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How objectively measured Twitter and Instagram use relate to self-reported personality and tendencies toward Internet/ Smartphone Use Disorder

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Abstract

Mounting evidence suggests meaningful relationships between personality and tendencies toward Internet Use Disorder (IUD), Smartphone Use Disorder (SmUD) and Social Networks Use Disorder (SNUD). Results of past research vary not only depending on methods applied, but also with respect to data and platforms investigated. With the present work, we aimed to examine links between objectively measured use of Twitter/Instagram and personality in a sample of $N = 331$ participants. We further investigated the relationship between actual social media usage and self-reported tendencies toward IUD/SmUD. We observed that active social media usage (number of posts) was negatively correlated with IUD/SmUD levels. Other users' reactions to one's posts (Likes and comments) on the other hand were positively associated with SmUD severity. Thus, our work contradicts the sometimes prevailing view that greater activity on social media in general predicts greater SmUD. Finally, we replicated most prior findings by showing that greater Extraversion, Conscientiousness, and Agreeableness were associated with more activity on social media (e.g. more posts on Twitter). Based on our results, some types of social media use seem to be beneficial to the individual and thus do not contribute to the development or maintenance of problematic tendencies in the context of social media applications.

KEYWORDS

big five model of personality, five factor model of personality, Instagram, Internet addiction, Internet use disorder, personality, problematic Internet use, problematic smartphone use, smartphone addiction, smartphone use disorder, social media, social media usage, Twitter

1 | INTRODUCTION

1.1 | Internet Use Disorder and Smartphone Use Disorder

Given the omnipresence of both desktop and mobile Internet and their undeniable importance in people's lives, a growing body of research has investigated Internet and smartphone overuse in the past few years. When used adaptively, the Internet and smartphones in particular offer many advantages in everyday life such as easy orientation, navigation, and communication with others. Nonetheless, excessive Internet and smartphone use have each been shown to negatively impact people's lives. For example, Duke and Montag (2017a) observed that excessive use of a smartphone is associated with decreased work productivity potentially due to constant interruptions. New work by Rozgonjuk, Sindermann, Elhai, and Montag (2020a) suggests that such an association might be driven by excessive social media use, because this study shows associations between higher tendencies toward social networks use disorder and lower productivity at work. Of note, excessive smartphone and Internet use are also associated with lower life satisfaction and lower empathy (Lachmann et al., 2018), higher depression levels and sleep problems, as well as higher levels of (social) anxiety (Demirci, Akgönül, & Akpinar, 2015; Elhai, Dvorak, Levine, & Hall, 2017; Elhai, Levine, Dvorak, & Hall, 2016; Elhai, Yang, & Montag, 2019; Peterka-Bonetta, Sindermann, Elhai, & Montag, 2019).

1.1.1 | Internet Use Disorder (IUD) and Smartphone Use Disorder (SmUD): Definitions

The term "Internet addiction" was coined by Young (1998) and appears in other studies under a variety of different terms such as Internet Use Disorder (IUD) or Problematic Internet Use (PIU, Shapira et al. (2003)) and refers to usage of the Internet in a way that has adverse consequences to the individual. While IUD describes the general phenomenon of pathological Internet use regardless of the device, increasing research has focused on specific, pathological use of the smartphone. This latter phenomenon has been referred to as Smartphone Addiction (Kwon et al., 2013), Smartphone Use Disorder (SmUD, Lachmann et al. (2018)) or Problematic Smartphone Use (Elhai et al., 2017) in existing articles. In a recent work it has been proposed that SmUD can be understood as a mobile form of IUD (Montag et al., 2020). In the following, we will adhere to the terminology IUD and SmUD and understand IUD as the overarching concept of pathological use of the Internet and—as mentioned—SmUD as being a subaspect of IUD. It has to be mentioned that neither IUD nor SmUD are listed in the current versions of the DSM (−5) and ICD (−11) as official diagnoses. We nevertheless use the term "disorder" because they are still constructs that involve adverse consequences and distress despite not being an official diagnosis. Moreover, the term Internet/Smartphone *Use Disorder* is based on the new diagnosis of Gaming Disorder, representing an officially recognized diagnosis in ICD-11 and a specific form of IUD (Montag, Schivinski, et al., 2019; Pontes et al., 2019).

1.1.2 | IUD and SmUD: Theoretical background

From a theoretical perspective, the I-PACE model by Brand, Young, Laier, Wölfling, and Potenza (2016) helps to understand the development of IUD due to a complex interaction of variables related to the person, affect, cognition, and executive functions. One of the predisposing factors for the development and maintenance of IUD in particular is personality (belonging to *P*-variables in the I-PACE model). Although the model was originally proposed to explain IUD and in light of considerable overlap between IUD and SmUD (e.g., see Montag, Sindermann, Becker, and Panksepp (2016) and Duke and Montag (2017b)) researchers have started using it to explain the development and maintenance of SmUD as a mobile form of IUD (Elhai, Yang, Rozgonjuk, & Montag, 2020; Wolniewicz, Rozgonjuk, & Elhai, 2020).

According to the cognitive-behavioral model by Davis (2001), IUD should be conceptualized as having two categories: Generalized IUD (GIUD) on the one hand and Specific IUD (SIUD) on the other hand. SIUD refers to the problematic use of specific activities conducted through the Internet such as excessively consuming pornographic material, sharing content with one's interests groups on social media and communicating (note that the new diagnosis Gaming Disorder falls in the realm of SIUDs), while GIUD has been defined as "a multidimensional overuse of the Internet itself" (Caplan, 2002, p. 556). Consequently, some individuals overusing the Internet and/or the smartphone in the sense of a SIUD are essentially engaging in one specific group of application but not in the Internet itself. Please note that there is a large overlap between Social Networks Use Disorder (SNUD; see below) and GIUD (Montag et al., 2015a; Müller et al., 2017).

