The Relation Between Social Media Use, Depression, and Personality: A Network Analysis

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Abstract

The relationship between social media use and depression has been extensively studied but the current empirical evidence remains inconclusive. The present study aimed to explore how user specific characteristics, such as neuroticism, extraversion, and gender, are interconnected with social media use and symptoms of depression in a group-level cross-sectional network based on a student sample of young adults (18 to 30 years old). Participants (*N* = 430) filled in an online questionnaire measuring symptoms of depression, loneliness, social media use, neuroticism, extraversion, and stress. Regularized partial correlation networks were estimated to produce an aggregate network, and separate networks for men and women. The male and female network (*n* = 66 each) were compared in terms of structure and overall connectivity. Results showed that symptoms of depression and social media use were sparsely connected and if so, weakly positively related, but the relationship was not directly affected by either neuroticism or extraversion. No statistical differences were found between the male and female network. In sum, we found no evidence for personality and gender affecting the relationship between symptoms of depression and social media use. Future research could use temporal networks to discover potential causal relationships, specifically focusing on idiographic networks to reveal individual differences that would otherwise remain obscured.

Keywords: social media, depression, personality, network analysis

The Relation Between Social Media Use, Depression, and Personality: A Network Analysis

The advent and widespread adoption of social media in the early 21st century has generated public and academic interest regarding the association between social media and mental health (Appel et al., 2019). Social media can generally be understood as online platforms for masspersonal, controlled communication and self-presentation where users supposedly derive value from user-generated content and perceived interaction with others (Carr & Hayes, 2015). However, using social media is now considered a potential risk factor for mental health, particularly for depression. (Appel et al., 2019). The association between social media use (SMU) and depression has therefore been extensively studied, especially among adolescents and young adults since SMU as well as the onset and increase of depression are the highest in this age cohort (Cunningham et al., 2021; Ivie et al. 2020; Lin et al., 2016; Vidal et al., 2020). Yet, the current empirical evidence seems inconclusive as both cross-sectional and longitudinal studies offer mixed results, showing either positive, negative, or nonsignificant associations between SMU and depression (Cunningham et al., 2021; Kross et al., 2020). Perhaps the relationship between SMU and depression may be better explained by exploring the numerous relations between different types of SMU and user specific characteristics, such as individual symptoms of depression and personality (Rodriguez et al., 2021; Verduyn et al., 2021).

Social Media Use and Depression

A substantial body of research, predominantly covering the effects of SMU on mental health, and more specifically on depression, posits that SMU can either benefit or harm mental health depending on how social media is used (Kross et al., 2020). Researchers generally differentiate between two types of SMU: active social media use (ASMU) and passive social media use (PSMU). ASMU involves actively engaging with others on social media (e.g., posting and commenting) whereas PSMU involves passively consuming social media content without engaging with others (e.g., scrolling through feeds; Verduyn et al., 2015). Following this dichotomy, the literature suggests that ASMU benefits mental health, but PSMU harms mental health (Kross et al., 2020). In support of this hypothesis, some empirical evidence shows that ASMU benefits mental health through improved affective well-being (Kross et al., 2013), increased received and perceived social support (Liu et al., 2018), expanded bonding and bridging social capital (i.e., connectedness within the own demographic group and between other demographic groups, respectively; Liu et al., 2016; Verduyn et al., 2017), and improved self-esteem by controlling self-presentation and self-disclosure (Best et al., 2014; Valkenburg & Peter, 2011). Conversely, PSMU supposedly harms mental health through diminished affective well-being (Kross et al., 2013; Verduyn et al., 2015), increased loneliness (Matilla et al., 2021), and diminished self-esteem as people tend engage more frequently in upward social comparison (i.e., comparing oneself with people who seem superior or more accomplished; Yang et al., 2021). In line with this, ASMU relates to alleviation of depressive mood while PSMU relates to worsening of depressive mood (Escobar-Viera et al., 2018; Frison & Eggermont, 2015; Thorisdottir et al., 2019).

However, despite some empirical evidence for the ASMU and PSMU hypothesis, meta-analyses report that most empirical studies do not support the hypothesis, showing weak and inconsistent associations between types of SMU and depression, and mental health in general (Hancock et al., 2022; Liu et al., 2019; Yin et al., 2019). The high heterogeneity of results within the literature may indicate various moderators influence the relationship between SMU and depression, such as differences in user specific characteristics, including personality and gender (Ivie et al., 2020; Valkenburg et al., 2022). High heterogeneity of results may also suggest differences in conceptual and measurement approaches (Ivie et al., 2020). To elaborate, most studies conceptualize depression as one distinct condition, often measured in the form of a sum-score, or measure only one symptom of depression as an indicator, such as depressive mood. However, depression is in itself heterogenous, and may best be understood as a cluster of individual symptoms, rather than a distinct condition and latent cause of symptoms (Fried, 2015). Not only do depressive symptoms differ per individual, but depressive symptoms also each have a unique impact on our psychological functioning and may share unique pathways with non-DSM symptoms or other external factors (Fried & Nesse, 2014; 2015). A closer focus on the individual symptoms of depression and their relations with other symptoms and external factors may offer new insights into the specific mechanisms at play in the association between SMU and depression. To explore these mechanisms, the present study applies a network approach.

A Network Approach to Social Media Use and Depression

From the network perspective, depression is understood as a heterogenous network of interacting symptoms in which each symptom may uniquely affect or be affected by external factors, such as SMU or user specific characteristics (Fried, 2015; Robinaugh et al., 2019). This contrasts with the common cause perspective that views depression as the underlying cause of its symptoms, and thereby suggests that symptoms are independent and of equal importance to the disorder (Fried, 2015). However, from a network perspective, increased loneliness may worsen the specific symptom of depressive mood rather than depression itself (Erzen & Çikrikci, 2018), and both loneliness and depressive mood may result in increased PSMU as one might use social media to alleviate feelings of loneliness and depression (Kross et al., 2013; Frison & Eggermont, 2015). In turn, PSMU may increase feelings of loneliness as people engage in upward social comparison and perceive a lack of social support, which in turn may worsen depressive mood

(Frison & Eggermont, 2015; Matilla et al., 2021). Furthermore, loneliness may also worsen hopelessness and self-esteem, resulting in effects along different pathways (Erzen & Çikrikci, 2018). Thus, a change in one (external) factor might trigger chain reactions in the network among specific depressive symptoms and other external factors, highlighting the unique importance of specific symptoms and partially explaining the association between SMU and depression as influenced by external factors. In addition, the example shows the effect depression may have on SMU which receives little attention in the literature compared to the effect of SMU on depression.

