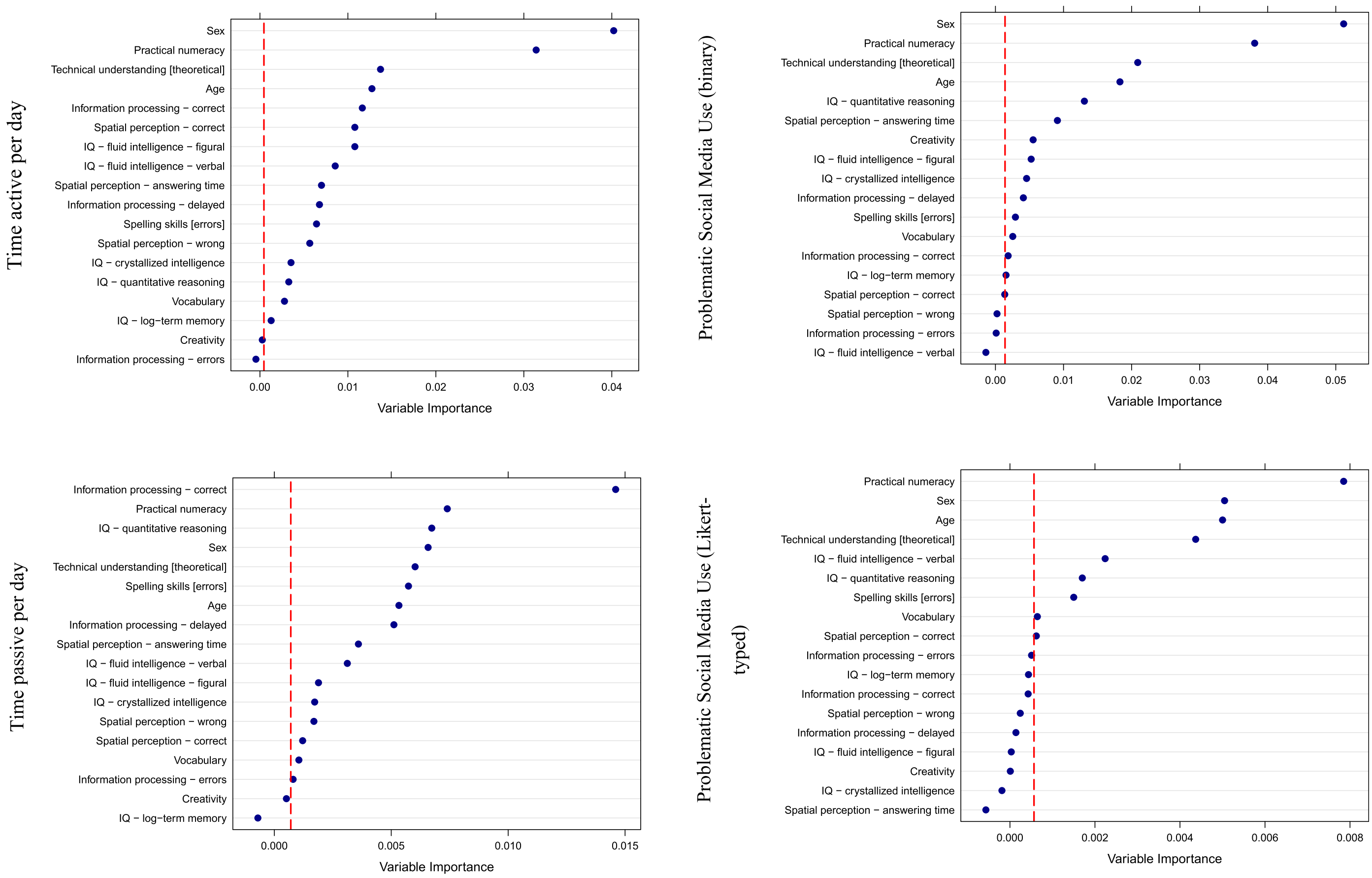

Fig. 1. Variable importance plots based on random-forest models. *Note.* Relative ranking of predictor importance. Variables with higher importance values are considered more important than those with lower importance values. Importance values should not be interpreted in absolute terms. Importance values exceeding the red-dashed vertical line (i.e., smallest positive importance score or absolute value of the largest negative importance score) are considered highly unlikely to be noise.

