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Idiographic network models of social media use and depression symptoms

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Abstract

Background: Disentangling the impact of social media use on well-being is a priority for psychological research. Numerous studies suggest that active social media use (ASMU) enhances well-being, whereas passive social media use (PSMU) undermines it. However, such research has conducted group-level analyses, potentially obscuring individual differences. We examined person-centered relationships between SMU and depression symptoms by using a publicly available experience sampling dataset (Aalbers et al., 2019). **Methods:** Dutch undergraduate students (*N* = 125) reported PSMU, ASMU, and depression symptoms 7 times daily for 14 days. We (a) visualized interindividual variability in temporal associations between social media use and individual depression symptoms, (b) compared the aggregate network model to idiographic models, and (c) determined the distribution of person-specific temporal associations. **Results:** Overall, we found that associations between social media use and depression symptoms differed substantially from individual to individual in both strength and kind. In addition, PSMU and ASMU were very weakly to weakly associated with depression symptoms for most individuals. **Conclusions:** Studying idiographic relationships between social media use and depression may help us (1) determine which individuals are most at risk of experiencing elevated depression symptoms after using social media and (2) personalize therapeutic treatments to alleviate symptoms.

Keywords: social media; depression; loneliness; self-esteem; idiographic; network analysis

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Introduction

Each day, billions of people around the globe use social media to connect with friends and family members (Clement, 2020). The rapid adoption of this technology has generated public concern over its effects on our well-being. Cross-sectional research has produced mixed evidence; some studies reveal positive effects of social media sites on mental health, whereas others suggest negative or nonsignificant effects (Verduyn, Gugushvili, & Kross, 2021). More recently, longitudinal studies and meta-analyses have concluded that social media might have a small, negative impact on mental health (Appel, Marker, & Gnambs, 2020; Kross, Verduyn, Sheppes, et al., 2020). However, the relationship between social media use and mental health may be modified by a variety of factors, including differential ways of interacting with social media, personality characteristics, and individual differences in mood.

Growing evidence suggests social media can either enhance or undermine mental health depending on how we use them (Kross et al., 2020). Researchers have distinguished between active social media use (ASMU; e.g., posting, commenting, and direct messaging) and passive social media use (PSMU; e.g., scrolling through one’s news feed without engaging with others) (Verduyn, Lee, Park, et al., 2015). In general, ASMU appears to enhance well-being (Kross et al., 2013), increase self-esteem (Best, Manktelow, & Taylor, 2014), enable users to strengthen social bonds (Liu, Baumeister, Yang, & Hu, 2019) and to build social capital (Verduyn, Ybarra, Résibois, et al., 2017). By contrast, PSMU appears to undermine well-being by increasing the frequency of upward social comparisons (Kross et al., 2020; Verduyn et al., 2015).

Less heavily investigated, but perhaps just as important in determining the effects of social media on mental health, are users’ individual differences. For instance, lonely individuals often turn to social media to cope with, and ultimately alleviate, feelings of loneliness (Song et al., 2014). However, they may be more likely to interpret online interactions as negative and threatening (Cacioppo & Hawkley, 2009), thus interacting with social media in a way that *increases*, rather than decreases, loneliness (Vanhalst et al., 2015). Consequently, lonely users may experience a feedback loop whereby they use social media to satisfy social needs but instead experience an exacerbation of loneliness (Frison & Eggermont, 2015). However, it remains unclear whether lonely (compared to non-lonely) individuals tend to feel lonelier after passively browsing through social media and actively engaging with others on social media.

Self-esteem may also affect the impact of social media on mental health (Verduyn, Gugushvili, Massar, That, & Kross, 2020). Individuals with low self-esteem may be particularly drawn to social media as a safe haven to express themselves (Forest & Wood, 2012) and boost their self-image by accruing "likes" and online followers (Andreassen, 2015). Nevertheless, social media often present an enhanced version of reality, and thus provide bountiful opportunities for upward social comparison (Rodriguez, Bellet, & McNally, 2020; Yang, 2016; Verduyn et al., 2020). Individuals who already feel inferior may feel even worse after comparing themselves to those they deem superior (Haferkamp & Krämer, 2011; Vogel, Rose, Roberts, & Eckles, 2014). However, an earlier longitudinal study suggests individuals with low self-esteem feel most connected after using social media (Steinfield, Ellison, & Lampe, 2008). Thus, further research is needed to disentangle how self-esteem impacts the effects of social media on our well-being.