When investigating IUD and/or SmUD, it is important to understand which application individuals use excessively to ultimately differentiate between generalized IUD and diverse forms of specific IUDs, which is crucial in a clinical context when deciding on appropriate interventions. In light of SmUD, social media/messenger apps represent such a candidate, with SmUD and WhatsApp Use Disorder being highly correlated (Rozgonjuk, Sindermann, Elhai, & Montag, 2020b; Sha, Sariyska, Riedl, Lachmann, & Montag, 2019). Past research has shown that high Neuroticism, low Conscientiousness and low Agreeableness were associated with high IUD and SmUD scores while Extraversion was negatively correlated with IUD but not SmUD, and Openness was negatively correlated with SmUD but not IUD (Lachmann, Duke, Sariyska, & Montag, 2019; Peterka-Bonetta et al., 2019; but see also a recent meta-analysis by Marengo et al., 2020b). In the present study, we focus our research efforts on the use of two widely popular social media platforms: Twitter and Instagram.

1.2 | Social media use

In order to not overpathologize everyday behavior (Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015), it is further important to identify components of social media usage associated with detrimental and with healthy usage. In that context, we would like to introduce the concept of meaningful interactions, something which should be at the heart of social media use (e.g., see initiatives such as the Center for Humane Technology; https://humanetech.com). The general idea behind this concept is that there are two ways of engaging in social media: an active, meaningful mode in which individuals share meaningful content, send and receive messages and comments; and a passive, less meaningful mode in which individuals mainly consume social media, for example, by passively scrolling through timelines, but do not socially interact much with their peers (see mixed evidence for this notion: Escobar-Viera et al. (2018) and Wang, Gaskin, Rost, and Gentile (2018)). We argue that individuals interacting in a meaningful way via social media with their peers are less at risk of developing IUD/SmUD than more passive individuals. Moreover, active social media use could help to build social capital (Erickson, 2011; Steinfield, Ellison, & Lampe, 2008). This again underlines that social media variables reflecting a meaningful interaction should negatively correlate with IUD/SmUD.

Twitter is a microblogging and social networking site, with currently 330 million users (Kemp, 2020). These users can share small pieces of text, sometimes accompanied by links, images, or videos via the platform. While Twitter is traditionally based on sharing text, Instagram is more focused on sharing visual content (see Lee, Lee, Moon, and Sung (2015) for more information on motivations to use Instagram). Instagram had 1 billion monthly active users in June 2018 and together with Twitter, they are two of the most widely used social networks (Kemp, 2020). Both Twitter and Instagram exist as desktop as well as mobile applications, but they are by far more widely used on mobile devices. In fact, 86% of the time users spend on Twitter comes from mobile devices, and for Instagram it is as much as 98% of the time (Statista, 2019a). Without a doubt, these two social networking platforms have become an integral part of modern everyday life and affect the way we interact and communicate with each other.

This evolution would not have been conceivable without the increasing popularity of smartphones and availability of mobile Internet, both being essential prerequisites for using mobile apps such as Instagram and Twitter. In the United States for example, the smartphone penetration rate has more than tripled between 2011 and 2017 and was as high as 84% in 2018 (Statista, 2019b) while 84% of the US population was using the Internet in the same year (Americas Statistics, n.d.). Of note, 3.3 billion people use a smartphone worldwide currently (Global mobile market report, 2019).

1.3 | Social media use and demographics

Most Instagram users are between 13 and 34 years old and these young users are equally likely to be males and females (Kemp, 2020). A slightly different picture arises when exclusively considering Instagram users from the US, the country with most Instagram users (Kemp, 2020). In fact, in the US there are more females with an Instagram account (*Instagram users in United States of America*, 2019), especially among teenagers (Teens, Social Media, & Technology Overview 2015, 2015; for new data see also Marengo et al., 2020a). The gender distribution among Twitter users in the US differs from Instagram because the majority of Twitter users are male (Kemp, 2020). A study conducted by Shane-Simpson, Manago, Gaggi and Gillespie-Lynch (2018) supports these outlined differences in gender distributions between Instagram and Twitter showing that female college students preferred using Instagram while male college students preferred Twitter. In addition, Instagram is preferred over Twitter among US teenagers (Piper Jaffray, 2019)

1.4 | Social media use and personality

Given the importance of personality in individuals' social media usage, a growing body of research has investigated associations between social media use (also Twitter/Instagram use) and personality. Some scholars reported correlations between self-report measures (Bachrach, Kosinski, Graepel, Kohli, & Stillwell, 2012; Correa, Hinsley, & de Zúñiga, 2010; Jain, Gera, & Ilavarasan, 2016; Sindermann, Elhai, & Montag, 2020), while a few recent papers attempted to predict personality based on digital traces (actual social media use) created while using social media (Azucar, Marengo, & Settanni, 2018; Bachrach et al., 2012; Bai, Zhu, & Cheng, 2012; Blackwell, Leaman, Tramposch, Osborne, & Liss, 2017; Correa, Bachmann, Hinsley, & de Zúñiga, 2013; Marengo & Montag, 2020; Quercia, Kosinski, Stillwell, & Crowcroft, 2011; Sumner, Byers, Boochever, & Park, 2012) or to predict social media usage patterns based on personality (Gil de Zúñiga, Diehl, Huber, & Liu, 2017; Hunt & Langstedt, 2014; Jenkins-Guarnieri, Wright, & Hudiburgh, 2012; Montag et al., 2015b; Özgüven & Mucan, 2013).