Through network analysis these psychological networks are estimated as models, visualizing each observed symptom and external factor as nodes as well as all associations between nodes, called edges (Epskamp et al., 2017). Following this approach, the results of Aalbers and colleagues (2019) show that at the group level (i.e., between-subjects) mean PSMU correlates positively with mean ASMU, depressed mood, loneliness, hopelessness, and feelings of inferiority. However, after controlling for all variables no unique correlations remain. Building on the study of Aalbers and colleagues (2019), the temporal individual models of Rodriguez et al. (2021) provide a possible explanation. Namely, their models show that the association between SMU and symptoms of depression differ greatly among individuals. That is, ASMU and PSMU may both alleviate or worsen symptoms of depression, depending on the individual. Thus, research on the association between SMU and depression should perhaps not focus solely on *how* social media is used, but also on *who* uses it. As stated before, user specific characteristics, such as personality and gender may influence the association between SMU and depression (Ivie et al., 2020; Valkenburg et al., 2022). Previous research indicates that specifically the personality traits of neuroticism and extraversion in combination with gender may affect the relationship between SMU and depression, but this has not yet been assessed in a network analysis (Grav et al., 2012; Nadkarni & Hofmann, 2012; Bowden-Green et al., 2020, 2021). The aim of this study is therefore to explore how individual characteristics, such as neuroticism, extraversion, and gender, are interconnected with social media use and symptoms of depression in a group-level network of young adults.

Influence of Neuroticism, Extraversion, and Gender

Neuroticism is a personality trait encompassing emotional stability. Individuals who are low in neuroticism are emotionally stable or calm whereas individuals who are high in neuroticism are susceptible to emotional distress and tend to exhibit anxiety, anger, depression, self-consciousness, impulsiveness, and insecurity (Gray & Bjorklund, 2017). The positive association between neuroticism and depression is not surprising as people high in neuroticism tend to perceive, appraise, and react to experiences and stimuli more negatively which relate to the two core symptoms of depression: depressive mood and anhedonia (Hakulinen et al., 2015; Liao et al., 2019; Tong, 2010). This negativity extends to social relationships as well as people high in neuroticism report more negative social interactions and are generally less satisfied with their social relationships, exacerbating feelings of loneliness (Buecker et al., 2020; Wieczorek et al., 2022). As illustrated in the previous section, loneliness is associated with increased depression (Erzen & Çikrikci, 2018; Matilla et al., 2021). High neuroticism strengthens the positive association between loneliness and depression (Vanhalst et al., 2011). Moreover, high neuroticism is linked to a greater susceptibility to stress, and stress can worsen symptoms of depression (Fried et al., 2015, Mineka et al., 2020). In the context of social media usage, people high in neuroticism do not necessarily use social media more excessively than others but they do engage more in PSMU than ASMU. This may be because ASMU, such as posting and commenting, induces worry about self-presentation and judgement of others, reflecting the relatively high self-consciousness and insecurity of people high in neuroticism (Bowden-Green et al., 2021). Even when people high in neuroticism do engage in ASMU, their content is likely considered socially unappealing as it is often relatively extensive, negative, low in self-disclosure, and often presents a false representation of themselves; the latter being associated with higher levels of depression and stress (Bowden-Green et al., 2021; Yang et al., 2021). However, the preference for PSMU over ASMU seems to leave people high in neuroticism with a small social network, resulting in loneliness and a craving for social interaction (Bowden-Green et al., 2021). Unsurprisingly, the harmful effects of PSMU on mental health through a lack of perceived social support or loneliness as well as through upward social comparison tend to especially affect people high in neuroticism (Yang et al., 2021).

Extraversion is a personality trait encompassing the tendency to be socially outgoing. Individuals who are low in extraversion, also known as introversion, are socially reserved whereas people high in extraversion are generally warm, gregarious, assertive, active, excitement-seeking, and positive in emotion (Gray & Bjorklund, 2017). Unlike people high in neuroticism, people high in extraversion appraise experiences and stimuli relatively more positively (Uziel, 2006). In addition, people high in extraversion experience relatively more positive affect in general and less negative affect from stress, which both protect against the development of depressive symptoms (Leger et al., 2016; Anglim et al., 2020). Furthermore, extraverts are less likely to experience loneliness – another factor protecting against developing depression – since extraverts tend to actively seek out social interaction (Vanhalst et al., 2011). For extraverts, social interaction is a key factor in experiencing positive affect, specifically the quality of the social interaction as defined by their perceived social contribution to the interaction

(Smillie et al., 2015). Unsurprisingly, social media is appealing to extraverts as it offers an opportunity to socially connect and interact with other people. Extraverts therefore use and contribute to social media relatively frequently and for longer periods of time, mostly engaging in ASMU by regularly posting content and commenting to others while maintaining relatively large social networks (Bowden-Green et al., 2020). Social media contributions of extraverts are often positive in nature, receive relatively more likes and comments, are high in self-disclosure, and consist of honest and authentic self-representations; the latter being associated with lower levels of depression and higher levels of self-esteem (Bowden-Green et al., 2020; Yang et al., 2021).

Regarding differences in gender, women tend to use social media more than men, both actively and passively (Twenge & Martin, 2020). Women also are on average more extraverted and more neurotic than men (Gray et al., 2012). Considering the ASMU and PSMU hypothesis and the effects of neuroticism and extraversion in the context of social media use, the beneficial and harmful effects of ASMU and PSMU in relation to depression, respectively, should then be greater for women than for men. Some studies indeed show that, for women especially, PSMU worsens depressive symptoms as it elicits social upward comparison and decreases perceived social support, while ASMU protects against depressive symptoms via received social support (Frison & Eggermont, 2015; 2015b; Nesi and Prinstein, 2015). Particularly upward comparison in terms of appearance is prominent among women using social media, causing women to have a more negative body image of oneself (Hogue & Mills, 2019). The potentially more harmful effects of PSMU for women may explain why spending more time on social media is associated with an increased risk of depression and emotional distress for especially women (Thorisdottir et al., 2019; Liu et al., 2022). Conversely, the potentially more beneficial effects of ASMU for women may explain why women with depressive symptoms tend to use social media more (Heffer et al., 2019). A more general explanation for the stronger effects of ASMU and PSMU on depression may lie in women's motivation to use social media. Men and women both use social media for self-enhancement (i.e., improving one's self-esteem and social standing), but women do so by using social media mostly as a social tool, maintaining and expanding one's social network and collecting social information, while men use social media mostly to collect general information in a broader context (e.g. world developments, work-related, personal interests, education), improving their competence and as a result their social standing (Krasnova et al., 2017). Thus, the social focus of women may draw them to social media but also seems to make them more sensitive to the harmful and beneficial effects of social media use.

In sum, research indicates that neuroticism is a risk factor for depression and related symptoms, such as loneliness and stress, while extraversion is a protective factor against depression and related symptoms. Similarly, whereas neuroticism may hinder social interaction on social media and amplify PSMU and its harmful effects related to depressive symptoms, extraversion may facilitate social interaction on social media and amplify ASMU and its beneficial effects related to depressive symptoms. Since women are generally more neurotic, extraverted, and are more socially focused than men, the harmful and beneficial effects of social media use may be more pronounced for women than for men.

Present Study

Despite the abundant research on the relationship between SMU and symptoms of depression, the nature of this relationship remains unclear. While the literature suggests that personality and gender may influence the relationship between SMU and symptoms of depression, few studies have considered such user specific characteristics. The following research question will therefore be answered: *How are neuroticism and extraversion interconnected with social media use and symptoms of depression in a network structure?* In addition, to assess the effect of gender, a network comparison is made between a female network and a male network.