An important limitation of previous research is that little is known about interindividual differences in the associations between social media use and mental health indicators, prompting researchers to call for more studies into person-specific associations between social media use and mental health (e.g., Aalbers, Vanden Abeele, Hendrickson, De Marez, & Keijsers, 2021; Beyens, Pouwels, van Driel, Keijsers, & Valkenburg, 2020). Our study answers this call by reanalyzing an openly available experience sampling dataset on (passive and active) social media use and depression symptoms (Aalbers et al., 2019). We (1) tested whether previously estimated bidirectional temporal associations between social media use and depression symptoms differ from person to person, (2) explored the distribution of person-specific associations between these constructs, and (3) tested whether these person-specific associations are associated with loneliness and self-esteem at the between-subjects level.

We began our investigation with several hypotheses. We predicted lonelier individuals are more likely to engage in PSMU and ASMU when feeling lonely (**H1a-b**) and are more likely to experience an increase in loneliness after doing so (**H2a-b**). We further predicted individuals with low self-esteem are more likely to engage in PSMU and ASMU when feeling inferior (**H3a-b**) and tend to feel more inferior after doing so (**H4a-b**). However, none of our hypotheses was supported by the data (See Footnote 1 for nonsignificant correlations[1]).

In the spirit of Kagan's (2021) "Baconian empiricism" (p. 10), we probed our data further in a series of exploratory analyses, investigating whether relationships between PSMU, ASMU, and depression symptoms differ significantly across individuals. To this end, we modelled and visualized interindividual variability in temporal associations between social media use and individual depression symptoms. As results showed that almost all associations differed across individuals, we then compared the aggregate network model (i.e., temporal associations averaged

[1] **H1:** Individuals did not differ in contemporaneous associations between any variable.
H2a: The correlation between average level of loneliness and person-specific associations from PSMU to loneliness was not significant, r = -0.033, 95CI = [-0.208, 0.143), t(123) = -0.372, p = 0.710.
H2b: The correlation between average level of loneliness and person-specific associations from ASMU to loneliness was not significant, r = -0.060, 95CI = [-0.234, 0.116), t(123) = -0.672, p = 0.503.
H3: Individuals did not differ in contemporaneous associations between any variable.
H4a: The correlation between average level of self-esteem and person-specific associations from PSMU to inferiority feelings was not significant, r = -0.041, 95CI = [-0.215, 0.136), t(123) = -0.452, p = 0.652.
H4b: The correlation between average level of self-esteem and person-specific associations from ASMU to inferiority feelings was not significant after Bonferroni correction for multiple testing (alpha = .05/4 = .0125), r = -0.20, 95CI = [-0.359, -0.021), t(123) = -2.216, p = 0.029.

across individuals; Aalbers et al., 2019) to idiographic network models (i.e., temporal associations specific to a given individual), specifically focusing on bidirectional associations between social media use and depression symptoms. Finally, we determined the distribution of person-specific temporal associations between PSMU, ASMU, and depression symptoms.

Method

Participants

We used publicly available data collected in an experience sampling study on links between social media use and individual depression symptoms (Aalbers et al., 2019). This study used a sample of Dutch undergraduate students (*N* = 132; 91 women) who were recruited via an online study participation website. Seven participants were excluded due to significant missing data (i.e., completed < 29 of 98 total measurements; see Aalbers et al., 2019). Thus, the final sample included in our analyses consisted of 125 participants (87 women, 38 men) with a mean age of 20.4 (*SD* = 1.96) who completed an average of 66.2 measurements (*SD* = 15.10, range: 29-92). As noted by Aalbers et al. (2019), our number of data points, which consisted of 8648 *in vivo* measures of social media use and depression symptoms, was notably larger than other recent studies employing a similar methodology (e.g., Beyens et al., 2020; Kleinman et al., 2017). Participants received undergraduate research credits as compensation.

Procedure

All procedures were approved by the University of Amsterdam's Institutional Review Board. Prior to data collection, each participant attended an individual instructional session with George Aalbers, who introduced the smartphone app (LifeData Company's RealLife Exp app; https://www.lifedatacorp.com/) and explained study procedures. Aalbers orally described PSMU to participants as: "You are using social media without commenting, posting, sharing, or chatting – that is, you are scrolling through the news feed, looking at photos, videos, and status updates shared by your social media contacts or public profiles that you follow." Then, participants completed a brief 12-item questionnaire seven times a day for 14 days. Participants received prompts to complete the questionnaires on their smartphones at fixed times, with measurements separated by brief intervals (± 2 hrs).