In the case of Extraversion, results from different studies uniformly showed that individuals scoring higher in Extraversion have more social media followers, shared more information, and were generally more active on social media applications than more introverted individuals (see literature presented in the last paragraph). Results for the remaining personality factors from the Big Five Model of Personality were less consistent. Openness was mostly positively correlated with social media variables (Azucar et al., 2018; Correa et al., 2010; Correa et al., 2013; Quercia et al., 2011). In the study by Gil de Zúñiga et al. (2017) however, Openness was positively associated with more frequent social media use, but negatively to news consumption and interaction with others. Conscientiousness was mostly positively associated with social media use (note that with problematic smartphone use results differ, e.g., Peterka-Bonetta et al. (2019)), except in Sumner et al. (2012), where it was negatively correlated with most Twitter linguistic features created by the authors and Twitter general information such as total number of tweets, number of retweets and number of favorites. In the case of Neuroticism, the picture is not clear. While different papers found a positive relationship between Neuroticism and instant messaging use (Correa et al., 2010), number of Facebook Likes and group memberships on Facebook (Bachrach et al., 2012), frequency of use of social media, news consumption and interaction with others (Gil de Zúñiga et al., 2017), some researchers reported a negative relationship between Neuroticism and general Twitter information (Quercia et al., 2011), photo sharing with friends (Hunt & Langstedt, 2014), number of Facebook friends (Bachrach et al., 2012), or even overall use of social media (Jain et al., 2016). Only little evidence can be found for the relationship between Agreeableness and social media usage. In some papers, Agreeableness did not significantly correlate with social media use (Bachrach et al., 2012; Jenkins-Guarnieri et al., 2012; Quercia et al., 2011) and in Gil de Zúñiga et al. (2017) Agreeableness was positively associated with frequency of use, news consumption and social media use for social interaction, whereas in Sumner et al. (2012) Agreeableness was negatively associated with the number of Twitter followers per friend and with number of tweets.

Another aspect in which past studies differed was the type of data used for analysis. Some scholars used general data available on the respective social media platform such as number of Twitter followers (Plank & Hovy, 2015; Quercia et al., 2011) or number of Facebook Likes (Bachrach et al., 2012) while others extracted features from textual (Twitter) data (Golbeck, Robles, Edmondson, & Turner, 2011; Plank & Hovy, 2015; Qiu, Lin, Ramsay, & Yang, 2012) or (Instagram) pictures (Ferwerda, Schedl, & Tkalcic, 2015; Ferwerda & Tkalcic, 2018) or a combination of both general data and textual/graphical features (Skowron, Tkalčič, Ferwerda, & Schedl, 2016). While Plank and Hovy (2015) found out that the best predictors of personality were linguistic features of tweets and metadata such as status count, research conducted by Skowron et al. (2016) showed that personality traits were best predicted by a model including linguistic, image, and metadata available from users on both Twitter and Instagram.

1.5 | The present study

While both the link between personality and IUD/SmUD and between personality and actual real world social media usage have been widely investigated, to our knowledge there is currently no research on the link between IUD and/or SmUD and objectively assessed social media usage. In a clinical context, knowing how individuals with pathological usage of the Internet and/or the smartphone differ from their non-overusing peers in their social media usage would help to further understand the phenomenon. Furthermore, there is only very little research investigating the differential, correlational patterns between personality traits and the usage of different social media platforms (e.g., Samani, Guntuku, Moghaddam, Preoţiuc-Pietro, and Ungar (2018)) and comparing how personality correlates with Instagram as opposed to Twitter use, in particular under consideration of real world variables obtained from the platforms. This study aims at bridging those gaps while replicating past findings.

In the present work, we test the correlations between social media usage and personality. We expect more active social media usage to be associated with higher Extraversion, higher Openness, higher Conscientiousness, and lower Neuroticism. Moreover, we will explore the correlation between Agreeableness and social media usage. We also expect to find an overlap between IUD and SmUD severity as reported in past studies (Lachmann et al., 2019). Additionally, we expect certain features of social media usage to negatively correlate with both IUD and SmUD because we assume these features represent meaningful interactions. For example, we expect posting content on Twitter and/or Instagram to represent a healthy interaction with the respective platform and thus a higher number of posts to be associated with lower IUD and SmUD scores. With respect to the relationship between social media use and IUD/SmUD, we explicitly hint toward the exploratory nature of our study because to our knowledge research in this area is scarce. Since the social media platforms investigated in the present work are mainly used on smartphones, we will emphasize the exploration of the relationship between social media variables and SmUD (see Supplement section). Finally, we will explore the differences in correlational patterns between the Big Five of Personality and Twitter versus Instagram.

2 | METHODS

2.1 | Participants

Participants were mostly recruited via the online platform Reddit and partly through articles in mass media. Questionnaires were administered in English (see Questionnaires section for more details on inventories used). As an incentive, participants were offered feedback about their Internet and social media use levels and their personality. The study received approval from the local ethics committee at Ulm University in Ulm, Germany. A total of 788 participants filled out the online questionnaire gathering data about personality, IUD, SmUD, impulsivity, social interaction anxiety, WhatsApp usage as well as Twitter and Instagram usernames. Participants younger than 16 were excluded, yielding an overall sample size of 763 participants. Data on the relationship between impulsivity and social interaction anxiety in the realm of IUD/SmUD was used in another research project and will not be mentioned in the present work (Peterka-Bonetta et al., 2019). Participants could specify if they had a Twitter and/or Instagram account and indicate their usernames. The entire sample of 763 participants was used in order to determine how many participants had Twitter and/or Instagram. For the remaining analysis only participants were included who had an Instagram and/or Twitter account, yielding a sample consisting of 331 participants with 108 males and 223 females. The mean age of the sample of 331 participants was 22.87 years (SD = 6.93). Participants came from 36 different countries altogether, the majority of 260 participants stemming from English-speaking countries (N_{USA} = 205, N_{UK} = 26, N_{Canada} = 23, $N_{Australia}$ = 3, $N_{NewZealand}$ = 3).

2.2 | Questionnaires

Internal consistency estimates reported in the following paragraphs were calculated on the sample of N = 331 participants.

Personality was assessed with a short form of the Trait Self-Description Inventory (TSDI, Schulze and Roberts (2006)) as proposed by Olaru, Witthöft, and Wilhelm (2015). In the present work, participants rated the 42 items on a 5-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). This short version of the TSDI measures personality in the five dimensions of Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Scores are available for each factor separately so that every participant obtains a score for each of the five personality dimensions. Good internal consistency was found for all five factors in the present sample ($\alpha_{Openness}$ = .78, $\alpha_{Conscientiousness}$ = .84, $\alpha_{Agreeableness}$ = .84, $\alpha_{Extraversion}$ = .82, $\alpha_{Neuroticism}$ = .84).