The present study is mainly an exploratory study on how the personality traits of neuroticism and extraversion are interconnected with social media use and symptoms of depression. However, based on the literature review, some findings are expected. Following the ASMU and PSMU hypothesis, as explained before, previous studies indicate ASMU benefits mental health by alleviating depressive mood, improving self-esteem, and protecting against loneliness whereas PSMU harm mental health by worsening depressive mood, decreasing self-esteem, and exacerbating loneliness (Kross et al., 2013, 2020). Therefore, it is expected that ASMU and PSMU share negative and positive associations, respectively, with loneliness and depressive symptoms, particularly the symptoms of depressive mood and low self-worth. Since the personality trait of neuroticism is linked to a susceptibility to negativity and emotional distress as well as difficulty in social relationships (Gray & Bjorklund, 2017; Buecker et al., 2020), it is expected that neuroticism is positively associated with depressive symptoms, stress, loneliness, and PSMU. Conversely, since the personality trait of extraversion is linked to experiencing positivity and seeking social interaction (Vanhalst et al., 2011; Gray & Bjorklund, 2017), it is expected that extraversion is negatively associated with depressive symptoms, stress, and loneliness, but positively associated with ASMU and time spent on social media. With regards to the effect of gender, it is expected that the associations of neuroticism and extraversion with the aforementioned variables are stronger in the female network than in the male network.

The study may offer new insights into how individual differences, such as personality, affect the relationship between social media usage and symptoms of depression from a network perspective. Particularly, if personality and gender indeed are influential factors in the relationship between social media usage and symptoms of depression, then specific symptoms of depression may be identified as important factors in the relationship, possibly informing future studies to study these specific symptoms in more detail in the context of social media usage. Furthermore, by taking a network approach, unique relations between user specific characteristics, SMU, and symptoms of depression may be discovered, possibly warranting further research to identify potential causal relationships. Thus, while findings would need to be replicated and investigated based on within-person longitudinal data, such findings could in the long-term inform clinical practitioners as well as people in general to be aware and mindful of the potential effects of social media usage in certain individuals.

Methods

The current study used baseline data of the WARN-D research project of Leiden University which aims to identify early warning signs for depression in students and utilize this knowledge to build personalized prevention programs (Leiden University, 2022). The WARN-D data collection was approved by the Psychology Research Ethics Committee of Leiden University on September 6th 2021 (reference number: 2021-09-06-E.I.Fried-V2-3406).

Participants

A total of 450 participants participated in the baseline survey in November 2021. Six participants did not complete the survey for unknown reasons and were therefore subsequently removed from the dataset. Since the literature focuses almost exclusively on adolescents and young adults, being the largest user groups of social media, participants older than 30 years old were not included in this study to produce comparable results (Lin et al, 2016; Shensa et al., 2017). Moreover, since the WARN-D research project only included people of at least 18 years old, this study does not include adolescents but focuses solely on young adults. Another 14 participants over the age of 30 were therefore removed, resulting in a final sample of 430 participants (mean age = 22.2, SD = 2.7, range = 18-30). In terms of biological sex, 66 (15.3%) participants were male, and 364 (84.7%) participants were female. Regarding highest level of obtained education, 172 (40.0%) participants completed a pre-vocational secondary education, 19 (4.4%) completed a secondary vocational education, 19 (4.4%) completed a higher vocational education, 213 completed an academic university education (49.6%), and 7 (1.6%) participants did not know their highest level of obtained education.

Procedure

Participants were recruited via posters, social media, e-mail newsletters, and word-of-mouth. People interested in participating could indicate their e-mail address in an online survey. People were then invited to online surveys in which inclusion and exclusion criteria were assessed and informed consent was asked in accordance with policy of Leiden University. The inclusion criteria required participants to (1) be at least 18 years old, (2) study at a Dutch higher education institution (i.e., pursuing an MBO, HBO or WO degree), (3) be fluent in either Dutch of English, (4) own a smartphone with an Android or iOS operating system, and (5) have a European bank account with an International Bank Account Number (IBAN). The exclusion criteria, as based on ethical and research concerns, required participants to not have a current diagnosis of (1) schizophrenia, psychosis, thought disorder, (2) major depressive disorder, (3) (hypo)mania or bipolar disorder, (4) primary substance use disorder, and (5) moderate or severe suicidal ideation. To assess criteria 1 through 4, participants were asked if they were currently waiting for or in treatment at a licensed psychologist or psychiatrist. Participants indicating yes were excluded. Next, validated self-report screeners were used to exclude potential participants meeting exclusion criteria 1 through 5. Lastly, since a daily calories burnt estimate is provided by a smartwatch during the EMA-phase of the WARN-D research project, participants were excluded if they indicated that seeing such an estimate would be very stressful. Participants received 7.5 euros as reimbursement for their time spent on filling in the baseline questionnaire.

Measures

Symptoms of Depression

To measure symptoms of depression, an adapted version of the Patient Health Questionnaire-9 (PHQ-9) was used (Kroenke et al., 2013). Building on the network analyses of Aalbers et al. (2019) and Rodriguez et al. (2021), only the following items of the PHQ were used to correspond with the commonly measured symptoms of depression in the most widely used depression questionnaires: loss of interest or pleasure, depressed mood, fatigue, concentration problems, worthlessness, and hopelessness (Fried, 2017). The items measured the degree to which participants were bothered by problems corresponding to a symptom of depression as experienced in the past two weeks on a 4-point scale of 0 to 3 (0 = *Not at all*, 3 = *Nearly every day*). For example, “Little interest or pleasure in doing things”.

Loneliness

Feelings of loneliness were measured as an average score of a 3-item questionnaire based on the UCLA Loneliness Scale (Russel et al., 1978). The items measured how often participants generally felt lacking companionship, left out, and isolated from others on a 3-point scale of 1 to 3 (1 = *Hardly ever*, 3 = *Often*). For example, by asking “How often do you feel that you lack companionship?”.

Social Media Use

The construct of social media use (SMU) consisted of two measures: time spent on social media and type of social media (i.e., ASMU or PSMU). To measure time spent on social media, an adapted measure from the Caring Universities questionnaire was used which measures how much time participants spend on social media (e.g., Facebook, Twitter, Instagram, Snapchat, TikTok) on a typical day, excluding private messaging, on a 7-point scale of 1 to 7 (1 = *I don't use social media*, 2 = *Less than half an hour*, 3 = *Half an hour to an hour*, 4 = *1-2 hours*, 5 = *3-4 hours*, 6 = *5-6 hours*, 7 = *More than 6 hours*)(Caring Universities, 2022). If participants indicated spending time on social media, then they were presented with the follow-up question on type of social media use. Type of social media use was measured by assessing how time spent on social media was relatively distributed by participants between ASMU (e.g., liking, up- and down-voting, sharing, commenting, posting) and PSMU (e.g., scrolling or browsing social media feeds or pages, reading, or watching content) on a continuous percentage scale where 0% indicates only PSMU and 100% indicates only ASMU.