Materials

The 12-item questionnaire was designed by Aalbers et al. (2019). At each measurement, participants received the following instructions: "Please indicate to what extent the following statements applied to you in the past 2 hours." Seven items measured depression symptoms (loneliness, feelings of inferiority, depressed mood, loss of interest, fatigue, concentration problems, and hopelessness). Two items assessed the amount of time participants spent on PSMU and ASMU, respectively. The remaining three items measured levels of stress, PSMU automaticity, and exposure to political news or issues via social media (included to mask the main study goals); however, these items were not used in the present study. The researchers intentionally focused on brevity in order to decrease attrition and reduce burden on participants (Aalbers et al., 2019). Thus, variables of interest (loneliness, inferiority, PSMU, ASMU) were each measured via a singular item. All items were assessed with a visual analog scale (0 = *not at all*; 100 = *very much*) and appeared in randomized order at each measurement.

Data Analysis

The dataset analyzed in the current study, as well as the RStudio code used in analyses, is available in the Open Science Forum repository: osf.io/c9hxv/. We applied the *mlVAR* package in R (Epskamp, Deserno, & Bringmann, 2017) to re-estimate the network model in Aalbers et al. (2019), making one adjustment to the original model specification. Rather than estimating the network model's random effects orthogonally, we allowed random effects of the contemporaneous associations (associations that occur in the same measurement window) and temporal associations (associations that occur between different measurement windows) to correlate with each other (Epskamp et al., 2018). This yields a set of partial correlations. We did so because our initial hypotheses required us to test these correlations, which means they should not be constrained to zero. Temporal associations reveal whether a variable at a certain timepoint (t) is predicted by other variables at the previous timepoint (t-1). Such an association indicates that one variable (t-1) precedes the other (t) (Epskamp et al., 2018).

We used *qgraph* (Epskamp et al., 2012) in R to visualize the standard deviation (*SD*) for each temporal association between social media use and depression symptoms. A significant *SD* of, say, the temporal association from loneliness during a previous time window and passive social media use during the next time window could indicate two things. First, the association might differ in strength between individuals. Second, the association might differ in kind between individuals. That is, some might tend to use social media when feeling lonely, whereas others might avoid using it. However, *SD*s are insufficient for exploring differences in kind.

We used the *qgraph* to visualize and describe a selection of idiographic network models of social media use and depression symptoms (Epskamp et al., 2012). We modelled idiographic networks for five participants, each of whom had >70 assessments. We further used the *ggplot2* package to visualize the distribution of person-specific parameters (Wickham et al., 2016). Of note, we do not report the *SD* of contemporaneous associations as these were nonsignificant. Therefore, we will not discuss idiographic contemporaneous networks, as our analysis suggests contemporaneous associations are homogenous across individuals.

Results

Figure 1 shows how strongly each temporal association between passive and active social media use and depression symptoms differs among individuals. Almost all associations differ across individuals. For instance, the association from active social media use (**M2**) to feeling inferior (**D6**) is subject to much interindividual variability, suggesting this association differs in strength and, potentially, in kind between individuals. For instance, if this association is more strongly positive for person A than for person B, the former might have a stronger tendency to feel inferior after actively using social media than the latter. Alternatively, the sign of this association might differ between two persons (i.e., a positive association for one and a negative association for another), indicating a *qualitative* interindividual difference. That is, whereas one person might tend to feel *more* inferior after actively using social media (i.e., a positive temporal association), another person might tend to feel *less* inferior (i.e., a negative temporal association).

Figure 2 demonstrates these differences by juxtaposing the aggregate network (estimated and discussed in Aalbers et al., 2019) and five idiographic networks that represent how variables are associated across time for each individual (visualizations of all idiographic networks are in the Online Supplementary Materials). This figure illustrates how strongly idiographic networks differ from the aggregated network as well as each other. For instance, in the aggregate network, active social media use (**M2**) at a previous measurement is negatively associated with fatigue (**D1**) at a subsequent measurement, but this link only occurs in participant 12's idiographic network. As Figure 2 indicates, each person has a unique constellation of temporal associations between depression symptoms and different uses of social media. For instance, we see that participant 9 tends to spend less time passively browsing social media (**M1**) after feeling more depressed (**D2**) and inferior (**D6**), but more so after experiencing a loss of interest (**D5**) and fatigue (**D1**). Participant 113 tends to feel lonelier (**D3**) after either actively or passively (**M1**) using social media but feels less inferior (**D6**) only after actively using social media. Participant 12 feels both less lonely and less inferior after actively using social media. Participant 48 tends to actively use social media when feeling depressed or inferior and passively use social media when feeling lonely. Participant 6 feels less depressed when passively, but not actively, using social media.