The short version of the Internet Addiction Test (s-IAT) by Pawlikowski, Altstötter-Gleich, and Brand (2013) was used to assess IUD. It is based on a two-factor model with the factors loss of control/time management and craving/social problems. Exemplary items are "How often do you lose sleep due to being online late at night?" (loss of control/time management) and "How often do you choose to spend more time online over going out with others?" (craving/social problems). In the present work, participants rated the 12 items on the following

6-point Likert scale: *does not apply* (0), *rarely* (1), *occasionally* (2), *frequently* (3), *often* (4), and *always* (5). Therefore, *does not apply* can be considered the equivalent of *never*. Both an overall s-IAT score and individual scores for the two factors loss of control/time management (short: control) and craving/social problems (short: craving) were obtained summing the respective item responses. The higher the score, the higher is the overuse tendency toward the Internet. Overall s-IAT scores technically could range between 0 and 60 in our work. Internal consistency of the overall scale was good with α = .84 ($\alpha_{Control}$ = .78, $\alpha_{Craving}$.= .78). Please note, that only the overall s-IAT scores were further investigated.

SmUD was assessed using the Smartphone Addiction Inventory (SPAI) from Lin et al. (2014). Participants rated the 26 items on a 4-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (4). An overall SPAI score can be built summing responses to all SPAI items, and the overall score thus technically could range between 26 and 104. Good internal consistency was found for the overall inventory (α = .93).

For both Twitter and Instagram, two types of information were collected and/or calculated. The first type is *general data* consisting of number of followers, number of users one follows and number of posts. This information was available for all users with an account, even for accounts that are set to private in the case of Instagram. Since those numbers highly depend on the time a participant has been registered on the platform, we decided to divide those variables by the number of days since sign-up, yielding the variables followers per day, following per day as well as posts per day. Note that these variables could only be calculated when additional, posting-related data was available. The second type of data used in the present work is additional posting-related data computed based on posts previously collected for each account (hereinafter referred to as *additional data*). For both platforms, we calculated the average number (per post) of characters, comments, hashtags and Likes as well as the followers ratio (number of followers divided by sum of following and followers). The higher the followers ratio, the more followers a participant has as compared to the number of users they follow. Participants with a high followers ratio can be thought of as so-called influencers. Note that Instagram allows users to set their account to private. In this case, no additional data could be collected. The same was true for suspended Twitter accounts and for participants who had not yet shared any content in their accounts. In such cases, only general data was collected. Furthermore, all tweets including retweets were used to compute the average number of posts per day in the case of Twitter, but we discarded retweets for the calculation of the other variables. We removed links from tweets before calculating the average number of characters.

2.3 | Data analysis

Data wrangling and data analyses were performed using R (Version 4.0.0; R Core Team, 2018) and the R-packages *papaja* (Version 0.1.0.9942; Aust & Barth, 2018), *psych* (Version 1.9.12.31; Revelle, 2018), and *tidyverse* (Version 1.3.0; Wickham, 2017) among others.

We first report descriptive statistics. Due to non-normally distributed IUD and SmUD scores, we opted for Spearman's *rho* to calculate the overlap between IUD and SmUD as well as the correlations between age and IUD/SmUD, and performed Mann Whitney U-tests to compare IUD/SmUD scores between genders. T-tests were performed to compare the mean age of participants with versus without a Twitter account and the mean age of participants with versus without an Instagram account. A chi-square test was used to test gender differences in having Twitter or Instagram accounts. We used non-parametric Mann Whitney U-tests to compare Twitter and Instagram variables across genders and Spearman's *rho* to correlate Twitter and Instagram variables with personality and IUD/SmUD, because the distribution of social media variables were skewed. All correlations of Twitter variables with personality as well as with IUD/SmUD were corrected for age and days since sign-up on Twitter. All correlations between Instagram variables and personality as well as with IUD/SmUD were corrected for age and days since sign-up on Instagram. We decided to do so because we expected correlations with age for many of the social media variables and because the amount of time individuals have been using Twitter or Instagram might also influence many social media variables but also potentially their addictive tendencies towards the smartphone/Internet and/or personality. Some social media variables were already divided by the number of days since sign-up (e.g. Instagram posts per day), but we decided to correct all aforementioned correlations for days since sign-up anyway in order to ensure easy comparability of the correlation coefficients. Additionally, the correlations between Twitter and Instagram variables with personality as well as with IUD/SmUD were calculated using bootstrap resampling (1000 samples). We further report bias-corrected and accelerated (BCa) bootstrap confidence intervals for said correlations to reinforce the validity of significance and at the same time provide the reader with an estimation of variability of the correlation coefficients (Haukoos & Lewis, 2005). Finally, the supplement (see supplement information online) reports the results of a hierarchical regression analysis performed predicting SPAI scores in order to obtain a better understanding of the impact and importance of each variable.

3 | RESULTS

3.1 | Descriptive statistics

Out of 331 participants, Twitter information could be gathered for 197 participants, Instagram information could be gathered for 277 participants, and for 143 participants both data could be gathered. These numbers are in line with our expectation to find more participants with an Instagram than Twitter account. Participants varied in their level of engagement with the respective platform. In fact, the vast majority of participants with Twitter had shared at least one tweet and only 5 had shared no tweets so far. Out of the 277 participants with Instagram, 2 participants did not follow any users and weren't followed back either, so that Instagram followers ratio could only be calculated for 275 participants. The remaining Instagram variables were calculated for 130 participants, because for 145 participants, the data was not available, either because their account was private or because they had not

TABLE 1 Descriptive statistics for Twitter variables

Variable	N	Median	*SD*	Min	Max
Twitter followers per day	160	0.14	1.39	0.00	15.00
Twitter following per day	160	0.19	4.52	0.01	54.00
Twitter posts per day	160	0.29	0.94	0.00	7.65
Twitter followers ratio	194	0.39	0.19	0.00	0.85
Twitter average likes per post	160	0.63	7.85	0.00	93.90
Twitter average comments per post	160	0.11	0.18	0.00	0.88
Twitter average characters per post	160	65.31	19.40	19.00	122.67
Twitter average hashtags per post	160	0.19	0.48	0.00	2.36