Neuroticism and Extraversion

To measure the personality dimensions of neuroticism and extraversion, the Big Five Inventory (BFI; John et al., 1991) and the shortened BFI-10 (Rammstedt & John, 2007) were used, respectively. The measure for neuroticism consisted of eight items whereas the measure for extraversion consisted of two items. Participants were asked to what extent they could identify themselves with a certain personality trait on a 5-point Likert scale of 1 to 5 (1 = *Strongly disagree*, 5 = *Strongly agree*). For example, “I see myself as someone who... is reserved.”. While it is common to express both measures as a sum score, the sum score scale of neuroticism and extraversion differ greatly due to difference in the number of items, causing possible confusion when interpreting the scores. Both neuroticism and extraversion are therefore expressed as the average score of its respective items after adjusting for reverse scores. Higher scores indicate higher levels of neuroticism and extraversion.

Stress

To measure stress, an adapted version of the Perceived Stress Scale (PSS-10) was used (Cohen et al., 1983). Participants were asked how often they had stress-related thought and feelings in the past two weeks on a 5-point Likert scale of 0 to 4 (0 = *Never*, 4 = *Very often*). Stress is expressed as the average score of its ten respective items after adjusting for reverse scores.

See Appendix A for the full questionnaire per measure.

Statistical Analyses

Three network analyses were performed after standardizing the data to create a model of an aggregate network, a male network, and a female network. In line with the exploratory nature of the current study, the aggregate network was created to explore and visualize how neuroticism and extraversion are interconnected with social media use and symptoms of depression. The male and female network were created to investigate the hypothesis that they significantly differ in network structure due to differences between the genders in the relations between neuroticism, extraversion, and social media use. In the network models, nodes represent observed variables or latent constructs, and edges represent the associations between variables (Epskamp et al., 2012). The aggregate network consists of 12 nodes, representing the seven variables of depression symptoms, the social media use variables (time and type), neuroticism, extraversion, and stress as mentioned in the measures section, giving 66 parameters (i.e., the associations between variables; see Formula A1 in Appendix A for parameter calculation). For sufficient statistical power, the sample size should be at least equal to but ideally five times greater than the number of parameters, giving a minimum sample size of 66 and an ideal sample size of 330 or more which is well within our sample size of 444 (Epskamp et al., 2017). Since the sample only contains 66 (15.3%) males, the number of parameters for the male network was reduced to 15 by converting the variables of depression symptoms into a single depression node, being the average score of six depression symptoms. The variable of loneliness was omitted from the male and female network as it is a concept that commonly occurs in the most widely used depression questionnaires but could not be combined with the other symptoms of depression into one depression node due to different measurement scales (Fried, 2017). Also, by omitting loneliness, power was retained. In order to compare the male and female network, the number of parameters for the female network was likewise reduced. The male and female network therefore consist of six nodes each, representing the depression construct, the social media use variables (time and type), neuroticism, extraversion, and stress. In addition, the sample size of the female network was matched to the sample size of the male network by randomly selecting participants from the original female sample, using SPSS Statistics, version 27 (IBM, 2020).

Due to the continuous and ordinal nature of the data, three Gaussian graphical model (GGM; Lauritzen, 1996) networks were estimated. In each estimated network, nodes correspond to variables or constructs and edges correspond to partial correlation coefficients, being the edge weight, as obtained from the inverse of the variance-covariance matrix. In other words, the edge between two nodes is the remaining association between two variables after controlling for all other variables in the network (Epskamp & Fried, 2018). To account for potential spurious correlations (i.e., Type I errors), the lasso (least absolute shrinkage and selection operator) regularization method with EBIC (Extended Bayesian Information Criterion) model selection was applied (Chen & Chen, 2008; Tibshirani, 1996). To elaborate, lasso regularization limits the sum of absolute estimated partial correlation coefficients as all estimates are shrunk, reducing some estimates to zero which also results in a sparser, more interpretable network model. EBIC model selection allows for controlling the sparsity of the network through adjusting its hyperparameter γ (gamma; Epskamp & Fried, 2018). Setting a suitable hyperparameter value depends on several factors, including the goal of the study, sample size, and population characteristics (Wysocki & Rhemtulla, 2019). For the current study, the hyperparameter was set to 0.5 as this results in a network model high in specificity but generally close to the true network structure, despite possibly omitting some true edges from the network (Foygel & Drton, 2010).

Three centrality measures were calculated to assess the relative importance or influence of each node within the network: node strength, closeness, and betweenness. Node strength refers to the sum of all absolute edge weights connected to a node, indicating how many other nodes directly influence a node or are directly influenced by a node. Closeness refers to the inverse of the sum of distances between a node and all other nodes in the network, indicating how well-connected a node is to other nodes and thus how quickly a node is affected by changes in other nodes. Betweenness refers to the relative number of shortest paths between two nodes, indicating how important a node is in the path between two other nodes. A node high in betweenness centrality acts as a funnel or gatekeeper of information or influence in the network (Bringmann et al., 2019; Costantini et al., 2015; Epskamp et al., 2017).

To the determine the overall accuracy and stability of each network bootstrapping techniques were applied, meaning the network models were re-estimated with resampled data. A non-parametric bootstrap was performed with 1,000 samples, forming a bootstrapped confidence interval (CI) to assess and to compare the accuracy of each estimated edge-weight. A case-dropping subset bootstrap was performed with 1,000 samples. A correlation stability (CS) coefficient was calculated in R, version 4.2.1 to assess stability of the centrality indices (R Core Team, 2022). A CS(cor = 0.7), being a large effect, indicates the maximum proportion of cases that can be dropped to say with 95% probability that the correlation between the centrality indices of the original dataset and that of the case-dropped subset of the data are 0.7 or higher (Epskamp et al., 2017). All network model estimations, centrality measurements, and bootstrapping techniques were performed using the statistical software JASP, version 0.16.2 (JASP Team, 2022).

Lastly, to assess the statistical difference between the male and female network in order to test Hypothesis 1, the R package NetworkComparisonTest (NCT) was used. The NCT employs a network invariance test to determine whether all edges in the male and female network are statistically different (Van Borkulo et al., 2022).

Results

Aggregate Network

Descriptive Statistics

For the aggregate network, the full sample of 430 participants was included in the analyses. As Table 1 shows, the depressive symptoms of loss of interest or pleasure, depressed mood, hopelessness, and worthlessness were on average not at all experienced by people in the past two weeks as mean values range from 0.56 to 0.76. However, fatigue and concentration problems were on average experienced for several days in the past two weeks, with mean values ranging from 1.09 to 1.45. Loneliness was on average only sometimes experienced, leaning to hardly ever experienced rather than often, as indicated by the mean value of 1.76. In terms of social media use, the mode and median of time spent on social media is 4.00, meaning that spending one to two hours on social media is most common and typical. The average person spent almost 25% of the time on social media engaged in ASMU (e.g., liking, up- and down-voting, sharing, commenting, posting), meaning that about 75% of the time was spent engaged in PSMU (e.g., scrolling or browsing social media feeds or pages, reading, or watching content). With regards to personality, the mean values for neuroticism (3.11) and extraversion (3.22) indicate that the average person within the sample is neither particularly neurotic or calm, nor highly extraverted or introverted. Lastly, stress was on average almost never or sometimes experienced in the past two weeks as indicated by the mean value of 1.73.