To summarize interindividual differences in temporal associations, Figure 3 depicts the distribution of person-specific temporal associations between passive and active social media use and depression symptoms. Figure 3 shows that passive and active social media use are very weakly to weakly associated with depression symptoms for most individuals. This applies to both associations from social media use to depression symptoms and from depression symptoms to social media use, barring some outliers (range beta = -0.61 to beta = 0.29). In 45.4% of participants, the temporal association from passive and active social media use to depression symptoms and stress is positive. In the opposite temporal direction, we see a positive effect in 61.8% of participants. All other associations are negative. However, in a small subgroup only, do temporal associations between social media use and depression symptoms exceed the smallest effect size of interest of 0.10. The association from social media use to depression symptoms is larger than 0.10 in 4.10% of all participants, and smaller than -0.10 in 1.90%. The association from depression symptoms to social media use was larger than 0.10 in 1.55% of participants, and smaller than -0.10 in 2.60%.

Discussion

This study modelled idiographic networks to investigate person-specific differences in temporal associations between social media use and depression symptoms. Overall, we found that the associations of social media use and depression symptoms differed substantially among individuals. Importantly, such associations differed both in strength and in kind; for instance, while some individuals felt more depressed after passively using social media, others felt less depressed after passively using social media. Our findings echo those of Beyens et al. (2020), who found significant variability in the effects of social media use on adolescent well-being.

Guided by previous research, we disentangled the effects of passive and active social media use (Verduyn et al., 2017). As ample evidence suggests that the effects of social media use on our psychological health depend on the nature of our engagement with the platform, several researchers have hypothesized that ASMU tends to promote well-being, whereas PSMU undermines it (Verduyn et al., 2020). Nevertheless, our idiographic networks indicate that both active and passive social media use may have positive or negative immediate psychological consequences, depending on the individual. Thus, our findings do not support the claim that PSMU is reliably to blame for the harmful effects of social media use. Consistent with this, Valkenburg et al. (2021) propose that the effects of social media may also depend on person-specific variables, including susceptibility to envy, inspiration, and enjoyment.

Such person-to-person differences may be obscured by examining a dataset in the aggregate. For instance, Aalbers et al. (2019) found that loneliness predicted both passive and active social media use over time, which is consistent with findings from Kross et al. (2013). However, this effect possibly differs from person to person, as loneliness at Time 1 did not consistently predict more social media use at Time 2 (i.e., two hours later) in all individuals. The relationship between social media and our well-being is more nuanced than aggregate studies – many of which combine data from hundreds, if not thousands, of participants – can reveal (Kross et al., 2020). Although some studies have found associations between social media use and declines in mental health over time among adult (Kross et al., 2013; Shakya & Christakis, 2017) and adolescent (Boers et al., 2019; Viner et al., 2019) samples, such associations may not apply to a subset – or even a majority – of individual participants within the sample.

Notably, most of the correlations between social media use and depression symptoms were weak, suggesting that most individuals experience highly limited (if any) short-term changes in well-being related to their social media use. Our findings diverge from other experience sampling studies. Faelens et al. (2021), who assessed participants six times per day for two weeks, found that both Facebook and Instagram use predicted reduced well-being. Kross et al. (2013), who assessed participants five times per day for two weeks, found that Facebook use predicted declines in state mood (i.e., how people felt moment to moment) and life satisfaction. Moreno et al. (2012), who assessed young adults aged 18-23 six times a day for one week, found a U-shaped association between social media use and depression symptoms. Of note, all three studies analyzed data at the group (i.e., interindividual) level, and did not examine associations between social media use and well-being at the intraindividual level.

In our study, we did not find evidence that social media use increases feelings of loneliness or decreases self-esteem in the short-term at the level of the individual. Yet, our temporal window (i.e., collecting data every two hours) may have influenced our findings. For example, it is possible that some effects may occur early in a two-hour time block but dissipate by the next measurement point. Alternatively, is possible that two weeks is an insufficient time frame to detect the long-term effects of social media on well-being and make substantial causal inferences. However, a recent eight-year longitudinal study following individuals from adolescence to early adulthood found that time spent using social media was neither associated with depression nor anxiety symptoms (Coyne et al., 2020). Nevertheless, longer follow-ups are needed to examine long-term relationships between social media use and psychological well-being.