TABLE 2 Descriptive statistics for Instagram variables

Variable	N	Median	*SD*	Min	Max
Instagram followers per day	130	0.22	5.15	0.00	44.00
Instagram following per day	130	0.26	5.12	0.00	47.00
Instagram posts per day	130	0.11	0.24	0.00	1.08
Instagram followers ratio	275	0.47	0.18	0.00	1.00
Instagram average likes per post	130	13.85	33.33	1.34	189.92
Instagram average comments per post	130	0.83	1.71	0.00	12.33
Instagram average characters per post	130	55.31	70.62	0.00	480.00
Instagram average hashtags per post	130	0.91	5.02	0.00	33.00

shared any posts so far. Out of the 197 participants with Twitter, 3 participants didn't have followers and/or weren't following other users, so that statistics for Twitter followers ratio could only be computed for 194 participants. The rest of the Twitter variables were computed for 160 participants, because for 34 participants, no additional data was available. Variables such as average likes and average comments could thus not be calculated for those 34 participants. Table 1 and Table 2 provide descriptive statistics including sample sizes, means, *SD*, minimums, and maximums for Twitter and Instagram variables, respectively. The sample (N = 331) shows a mean s-IAT score of 22.95 (*SD* = 8.88) and a mean SPAI score of 48.01 (*SD* = 14.90). A visual inspection reveals that neither s-IAT nor SPAI scores were normally distributed, and the SPAI scores showed a strong skewness. As expected, s-IAT and SPAI correlated significantly with each other, $r_s(329) = .55$, $p < .001$.

3.2 | Gender and age

As calculated with a one-tailed *t*-test, $t(689.50) = -3.00$, $p = .001$, participants with Instagram accounts (M = 22.44, *SD* = 6.21) were significantly younger than participants without an Instagram account (M = 24.00, *SD* = 7.94). Contrary to our expectations, age was not associated with having a Twitter account. Regardless of their age, participants were equally likely to have a Twitter account, $t(343.30) = -0.45$, $p = .674$. Note that these tests were performed on the overall sample of 763 participants. Mean-age of Instagram users (M = 22.44) was descriptively lower than mean-age of Twitter users (M = 23.23). Furthermore, younger participants had both higher s-IAT ($r_s = -.21$, $p < .001$) and SPAI scores ($r_s = -.20$, $p < .001$).

While males and females were equally likely to have a Twitter account (37.50% of males and 42.40% of females had a Twitter account), females were more likely to have an Instagram account than males (males: 37.84%, females: 61.67%). A one-tailed chi-square test confirmed that the difference was significant, χ^2 (1) = 40.31, $\varphi = -.23$, $p < .001$. Note that this test was performed on the overall sample of 763 participants. We further hypothesized that females would be more active on Instagram, and males would be more active on Twitter, due to their respective platform preferences. A one-tailed Mann Whitney U-test indicated that indeed females posted significantly more on Instagram per day (females: *Mdn* = 0.12, males: *Mdn* = 0.07), U = 2,161.00, $p = .004$. Although males had a higher average number of posts per day on Twitter (males: M = 0.64, females: M = 0.45), the respective medians suggested an inverse trend (males: *Mdn* = 0.23, females: *Mdn* = 0.34). Unsurprisingly, the corresponding one-tailed Mann-Whitney U-test confirmed that males did not post significantly more tweets per day, U = 2,516.00, $p = .942$. On average, males and females had similar s-IAT scores (M_{males} = 23.25, $M_{females}$ = 22.80) and the difference was not significant (two-sided, U = 11,586.50, $p = .577$). For SPAI, another picture arose. In fact, females had higher SPAI scores than males on average (M_{males} = 45.85, $M_{females}$ = 49.06) and the difference was almost significant (two-sided, U = 13,616.50, $p = .054$).

3.3 | Twitter and personality

Several Twitter variables were positively correlated with Agreeableness, Conscientiousness, and Extraversion and negatively correlated with Openness and Neuroticism (but not always significantly). Table 3

TABLE 3 Correlations between Twitter variables and personality, corrected for age and days since sign-up on Twitter

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
General data					
Twitter followers per day	−.10	.29***	.42***	.19*	−.12
95% CI	[−0.27;0.05]	[0.12;0.40]	[0.29;0.54]	[0.02;0.33]	[−0.28;0.04]
Twitter following per day	.01	.11	.25**	.16*	−.05
95% CI	[−0.16;0.17]	[−0.03;0.27]	[0.11;0.38]	[0.01;0.32]	[−0.23;0.12]
Twitter posts per day	−.12	.25**	.23**	.18*	.07
95% CI	[−0.26;0.05]	[0.09;0.39]	[0.09;0.37]	[0.03;0.33]	[−0.11;0.22]
Twitter followers ratio	−.17*	.27***	.31***	.11	−.09
95% CI	[−0.31;0.00]	[0.13;0.42]	[0.16;0.44]	[−0.04;0.25]	[−0.26;0.06]
Additional data					
Twitter average likes per post	−.07	.29***	.25**	.07	−.09
95% CI	[−0.22;0.09]	[0.15;0.42]	[0.10;0.40]	[−0.10;0.23]	[−0.24;0.07]
Twitter average comments per post	−.12	.23**	.18*	.03	−.07
95% CI	[−0.28;0.04]	[0.10;0.38]	[0.03;0.33]	[−0.13;0.19]	[−0.21;0.09]
Twitter average characters per post	.12	−.10	−.01	−.06	.03
95% CI	[−0.06;0.27]	[−0.25;0.04]	[−0.18;0.14]	[−0.21;0.09]	[−0.14;0.19]
Twitter average hashtags per post	−.05	−.13	−.11	.01	−.11
95% CI	[−0.18;0.10]	[−0.27;0.01]	[−0.27;0.06]	[−0.14;0.17]	[−0.26;0.05]