Pearson correlation tests (see Table C1 in Appendix C) revealed significantly moderate to strong positive correlations between all depressive symptoms, including loneliness. Time spent on social media had significant yet weak positive correlations with the depressive symptoms of fatigue, worthlessness, and concentration problems. Type of SMU did not significantly correlate with any depressive symptom but did show a moderate positive correlation with time spent on social media, meaning more ASMU is associated with more time spent on social media. Neuroticism had significant moderately positive correlations with all depressive symptoms, including loneliness, but no correlation with either time spent on social media or type of SMU. Extraversion, on the other hand, had significantly weak to moderate negative correlations with depressive symptoms, including loneliness but excluding concentration problems. A significantly weak positive correlation was found between extraversion and type of social media use, indicating higher extraversion is associated with more ASMU. Significantly strong positive correlations were found between stress and all depressive symptoms as well as neuroticism. Significantly weak positive correlations were found between stress and time spent on social media as well as extraversion. Since the Pearson correlation tests do not account for the presence of other variables, partial correlations as presented in the network analysis can provide more insight.

Table 1

Descriptive Statistics of Variables

Variable	*N*	*Mean*	*St. Dev.*	*min*	*max*
Loss of interest or pleasure	430	0.73	0.76	0.00 (0.00)	3.00 (3.00)
Depressed mood	430	0.73	0.72	0.00 (0.00)	3.00 (3.00)
Hopelessness	430	0.56	0.70	0.00 (0.00)	3.00 (3.00)
Fatigue	430	1.45	0.89	0.00 (0.00)	3.00 (3.00)
Worthlessness	430	0.76	0.83	0.00 (0.00)	3.00 (3.00)
Concentration problems	430	1.09	0.94	0.00 (0.00)	3.00 (3.00)
Loneliness	430	1.76	0.55	1.00 (1.00)	3.00 (3.00)
Time spent on social media	430	3.84	1.35	1.00 (1.00)	7.00 (7.00)
Type of SMU	406	24.58	22.92	0.00 (0.00)	100.00 (100)
Neuroticism	430	3.11	0.77	1.00 (1.00)	5.00 (5.00)
Extraversion	430	3.22	0.93	1.00 (1.00)	5.00 (5.00)
Stress	430	1.73	0.65	0.20 (0.00)	3.80 (4.00)

Note. SMU = social media use. *N* for ‘Type of SMU’ is 406 as 24 participants indicated that they do not use social media and therefore were not presented with the question on ‘Type of SMU’. Numbers in parentheses indicate the minimum or maximum value of the scale on which the variable was measured.

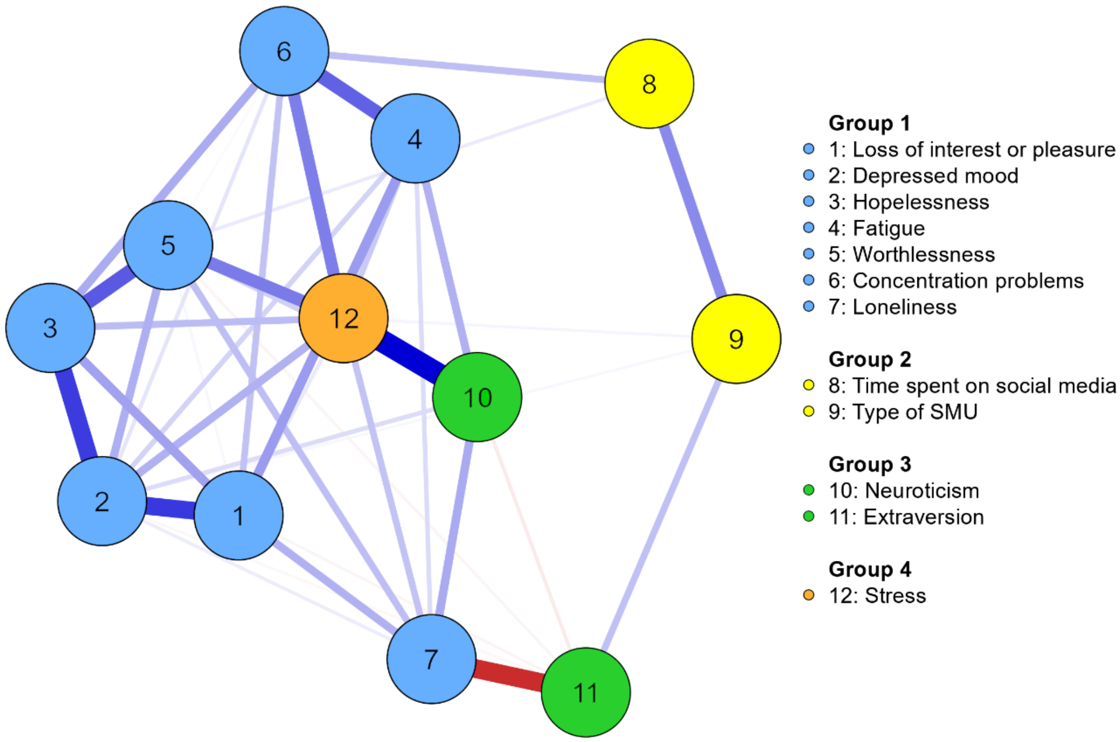
Network Analysis

To allow of correct interpretation of the estimated network model, the accuracy and stability of the network parameters and measures need to be assessed. A nonparametric bootstrap and a case-dropping bootstrap were performed to assess the accuracy of the estimated edge-weights and the stability of the centrality indices, respectively (see Figure C1 and C2 in Appendix C). Visual inspection of the confidence intervals of the estimated edge-weights indicated relatively little to moderate variation, meaning the order of the edge-weights is accurate enough to allow for interpretation. Visual inspection of the plotted centrality indices of the bootstrapped samples indicates that the strength and closeness centrality estimates are stable. However, due to the low stability of the betweenness centrality estimates the order of betweenness should not be interpreted. CS-coefficients confirmed this notion.

The network visualization of the aggregate network is presented in Figure 1. Edge weights ranged from –0.315 (*Extraversion*(11) – *Loneliness*(7)) to 0.378 (*Stress*(12) – *Neuroticism*(10)). The aggregate network featured predominantly positive partial correlations. The symptoms of depression correlated relatively strongly with each other, meaning that, on average, people who present one symptom of depression also tend to present other symptoms of depression. This particularly the case for connections between *Loss of interest or pleasure*(1) – *Depressed mood*(2) (r = .294), *Depressed mood*(2) – *Hopelessness*(3) (r = .290), and *Hopelessness*(3) – *Worthlessness*(5) (r = .245). Most notably, *Stress*(12) was the most central node in the network as indicated by its relatively high degree and closeness centrality as seen in Figure 2. *Stress*(12) was especially central among the symptoms of depression as indicated by the positive correlations of mostly moderate magnitude. As *Neuroticism*(10) had the strongest connection in the whole network with *Stress*(12) (r = .378) but few other direct connections, the