Strengths, Limitations, and Future Directions

Our study has several strengths. First, although the field of social media effects research has long relied on cross-sectional data (Kross et al., 2020), our study employs robust experience sampling methods to examine longitudinal relationships between social media use and depression symptoms. Experience sampling is an ecologically valid approach, as it monitors individuals in daily life (Aalbers et al., 2019). As experience sampling prompts participants to report their momentary affective states throughout the course of a day, it circumvents many of the drawbacks of retrospective measures. Across two studies examining stress and self-esteem, Ellison et al. (2020) found significant discrepancies between retrospective ratings and ESM ratings. Data collected via experience sampling were substantially more accurate and precise, as retrospective measures of psychological phenomena are prone to biases and inaccuracies (Ellison et al., 2020). For this reason, over the past decade, experience sampling methods have been encouraged for clinical and psychological research studies.

Second, we used a person-centered, innovative analytic approach to clarify how social media use relates to depression symptoms within individuals. Our idiographic networks model correlations between psychological phenomena within a single person, averaged over various time points (Howe, Bosley, & Fisher, 2020). As such, idiographic methods consider individual differences in thoughts, feelings, and behaviors, which previous research suggests are person specific (Aalbers et al., 2021; Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017). The strength of this person-centered approach is that it enables us to discover patterns within individuals that are obscured in group-level models (Howe et al., 2020). Most studies examining relationships between social media use and well-being have done so at the group (i.e., interindividual) level (e.g., Kross et al., 2013; Verduyn et al., 2015; Aalbers et al., 2019); however, relationships among variables at the group level do not necessarily apply at the individual level (Molenaar, 2004). McNally (in press) cautions against falling prey to the “ecological fallacy,” whereby findings emerging at the group level are generalized to particular individuals within the group. In fact, the direction of a correlation at the group-level may reverse when comparing associations to the individual-level (cf. Keijsers & Van Roekel, 2018; McNally, 2018). Thus, our study extends prior work on social media and well-being by considering individual variation via idiographic analyses instead of relying on group-level data.

Our study is not without limitations. First, although our study differentiates between active and passive forms of social media use, it does not differentiate between different types of social media platforms. Indeed, not all social media platforms are equally conducive to fostering social connection (Aubrey & Rill, 2013; Burke, Kraut, & Marlow, 2011). For instance, among a sample of adolescents, Beyens et al. (2020) found that passive use of WhatsApp improved well-being at the group and individual levels; however, passive use of Instagram did significantly differ from adolescent to adolescent. Beyens et al. (2020) hypothesize that WhatsApp yields more consistent benefits to adolescents' well-being because it is a personal, private platform used for one-on-one or group conversations with friends and acquaintances, whereas Instagram is a public platform that promotes upward social comparison (Waterloo, Baumgartner, Peter, & Valkenburg, 2017). Consistent with this observation, one study found that more frequent Instagram use predicted greater depression symptoms for people who followed more strangers, but lower depression symptoms for those who followed fewer strangers (Lup, Trub, & Rosenthal, 2015). Ultimately, further research is needed to investigate the differential effects of social media platforms (Frison & Eggermont, 2016), as well as the processes that different platforms activate (Kross et al., 2020), on well-being.

Second, although categorizations of ASMU and PSMU have become increasingly common in the literature (e.g., Verduyn et al., 2021), they fail to encompass the wide variety of activities individuals engage in while using social media. As many researchers have noted, PSMU can expose us to highlight reels of other people's lives, and may lead us to feel inferior; however, PSMU may also showcase information that induces positive emotions (e.g., a beautiful image, an excerpt from a piece of literature, or a poignant video). In addition, although passive viewing of other people's profiles tends to reduce well-being, passively viewing one's own profile has the reverse effect and can increase self-esteem (Gonzales & Hancock, 2011). Further, although ASMU enables direct communication, it may undermine well-being if social interactions are harmful; as Kross et al. (2020) note, social media provide new opportunities to hurt others (e.g., via cyberbullying, trolling, spreading moral outrage). In addition, evidence suggests that excess use of social media – regardless of the type – impairs physical and mental health, as in the case of online social network site addiction (Andreassen, 2015). Thus, future research is needed to examine subcategories of active and passive social media use, and move beyond the helpful, but rudimentary, dichotomization of passive and active use.

Third, our analysis is limited in that it exclusively modeled linear relationships and did not test how much variance these relationships explain in new data. Because we exclusively modelled linear relationships between PSMU, AMSU, and depression symptoms, our model could not detect potential non-linear relationships (e.g., U-shaped, as suggested in Moreno et al., 2012). Further, as our model comprises a large number of parameters, it is possible it overfit the data and has limited predictive accuracy on new data (e.g., our model's predictions might be worse than predictions made by a random intercept model). Future research should test to what extent these models predict variance in depression symptoms on future (i.e., unseen) observations.