Note: Two-tailed, bootstrap resampling.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

TABLE 4 Correlations between Twitter variables and personality by gender, corrected for age and days since sign-up on Twitter

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Males					
Twitter followers per day	.01	.24	.51***	.05	−.24
Twitter following per day	.16	−.08	.20	−.06	.03
Twitter posts per day	.07	.29*	.46***	.22	−.14
Twitter followers ratio	.06	.38**	.38**	.24	−.27*
Twitter average likes per post	.06	.20	.19	−.12	−.12
Twitter average comments per post	.12	.19	.17	.04	−.14
Twitter average characters per post	.13	−.07	.00	−.05	.01
Twitter average hashtags per post	−.08	−.23	−.19	−.02	.05
Females					
Twitter followers per day	−.14	.27**	.35***	.30**	−.15
Twitter following per day	−.05	.20*	.27**	.29**	−.09
Twitter posts per day	−.25*	.21*	.09	.18	.07
Twitter followers ratio	−.19*	.12	.16	.15	−.19*
Twitter average likes per post	−.09	.32**	.27**	.25*	−.18
Twitter average comments per post	−.21*	.23*	.18	.09	−.13
Twitter average characters per post	.09	−.12	−.06	−.14	.11
Twitter average hashtags per post	−.07	−.05	−.09	−.04	−.09

Note: two-tailed.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

shows a detailed overview of correlation coefficients between Twitter variables and personality and their corresponding levels of significance. Twitter variables differed in their level of correlations with personality. In the case of Conscientiousness for example, the average number of Likes was strongly correlated, $r_s(158) = .29$, $p < .001$, while the number of characters per post had a correlation coefficient of $r_s(158) = -.10$, $p = .244$. Personality factors that most strongly correlated with Twitter variables after correcting for age and time since Twitter sign-up were Conscientiousness and Extraversion. The strongest correlations between Conscientiousness and Twitter variables and Extraversion and Twitter variables were all positive, while also weak non-significant negative correlations could be found (e.g. between Conscientiousness and Twitter average hashtags and Extraversion and Twitter average hashtags).

We investigated correlations between Twitter variables and personality for each gender separately correcting for age and days since Twitter sign-up and report the results in Table 4. Note that said correlations were calculated without bootstrap resampling. The results were mostly similar to results from the overall sample reported above with mostly positive correlations between Twitter variables and Conscientiousness as well as Extraversion and mostly negative correlations between Twitter variables and Neuroticism. Some differences between males and females appeared in the case of Openness and Agreeableness.

Openness was significantly, negatively correlated with several Twitter variables in the case of females, but none of the Twitter variables was significantly associated with Openness in males. Agreeableness was significantly, positively correlated with several Twitter variables for females, but not significantly in males.

3.4 | Instagram and personality

For Instagram, a similar correlational pattern arose. Instagram variables were generally positively (although oftentimes not significantly) correlated with Conscientiousness, Extraversion, and Agreeableness and mostly negatively (although oftentimes not significantly) correlated with Neuroticism (see Table 5 for a detailed overview of correlation coefficients and their corresponding levels of significance). Openness did negatively correlate with the variables Instagram following per day and Instagram average comments, but said correlations were weak and not significant (the remaining correlations were even smaller).

When investigating correlations between Instagram variables and personality by gender corrected for age and days since Instagram sign-up, we found a similar correlational pattern as for the overall sample, but with important differences: Extraversion was significantly, positively correlated with several Instagram variables for females, whereas in the case of males, there was one significant, negative correlation between Extraversion and Instagram following per day (see Table 6). Furthermore, Neuroticism often correlated negatively with Instagram variables for females, but for males Neuroticism was positively correlated with some Instagram variables such as Instagram posts per day.

TABLE 5 Correlations between Instagram variables and personality, corrected for age and days since sign-up on Instagram

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
General data					
Instagram followers per day	−.07	.20*	.20*	.21*	−.14
95% CI	[−0.24;0.13]	[−0.01;0.36]	[0.01;0.37]	[0.04;0.37]	[−0.32;0.03]
Instagram following per day	−.13	.14	.08	.12	−.17
95% CI	[−0.30;0.04]	[−0.04;0.31]	[−0.12;0.28]	[−0.08;0.31]	[−0.36;−0.01]
Instagram posts per day	.01	.12	.09	.10	.11
95% CI	[−0.17;0.18]	[−0.08;0.28]	[−0.09;0.30]	[−0.08;0.28]	[−0.08;0.30]
Instagram followers ratio	.06	.07	.17	.09	.01
95% CI	[−0.12;0.23]	[−0.10;0.21]	[−0.01;0.33]	[−0.09;0.26]	[−0.19;0.19]
Additional data					
Instagram average likes per post	−.07	.16	.12	.17	−.28**
95% CI	[−0.26;0.12]	[0.00;0.32]	[−0.06;0.28]	[−0.01;0.34]	[−0.43;−0.13]
Instagram average comments per post	−.12	.04	.12	.07	−.17
95% CI	[−0.27;0.04]	[−0.15;0.20]	[−0.07;0.28]	[−0.11;0.24]	[−0.34;0.01]
Instagram average characters per post	.07	.02	.15	.10	−.03
95% CI	[−0.11;0.26]	[−0.17;0.19]	[−0.03;0.32]	[−0.09;0.26]	[−0.19;0.14]
Instagram average hashtags per post	.02	.03	.12	.03	.01
95% CI	[−0.14;0.21]	[−0.14;0.20]	[−0.05;0.30]	[−0.14;0.20]	[−0.15;0.18]

Note: two-tailed, bootstrap resampling.
$^*p < .05$, $^{**}p < .01$.