Figure 1

Aggregate Network

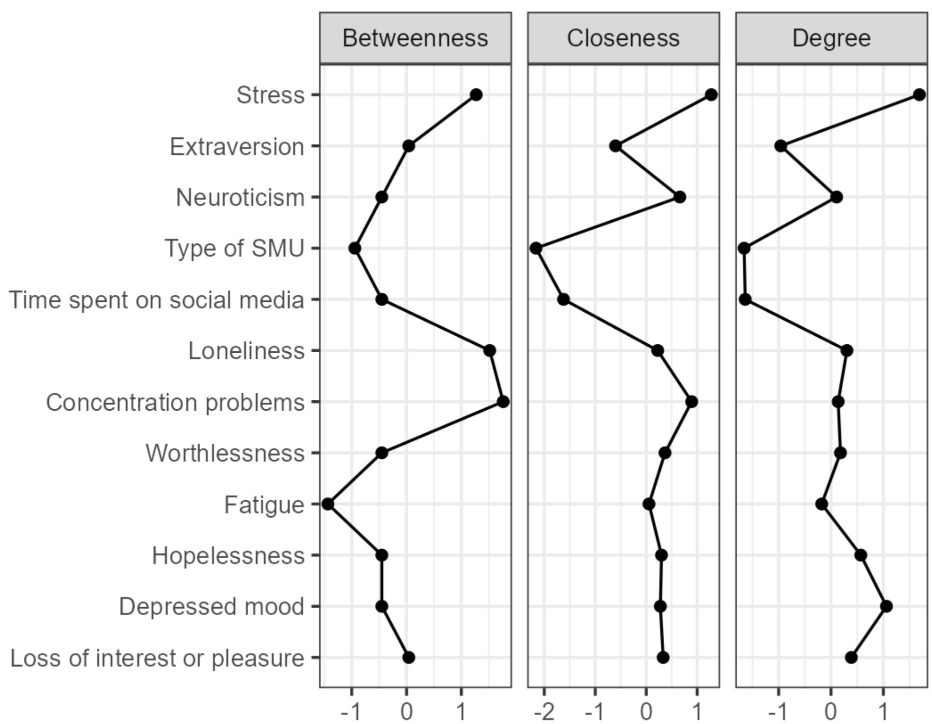


Note. Regularized partial correlation network (tuning-parameter gamma = 0.5). Nodes represent symptoms of depression (group 1), social media usage (group 2), personality traits (group 3), and stress (group 4). Blue colored edges indicate positive, regularized partial correlations. Red colored edges indicate negative, regularized partial correlations. Edge thickness indicates the magnitude of the regularized partial correlation.

closeness centrality of *Neuroticism*(10) was relatively high while its degree centrality was close to zero. The nodes related to social media usage, *Time spent on social media*(8) and *Type of SMU*(9) were the least central in the network as indicated by relatively low strength and closeness centrality. *Time spent on social media*(8) and *Type of SMU*(9) shared a moderate positive correlation with each other (*r*. = .173). Furthermore, *Time spent on social media*(8) had a relatively moderate positive correlation with *Concentration problems*(6) (*r* = .096) and a weak positive correlation with *Worthlessness*(5) (*r* = .031). *Type of SMU*(9) had a relatively moderate positive correlation with *Extraversion*(11) (*r* = .093) and very weak positive correlations with *Stress*(12) (*r* = .016) and *Depressed mood*(2) (*r* = .012). See Table C2 and Table C3, respectively, in Appendix C for all edge-weights and standardized centrality values of the aggregate network.

Figure 2

Centrality Measures of the Aggregate Network



Note. Betweenness, closeness, and degree (i.e., strength) centrality of the nodes in the aggregate network. The x-axis represents standardized centrality scores.

Male and Female Network

Descriptive Statistics

For the male and female network, a sample size of 66 participants was used in the analyses for both gender groups. As Table 2 shows, the female group had slightly higher mean

Table 2

Descriptive Statistics of Variables per Gender Group

Group	*Variable*	*N*	*Mean*	*St. Dev.*	*min*	*max*
Male	Depression	66	0.78	0.62	0.00 (0.00)	2.83 (3.00)
	Time spent on social media	66	3.39	1.24	1.00 (1.00)	6.00 (7.00)
	Type of SMU	60	23.83	23.50	0.00 (0.00)	93.00 (100)
	Neuroticism	66	2.64	0.73	1.00 (1.00)	4.00 (5.00)
	Extraversion	66	3.18	1.02	1.00 (1.00)	5.00 (5.00)
	Stress	66	1.57	0.66	0.40 (0.00)	3.40 (4.00)
Female	Depression	66	0.85	0.62	0.00 (0.00)	3.00 (3.00)
	Time spent on social media	66	3.68	1.46	1.00 (1.00)	7.00 (7.00)
	Type of SMU	59	27.59	23.90	0.00 (0.00)	91.00 (100)
	Neuroticism	66	3.18	0.74	1.38 (1.00)	4.75 (5.00)
	Extraversion	66	3.38	0.93	1.50 (1.00)	5.00 (5.00)
	Stress	66	1.71	0.62	0.20 (0.00)	3.60 (4.00)

Note. SMU = social media use. *N* for ‘Type of SMU’ is 60 for males and 59 for females as six and seven participants, respectively, indicated that they do not use social media and therefore were not presented with the question on ‘Type of SMU’. Numbers in parentheses indicate the minimum or maximum possible value of the scale on which the variable was measured.

values on all variables while the standard deviation of each variable was similar between groups. Thus, on average, women experienced depressive symptoms more frequently in the past two weeks than men. The average time spent on social media is closer to one to two hours for women while for men it is closer to half an hour to one hour as indicated by a mean of 3.68 and 3.39, respectively. Though, the mode and median of time spent on social media is 4.00 for both men and women, meaning that spending one to two hours on social media is the most common and typical among both men and women. Whereas the average man used social media actively for about 24% of their time on social media, the average woman used social media actively for about 28% of their time on social media. In terms of personality, men are on average less neurotic (2.64 vs. 3.18) compared to women as well as less extraverted (3.18 vs. 3.38). With regards to stress, men also experienced less stress on average in the past two weeks compared to women (1.57 vs. 1.71). However, independent samples t-tests indicate that none of the mean differences are statistically significant after correcting for multiple comparisons by means of a Holm-Bonferroni correction, except for the mean difference in neuroticism (both in the full sample as in the male-female sample).