Fourth, our sample consisted of undergraduate psychology students at a large university in the Netherlands. Thus, our findings may not generalize to other age groups (e.g., middle-aged or older adults) or individuals in other countries. Finally, self-reports of social media use may be subject to recall biases, and participants may engage in active or passive social media use habitually or without awareness (Aalbers et al., 2019; Rodriguez et al., 2020). Nevertheless, the fact that data were collected in real time via an experience sampling design, rather than retrospective self-report, increases our confidence that such recall biases were minimized.

Conclusions

As noted by Kross et al. (2020), it is imperative for future research to move beyond asking whether social media is good or bad for us. Instead, we must examine the differential impact that social media have on our well-being, and how their effects may differ depending on our demographic characteristics, personality traits, and cultural backgrounds (Nadkarni & Hofmann, 2012). Our findings indicate that relationships between social media use and depression symptoms at the group level do not apply to every individual within the group, and that neither passive nor active social media consistently produces positive or negative effects on well-being. However, further research is needed to identify personal characteristics that may modify the effects of social media use on our well-being. We encourage future work to examine whether certain baseline constructs (e.g., self-esteem, susceptibility to envy) predict individuals' person-specific parameters to shed light on factors that explain why using social media may positively affect some, and negatively affect others. Such work may have clinical implications, as it may (1) help us determine *which* individuals are most at risk of experiencing elevated depression symptoms after using social media, and (2) personalize interventions and treatments to alleviate symptoms. As social media platforms play a key role in the social lives of adolescents and adults alike, it is crucial to elucidate when, for whom, and in what ways they negatively (or positively) impact our psychological well-being.

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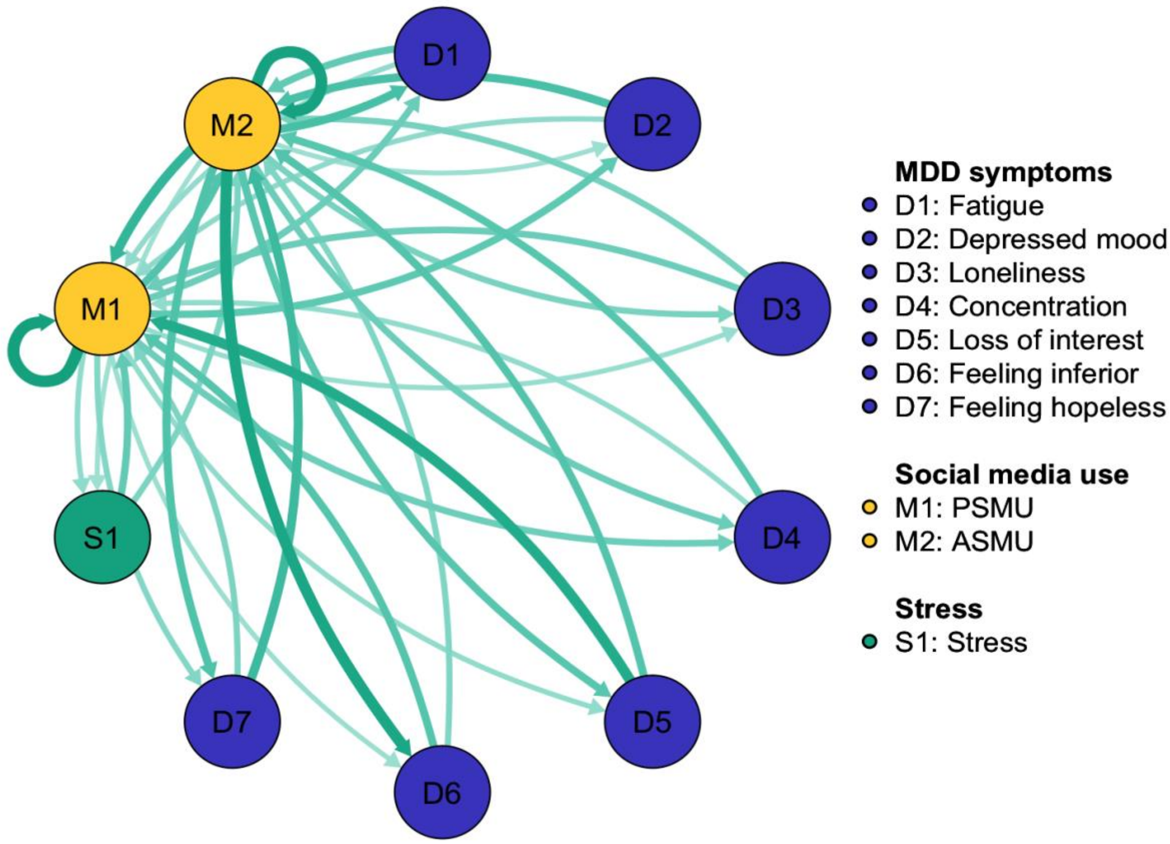