TABLE 6 Correlations between Instagram variables and personality by gender, corrected for age and days since sign-up on Instagram

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Males					
Instagram average characters per post	−.20	.03	.28	.20	.22
Instagram average comments per post	−.30	.21	.00	.20	−.16
Instagram average hashtags per post	−.12	.08	.21	.15	.11
Instagram average likes per post	−.31	.32	.05	.29	−.33*
Instagram followers per day	−.11	.25	−.06	.29	.01
Instagram followers ratio	−.07	.05	.19	.12	.06
Instagram following per day	−.24	.05	−.35*	.05	−.08
Instagram posts per day	.09	−.10	.10	.23	.31
Females					
Instagram average characters per post	.18	−.02	.08	.06	−.13
Instagram average comments per post	.00	−.01	.18	.02	−.25*
Instagram average hashtags per post	.07	−.02	.05	−.02	−.02
Instagram average likes per post	.09	.12	.19	.12	−.38***
Instagram followers per day	−.01	.20	.37***	.19	−.34**
Instagram followers ratio	−.13	.12	.28***	.14*	−.20**
Instagram following per day	−.10	.17	.25*	.17	−.21*
Instagram posts per day	−.09	.11	.06	.02	.07

Note: two-tailed.
**p* < .05, ***p* < .01, ****p* < .001.

TABLE 7 Correlations between Instagram variables/Twitter variables and s-IAT/SPAI corrected for age and days since sign-up on Twitter or Instagram

	s-IAT		SPAI	
	Twitter	Instagram	Twitter	Instagram
Additional data				
Average characters per post	−.05	.05	−.07	.02
95% CI	−[0.20;0.10]	[−0.12;0.22]	[−0.22;0.08]	[−0.17;0.20]
Average comments per post	−.03	.06	.18*	.26**
95% CI	−[0.18;0.13]	[−0.09;0.24]	[0.03;0.33]	[0.09;0.42]
Average hashtags per post	−.07	−.02	−.06	−.04
95% CI	−[0.23;0.10]	[−0.20;0.16]	[−0.23;0.10]	[−0.22;0.14]
Average likes per post	−.06	−.01	.16	.21*
95% CI	−[0.19;0.10]	[−0.18;0.14]	[−0.01;0.30]	[0.04;0.36]
General data				
Followers per day	−.09	−.09	.11	.09
95% CI	−[0.23;0.08]	[−0.25;0.09]	[−0.05;0.26]	[−0.08;0.26]
Followers ratio	−.04	.05	.20*	.06
95% CI	−[0.19;0.11]	[−0.14;0.23]	[0.04;0.34]	[−0.13;0.24]
Following per day	−.05	−.13	−.03	.07
95% CI	−[0.20;0.10]	[−0.30;0.05]	[−0.21;0.12]	[−0.13;0.27]
Posts per day	−.20*	−.19*	−.05	−.20*
95% CI	−[0.34;−0.05]	[−0.35;−0.02]	[−0.22;0.12]	[−0.37;0.01]

Note: two-tailed, bootstrap resampling.
**p* < .05, ***p* < .01.

3.5 | Similarities and differences between Instagram and Twitter and their link to personality

Generally speaking, correlational patterns between personality factors and variables from both Twitter and Instagram were similar. For instance, Conscientiousness, Extraversion, and Agreeableness were mostly positively correlated with social media variables, whereas Neuroticism was mostly negatively correlated with social media variables (although only some of these correlations were significant). Openness was widely uncorrelated with most social media variables, but some negative correlations could be observed on both platforms with one significant correlation with Twitter followers ratio.

Differences can be found in the type of social media variables that correlated with personality. For instance, in the case of Instagram, Conscientiousness, Extraversion, and Agreeableness only significantly, positively correlated with followers per day whereas in the case of Twitter, many more variables showed strong correlations with these personality variables (e.g., posts per day and followers ratio).

A simplified summary: Correlations between social media variables and personality factors were stronger and more often significant in the case of Twitter.

3.6 | Correlations between Twitter/Instagram and s-IAT/SPAI

s-IAT scores were significantly, negatively correlated with posts per day on both platforms. SPAI scores on the other hand positively correlated with some Twitter and Instagram variables but also negatively correlated with Instagram posts per day, $r_s(126) = -.20$, $p = .029$. See Table 7 for a complete overview of correlations between s-IAT/SPAI and Twitter/Instagram variables.

More specifically, s-IAT scores were significantly, negatively correlated with Twitter posts per day, $r_s(158) = -.20$, $p = .014$, and Instagram posts per day, $r_s(126) = -.19$, $p = .033$. SPAI scores were significantly, positively correlated with Instagram average comments, $r_s(129) = .26$, $p = .003$, Twitter average comments, $r_s(158) = .18$, $p = .022$, Twitter followers ratio, $r_s(192) = .20$, $p = .014$ and Instagram average Likes, $r_s(129) = .21$, $p = .016$.

As Table 7 shows, social media variables were generally more often significantly associated with SPAI scores than with s-IAT scores (as mentioned above posts per day was the only variable which was associated with s-IAT scores). Interestingly, average comments and average Likes per post (the latter only significantly for Instagram) were positively correlated with SPAI scores, but not with s-IAT scores. On the other hand, a smaller number of posts per day was associated with both higher SPAI (Instagram) and higher s-IAT scores (Twitter and Instagram).

4 | DISCUSSION

Our results support theory and findings from past research, especially those regarding Instagram use. For instance, we found that more study participants had an Instagram than a Twitter account, Instagram users were on average younger than Twitter users (although this difference was not significant), but contrary to our expectations, age was not associated with having a Twitter account. We further found that women were more likely to have an Instagram account. Women were expectedly more active on Instagram, posting more per day than men (see also recent work by Marengo, Sindermann, Elhai and Montag (2020a)). On Twitter however, men were not more active than women as originally assumed. One possible explanation is that our sample of Twitter users was somewhat small. Additionally, even though they had an account, some participants were not very active on Twitter (e.g., some of them shared less than 5 posts in total) making it difficult to test our hypothesis with regard to levels of Twitter activity. Future research should involve a higher number of participants and remove participants under a certain, meaningful activity threshold. We also found that men and women did not significantly differ in their IUD and SmUD levels.