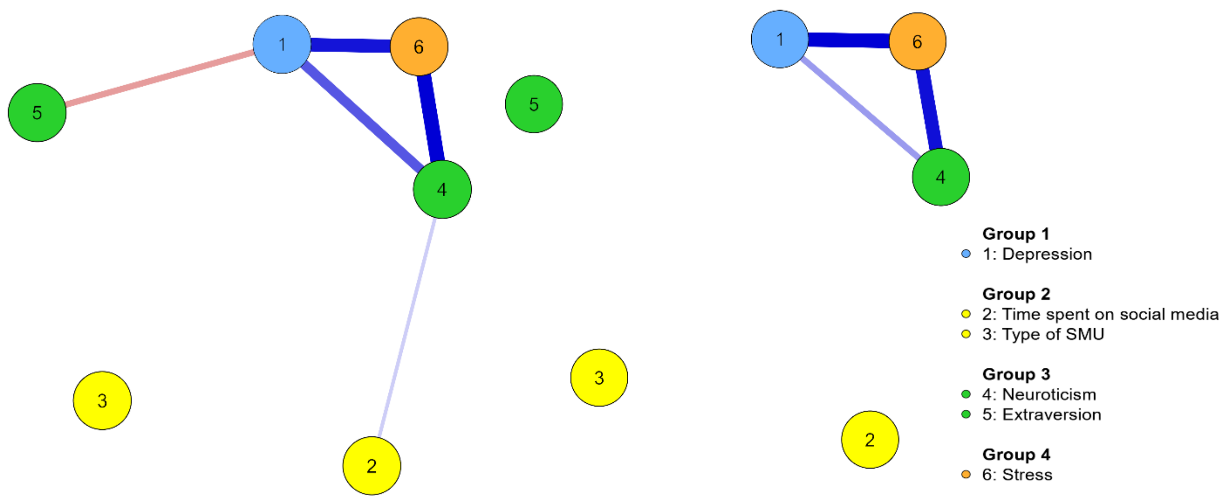
Male and Female Network

Network Analysis

To assess the accuracy of the estimated edge-weights and the stability of the centrality indices, a nonparametric bootstrap and a case-dropping bootstrap were performed for both the male and female network. Visual inspection of the confidence intervals of the estimated edge-weights indicated relatively large variation (see Figure D1 and Figure D2 in Appendix D). The order of the edge weights in both the male and female network should therefore be interpreted with caution. As for the case-dropping bootstrap, visual inspection of the plotted centrality indices of the bootstrapped samples indicates that the centrality indices should not be interpreted (see Figure D3, Figure D4, and Figure D5 in Appendix D). The relatively low accuracy and stability of both networks may suggest a lack of statistical power, which is related to small sample size of both groups.

Figure 3

Male *Female*



Note. Regularized partial correlation networks of male (left) and female (right) group (tuning-parameter gamma = 0.5). Nodes represent depression (group 1), social media usage (group 2), personality traits (group 3), and stress (group 4). Blue colored edges indicate positive, regularized partial correlations. Red colored edges indicate negative, regularized partial correlations. Edge thickness indicates the magnitude of the regularized partial correlation.

The network visualizations of the male and female network are represented in Figure 3. Edge weights ranged from –0.094 (*Extraversion*(5) – *Depression*(1)) to 0.241 (*Stress*(6) – *Neuroticism*(4)) in the male network, and from 0.000 (multiple edges) to 0.333 (*Stress*(6) – *Depression*(1)) in the female network. In both the male and female network, relatively moderate to strong partial correlations appeared for *Stress*(6) – *Depression*(1)(male: r = .222; female: r = .333), *Depression*(1) – *Neuroticism*(4)(male: r = .159; female: r = .132), and *Neuroticism*(4) – *Stress*(1)(male: r = .241; female: r = .314). Whereas *Extraversion*(5) and *Time spent on social media*(2) featured no partial correlations with other variables in the female network, a weak negative correlation for *Extraversion*(5) – *Depression*(1)(r = -.094) and a weak positive correlation for *Time spent on social media*(2) – *Neuroticism*(4)(r = .047) featured in the male network. *Type of SMU*(3) shared no correlations with any other variable in both networks.

The male and female network were compared for statistical differences by utilizing a NetworkComparisonTest (NCT), consisting of three separate invariance tests. The NCT indicated no statistical differences in terms of network structure according to the omnibus network invariance test (M = .11, p = .92) nor in terms of the overall network connectivity (i.e., the number of edges in the network; Epskamp & Fried, 2018) according to the global strength invariance test (S = .02, p = .99). Since the omnibus network invariance test was not significant, differences in individual edges were not investigated. The NCT did not show a statistically significant difference between the male and female network.

Discussion

Despite public concern and academic interest regarding the relationship between SMU and depression, no conclusive answer has been found on the exact nature of this relationship. Rather than solely focusing on *how* social media is used (i.e., ASMU or PSMU), considering *who* uses social media by focusing also on individual characteristics, such as personality traits and gender, may offer more insight into the nature of the relationship between SMU and depression. By applying a network approach, this study aimed to explore how individual characteristics, such as neuroticism, extraversion, and gender, are interconnected with social media use and symptoms of depression in a group-level network of young adults.

The following key findings were discovered. First, the results indicate that social media use and symptoms of depression were not or were at most very weakly related. In addition, the variables related to social media use have the least central positions in the network, indicating that the variables were not influential. While similar findings have been reported in the literature (Hancock et al., 2022; Liu et al., 2019; Yin et al., 2019), the results contrast with expectations. Namely, following the ASMU and PSMU hypothesis, it was expected that ASMU alleviates whereas PSMU worsens depressed mood, low self-worth, and loneliness (Kross et al., 2020). However, the results indicate that people who on average use social media more actively tend to experience slightly greater depressed mood and stress on average, while no direct relation was found with worthlessness and loneliness. Although, the partial correlations were very weak and therefore almost negligible. Moreover, rather than type of SMU, the results show that time spent on social media was more strongly related to depressive symptoms, specifically to concentration problems and to a weaker extent to worthlessness.

Second, it was expected that higher neuroticism would be associated with greater depressive symptoms, including loneliness, stress, and PSMU, while it was expected that higher extraversion would be associated with lower depressive symptoms, including loneliness, and stress, but more ASMU and time spent on social media. The results indeed show that neuroticism was directly associated with loneliness, fatigue, and depressed mood, and indirectly with other depressive symptoms via its relatively strong correlation with stress. Yet, neuroticism was not directly linked to type of SMU or time spent on social media, meaning we did not find associations between neuroticism and PSMU, contrary to expectations. As expected, extraversion was strongly negatively related to loneliness and weakly negatively related to worthlessness, depressed mood and loss of interest or pleasure. Also, extraversion was positively related to type of SMU, meaning that, on average, extraverts tended to use social media more actively. However, extraversion was not directly related to the time spent on social media, only indirectly via type of SMU. That is, extraversion is related to more ASMU, which itself is related to more time spent on social media.

Third, in terms of gender, it was expected that the associations of neuroticism and extraversion with the variables of social media use and depression are stronger in the female network than in the male network. Initial findings confirmed that women are on average more neurotic than men, but not more extraverted than men. However, neither the male or female network featured particularly noticeable or different associations between personality traits, depression, and social media use variables except for moderate to strong associations between depression, stress, and neuroticism in both networks. In line with this, the network comparison test revealed that the male and female network do not statistically differ in network structure or overall connectivity.

In the following two sections, the findings will be discussed in more detail in the context of the theoretical and methodological background of this study. Next, implications are considered, followed by a discussion of the limitations of this study. Lastly, some recommendations for future research are given.