Figure 1. Interindividual differences in the associations between social media use and depression symptoms. Purple circles represent depression symptoms, yellow circles represent social media use, the teal circle represents stress. Teal arrows indicate that a given temporal association has a significant standard deviation. For instance, the arrow from M2 to D6 indicates that individuals differ regarding the extent to which active social media use tends to be followed by feelings of inferiority.

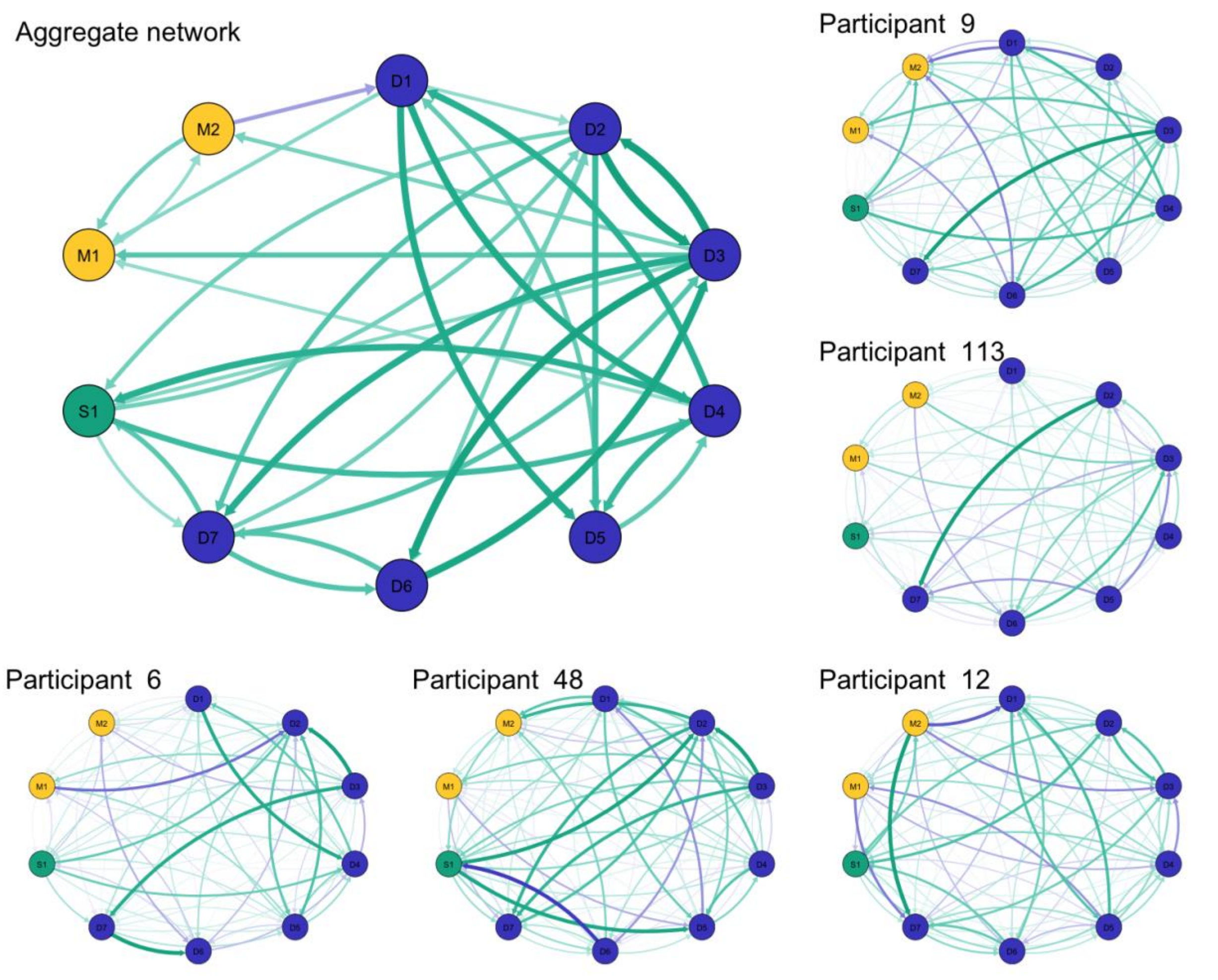

Figure 2. Aggregate network from Aalbers et al. (2019) as well as idiographic network models of five participants. Purple circles represent depression symptoms, yellow circles represent social media use, the teal circle represents stress. Teal arrows represent positive associations, purple arrows represent negative associations. In an idiographic network, arrows starting in circle A and ending in circle B represent the extent to which variable A at time *t-1* tends to be followed by variable B at time *t* (after controlling for all variables in the network, including variable B, at time *t-1*) in one