However, the results are interesting from another point-of-view, namely the impact of social media use on cognitions *in general*, such as the ability to concentrate, hold attention, keep information in memory, and executive functioning (for a review, see Wilmer et al., 2017). Previous research has found evidence that even short-term interaction with smartphones can impact ongoing cognitions by impairing the ability to concentrate or distort attention (Wilmer et al., 2017). For example, one oft-described aspect of smartphone usage in everyday life is multitasking (Judd, 2014), which can have negative effects, such as delayed completion of primary tasks (e.g., Leiva, Böhmer, Gehring, & Krüger, 2012, September) but also positive ones, such as better task-switching abilities (Alzahabi & Becker, 2013) or better multisensory integration (Lui & Wong, 2012). Furthermore, past research has found that even the mere presence of a smartphone can reduce cognitive capacity, resulting in lower scores on intelligence tests (e.g., working memory, fluid intelligence; Ward et al., 2017) or reduced task performance, especially for tasks with high cognitive demands (Thornton et al., 2014).[4] Similar studies exist about children doing a school test (Beland & Murphy, 2016; Levine et al., 2007).

Looking at the pattern of effects in Table 1, the directions of effects largely correspond to these earlier results. Negative significant associations were predominantly found on tests with high cognitive demand (intelligence test, spatial perception test, technical understanding, practical numeracy, spelling skills [although less spelling errors for highly active social media users]), which were all speeded tests with time restrictions. In contrast, significant *positive* associations were found on the speeded test with *low* cognitive demand, namely the information processing test (i.e., more correct answers, fewer errors), which uses simple reaction time tasks. Therefore, the effect pattern could also mean that adolescents do not have lower abilities on the tested concepts (e.g., intelligence, spatial perception), but instead have difficulties with the test procedures themselves because they needed to concentrate and focus their cognitions on a specific task under time constraints. This would also explain why these adolescents performed better in the information perception task. Here, multitasking is beneficial: coordinating information from different senses (seeing, hearing) to perform different hand/foot coordination tasks by pressing buttons. Although this might be a possible reason why we found detrimental effects on low vs. high cognitive demand tests, we do not have direct evidence for that based on the current data, though this would be a fruitful approach for future research.

The present study has also limitations. First, some of the measures (2.2.6 to 2.2.10) were developed and validated in-house at VIC and are not published in any peer-reviewed journal. Nevertheless, all measures were developed over several years under the premisses of being valid, reliable, practical, easy-to-administer, and short. Most of them have a clear face validity (e.g., technical understanding, practical numeracy) and a clear and objective test score calculation (e.g., sum of correct answers). Tests are frequently re-standardised as suggested by the DIN 33430 norm.[5] Furthermore, in the present study we assessed the time of

[4] During the testing sessions at the vocational center, adolescence have to keep their smartphones in their bags, i.e., are not allowed to use them or wear them on their body during testing sessions.

[5] https://de.wikipedia.org/wiki/DIN_33430.

social media usage subjectively. Because past research found that subjectively assessed usage time does not necessarily correspond to objectively assessed usage time (e.g., through software-based accurate time assessments; Ellis et al., 2019; Sewall et al., 2020), future research should try to replicate the present findings by using an objective measure of social media usage. Because past research found lower associations between objective social media use with, for example, well-being (Sewall et al., 2020), it could be that when focusing on the present results, the uncovered low effect sizes could drop. Another limitation comes from the conceptual distinguishing between active and passive social media use, which has frequently been questioned (for a thoughtful discussion, see Meier & Krause, 2022, March 22), as well as the rather unspecific focus of the measure without explicitly differentiating between the broad range of possible behaviours from texting to watching videos. Because all measures were self-assessed by adolescents, we also cannot rule out a possible shared method-specific variance of the used psychometric tests with social media use. Using objective measures of social media use in future research would resolve that issue.

In conclusion, we did not find any substantial negative associations between social media use and the tested concepts. The effects found did not substantially outperform other known effects, such as sex- or age-differences (except a slightly higher value for practical numeracy on PSMU) if at all. To conclude, although past research found negative effects of social media use in early adolescents (<11 years of age; e.g., Charmaraman, Lynch, Richer, & Grossman, 2021) or children (e.g., 4 and 8 years; Skalická et al., 2019; for a review, see Wiederhold, 2019), cognitive abilities and skills of adolescents between 12 and 16 years of age do not seem to be overly affected by social media use.

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Author contributions

Stefan Stieger: Conceptualization; Formal analysis; Methodology; Project administration; Supervision; Visualization; Writing - original draft; Writing - review & editing.

Sabine Wunderl: Data curation; Investigation; Methodology; Project administration; Resources; Supervision; Writing - review & editing.

Declaration of competing interest

The authors declare that they have no potential conflicts of interest.

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