Our results show that the links between IUD severity and Twitter/Instagram variables were weak, but mostly negative in nature. To be more precise, more posts per day were associated with lower IUD and SmUD scores. This finding makes sense in the context of meaningful interaction: individuals with Internet overuse tendencies might be rather passive, scrolling through timelines but without taking active part whereas healthy individuals use social media in a different way, namely actively posting. Further research needs to investigate this assumption since the variables in the present work could not measure passive usage of social media. More concretely, a smaller number of posts are not only explained by passive usage of social media but also by decreased usage and in the current work, those different scenarios cannot be differentiated from each other. In the case of SmUD, several social media variables representing other users' actions on one's post (comments and Likes) showed a positive relationship with SmUD levels whereas one's own activity (posts per day) was negatively linked to SmUD scores. The negative link between SmUD severity and a participants' activity on social media can be understood once again in the context of meaningful interaction. Furthermore, the reactions of others to one's posts on social media may foster addictive tendencies. The results also show that SmUD scores are more strongly associated with social media variables than IUD scores. This could be explained by the fact that both social media platforms investigated in the present work are mainly accessed via smartphones and the questionnaire measuring IUD may thus not be specific enough. To sum up, the number of posts per day seemed to represent a meaningful interaction and individually engaging in a meaningful way with social media had lower IUD scores.

That being said, the received number of Likes as well as the number of followers are the most critical elements we investigated in the supplement to predict levels of smartphone overuse (here, smartphone is clearly meant as a vehicle to access social media). The regression model presented in the supplement comprising of age, gender, personality variables and social media variables as predictors underlines that a higher number of Likes and followers on Instagram might initiate a reinforcement cycle bringing users back to the online platform to seek for gratification. The Like feature is criticized by many researchers due to its effect on social comparison and so forth (Montag et al., 2019), and both Instagram and Facebook currently experiment with hiding the number of Likes a post receives to reduce problems related to social upward comparison processes. Nevertheless, the number of Likes is still visible for the person who has posted a comment or picture, therefore the problems arising from Likes are still not alleviated.

In the case of SmUD, Instagram posts per day was negatively correlated with SmUD scores, hence actively posting on Instagram is associated with lower SmUD. This again might speak to passive use of Instagram probably reflecting the detrimental use of social media, perhaps too often resulting in upward social comparison processes and lower self-esteem (Vogel, Rose, Roberts, and Eckles (2014)), but see for complexities of this area Stapleton, Luiz, and Chatwin (2017) and Yang (2016).

As for correlations of personality factors with Twitter and Instagram variables, we found that those were widely similar on both platforms and in the same direction: Extraversion was mostly positively correlated with both Twitter and Instagram variables (stronger associations could be observed for Twitter), whereas Conscientiousness and Agreeableness were positively correlated with most of the Twitter variables and Instagram variables. Neuroticism was mostly negatively correlated with Twitter and Instagram variables (only significant in the case of one Instagram variable). Openness weakly, negatively correlated with some social media variables (only significant in the case of one Twitter association). For Extraversion, Conscientiousness, Neuroticism, and Agreeableness, correlation results were mostly in line with past findings (Gil de Zúñiga et al., 2017; Hunt & Langstedt, 2014; Quercia et al., 2011). In the case of Openness however, results differed from past findings (Azucar et al., 2018; Quercia et al., 2011). In fact, we expected Openness to be positively correlated and Agreeableness to be negatively correlated with Twitter and Instagram variables based on existing literature. It is conceivable that being open to experiences is a trait that makes individuals prefer offline activities over online sharing of content thus leading to a negative correlation with social media usage. Furthermore, we found higher correlations between personality factors and social media variables in women in the case of Instagram, perhaps showing that personality associations only appear strongly in the group of users which shows the greatest interest in the topic.

Note that we do not think that distinguishing between general profile data and additional data as we did makes much sense from a theoretical perspective because additional data such as number of Likes and comments depends on general data such as number of followers. Nonetheless, the distinction makes sense from the perspective of data collection because general data are openly available and can easily be collected as opposed to what we called additional data, which depends on a user's permissions and the respective platform's terms and conditions.

In general our work provides further insights into the feasibility to predict personality and smartphone overuse from real world social media data, here harvested from Twitter and Instagram. That being said, the correlations are in most cases not higher than .40, which is in line with other studies predicting personality from social media data or smartphones (Azucar et al., 2018; Marengo & Montag, 2020; Montag et al., 2014; Montag, Baumeister, et al., 2019; for privacy concerns, see the work by Montag, Sindermann, and Baumeister (2020)). At least with classic inferential statistical analysis this area of effect size seems to be the upper limit of predicting personality and other metric psychological states (here overuse tendencies) from the available data. In sum, it is possible to make predictions for personality and overuse tendencies toward IUD/SmUD on group but not on individual level.

The results have to be interpreted keeping in mind several limitations. On the one hand, the number of participants with Twitter and/or Instagram accounts was limited and further research should invest more effort in gathering a larger sample size. On the other hand, several participants had only very few posts, making testing hypotheses related to their activity on social media difficult. Furthermore, variance in SmUD and IUD severity was rather low with extreme cases being rare, making inferences about individuals with higher scores difficult. Additionally, our sample comprised a great variety of different nationalities, potentially dissipating effects. Because there were too few participants from countries other than the US, it was not possible to conduct intercultural comparisons.

Future research could take into account nationalities when investigating social media usage in general and Twitter and Instagram usage in particular, as motives for using any of those platforms are likely to vary across nationalities and cultures. Future work should also implement questionnaires directly assessing social media use disorder symptoms, whereas our inventory assessing SmUD could only be an approximator clearly comprising other facets of excessive smartphone use going beyond the social media topic. Finally, it is worth noting that participants were mostly recruited via the platform Reddit, which may introduce a bias in the sample. Further research needs to reproduce the findings on samples drawn from a different (online) population to ensure generalizability of the results.

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CONFLICT OF INTEREST

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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