specific individual. The interpretation is the same in the aggregate network, with the important difference that each association in this network represents the *average* of this association in each idiographic network.

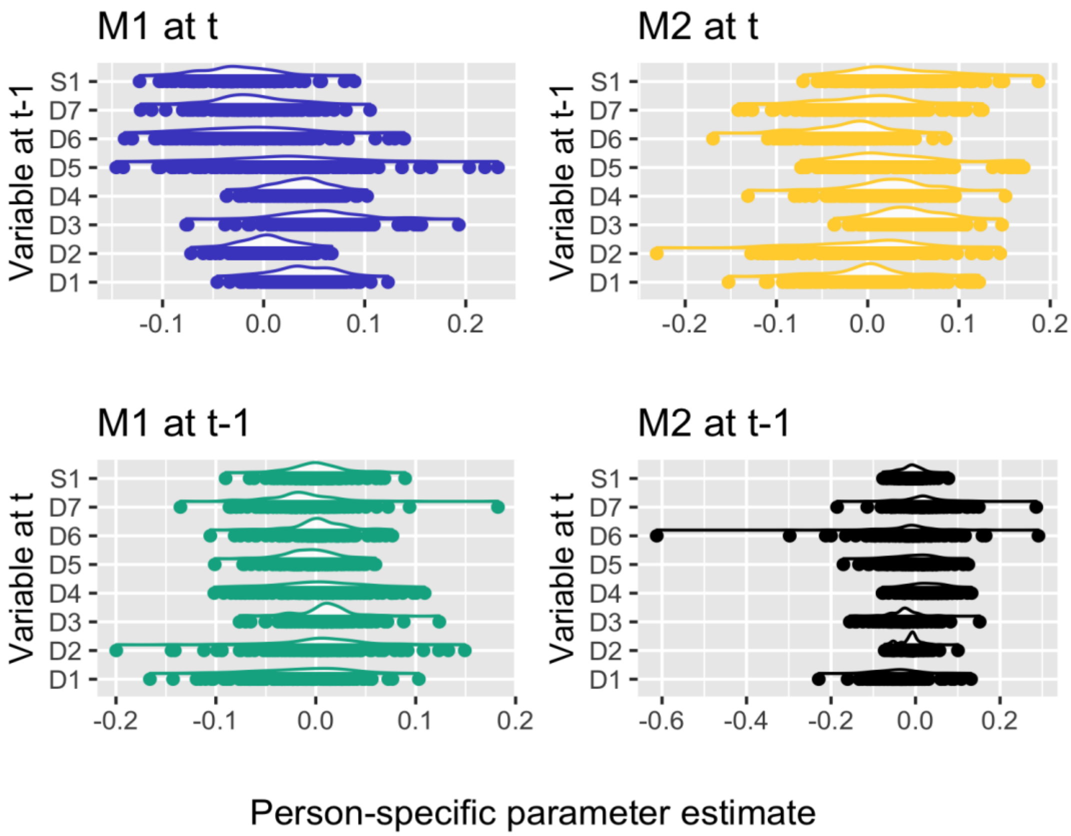

Figure 3. Distributions of person-specific parameters. Each point represents a person-specific association. Density plots on top of points represent how many points occur within each part of the unidimensional parameter space. The upper panels depict the association from depression symptoms and stress at a previous time window (*t-1*) to social media use at the current time window (*t*). The lower panels depict the opposite association: from social media use at the previous time window (*t*) to depression symptoms and stress at the current time window (*t*).

Compliance with Ethical Standards

Ethics approval: All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent: All participants gave informed consent.

Conflict of Interest: The authors declare that they have no conflict of interest.

Animal Rights: No animal studies were carried out by the authors for this article.