Social Media Use and Symptoms of Depression

As only few relationships were found between how social media is used and symptoms of depression while accounting for the personality traits of neuroticism and extraversion, this study adds to the empirical evidence that questions the ASMU and PSMU hypothesis, furthering the complicated discussion regarding the topic within the literature (Hancock et al., 2022; Liu et al., 2019; Yin et al., 2019). Whereas some studies suggest that ASMU can benefit mental health by improving affective well-being (Kross et al., 2013), protecting against loneliness via social support (Liu et al., 2016; Liu et al., 2018; Verduyn et al., 2017), boosting self-esteem (Best et al., 2014; Valkenburg & Peter, 2011), and alleviating depressive mood (Frison & Eggermont, 2015b), this study indicates that on average more ASMU corresponds with slightly more depressed mood and stress. Of course, since the findings concern associations based on cross-sectional data no causal inferences can be made. Therefore, it may very well be that people who are suffering from depressed mood or stress purposefully use social media more actively to alleviate their emotional distress and may successfully do so over time (Ivie et al., 2020). For example, posting and commenting on social media may act as a coping mechanism as people seek a place for social support, distraction, to vent, or to solve their issues, which may benefit their mental health as suggested by the ASMU and PSMU hypothesis (Wolfers & Utz, 2022). However, it should also be considered that ASMU could induce stress and depressive moods as actively posting content and comments on social media may involve or result in unpleasant experiences, such as negative feedback, online arguments, or cyberbullying, which may cause people to feel alienated, emotionally distressed, and even suicidal (Escobar-Viera et al., 2018; Vidal et al., 2020). To elaborate, actively posting content and comments on social media may cause stress as people engage in self-presentation to a relatively large audience, hoping to receive positive feedback but simultaneously fearing negative feedback (Wolfers & Utz, 2022). In turn, stress can worsen depressive symptomology (Fried et al., 2015); a finding that is supported by this study as stress shared positive associations with all depressive symptoms, being an influential factor within the network. Moreover, Frison and Eggermont (2016) found that ASMU predicted depressed mood in adolescent males and suggested that this may be because boys are less socially skilled and more involved in online arguments and cyberbullying, both as perpetrator and victim, compared to girls. Clearly, there are multiple potential pathways for ASMU to negatively affect mental health which at the very least casts some doubt on the credibility of the ASMU and PSMU hypothesis.

Furthermore, this study indicates that rather than type of SMU, time spent on social media is more strongly positively related to symptoms of depression, specifically to concentration problems. To our knowledge, no study has found that the amount of time spent on social media is more strongly related to symptoms of depression rather than how social media is used. The lack of evidence for this finding may be due to methodological preferences and developments. Namely, while early studies measured only time spent on social media, later studies measured time spent on social media in terms of passive or active use, thus combining the measure of time spent on social media and type of SMU (Verduyn et al, 2017). This obscures the unique effect of time spent on social media as effects are attributed to either passive or active usage of social media. Nevertheless, most studies investigating the relationship between time spent on social media and depression found a weak positive correlation (Cunningham et al., 2021). A more recent study conducted by Liu and colleagues (2022) even found that the risk of depression symptoms increased by 13% for each extra hour of social media use. Regarding the symptoms of concentration problems and feelings of worthlessness in particular, multiple studies have reported similar positive associations between time spent on social media and concentration problems as well as feelings of worthlessness (Aalbers et al., 2019; Appel et al., 2019; Yang et al., 2021). While spending time on social media may, for example, lead to concentration problems due to increasing attention deficits (Baumgartner et al., 2017) or lead to feelings of worthlessness due to upward social comparison (Yang et al., 2021), it may also be that concentration problems and feelings of worthlessness lead to more time spent on social media as social media may, respectively, offer a readily accessible distraction (Baumgartner et al., 2017) as well as be a place to boost one's self-esteem (Valkenburg & Peter, 2011; Best et al., 2014).

Influence of Personality

With regards to personality, findings were consistent with previous studies on the relationship between personality traits and symptoms of depression. Namely, that higher neuroticism was directly associated with more loneliness (Buecker et al., 2020; Wieczorek et al., 2022), and indirectly associated with more symptoms of depression through loneliness (Erzen & Çikrikci, 2018; Matilla et al., 2021; Vanhalst et al., 2011) and through stress (Fried et al., 2015, Mineka et al., 2020). Additionally, higher extraversion was directly and strongly associated with less loneliness (Vanhalst et al., 2011) and less symptoms of depression, such as worthlessness, depressed mood, and loss of interest or pleasure (Leger et al., 2016; Anglim et al., 2020). It thus remains plausible that, besides the inherent aspects of neuroticism (i.e., emotional instability, negativity) and extraversion (i.e., socially outgoing, positivity; Gray & Bjorklund, 2017), the frequency and quality of social interaction is an influential factor in how neuroticism and extraversion are related to symptoms of depression. However, in contrast to the findings of Bowden-Green and colleagues (2021), this study found no evidence that the factor of social interaction also extends to social media use as no associations were found between neuroticism and social media use. Therefore, it cannot be said whether people higher in neuroticism tend to engage more in PSMU, supposedly because of their difficulties in social relationships, as was initially expected. Even if neuroticism and PSMU were associated, this study found no evidence for an association between PSMU and depression, which means it is unclear whether neuroticism is indirectly associated with more symptoms of depression via PSMU. Extraversion, on the other hand, was found to be positively associated with type of SMU, meaning that extraverts tend to engage in actively posting and commenting on social media, similar to the findings of Bowden-Green and colleagues (2020). Yet, despite the tendency of extraverts to socially interact on social media, there is no indication that ASMU is associated with lower symptoms of depression. In fact, as mentioned before, this study found ASMU to be associated with slightly more depressed mood as well as the risk factor of stress. Thus, while this study seems to confirm that neuroticism and extraversion are respectively risk and protective factors for symptoms of depression, it does not provide any clear indication that personality traits may influence the relationship between social media use and symptoms of depression.

Influence of Gender

Contrary to expectations, this study found no differences between men and women in how social media use, depression, and the personality traits of neuroticism and extraversion are related. However, we cannot assume that no differences exist as there is evidence with the literature of gender differences in the relationship between social media use and depression. For example, Frison and Eggermont (2016) found that particularly girls are negatively affected by passive social media use while they are positively affected by active social media use. Moreover, the positive association between time spent on social media and the risk of developing depression or experiencing emotional distress is stronger for girls (Liu et al., 2022; Thorisdottir et al., 2019). Heffer and colleagues (2019) even found that greater symptoms of depression predicted more social media use among girls. Of course, while it remains plausible that no gender difference exists, it should be considered that the lack of gender difference in the present study may be an issue of sample size. To elaborate, the sample size of the male and female group was relatively small which negatively affects the sensitivity of the EBICglasso estimation

(Wysocki & Rhemtulla, 2019). Sensitivity is further negatively affected due to the presence of strong partial correlations, such as those found between stress, depression, and neuroticism in both the male and female network (Wysocki & Rhemtulla, 2019). One could choose to set the tuning parameter to a lower value, but this would increase sensitivity at the cost of specificity, increasing the chance of false positives (Epskamp & Fried, 2018).

Implications

From a theoretical perspective, the findings do not support the ASMU and PSMU hypothesis. In fact, the findings partially contradict the hypothesis as ASMU shares a positive association with depressive mood, rather the hypothesized negative association. The present study thereby adds to the empirical evidence that does not support or even contradicts the ASMU and PSMU hypothesis (Hancock et al., 2022; Liu et al., 2019; Yin et al., 2019). Moreover, it strengthens the argument to refine the ASMU and PSMU hypothesis as it is too simplistic in its current form, failing to capture the complexity and nuance of using social media. To elaborate, both active and passive use of social media may have positive and negative effects on mental health. For example, one could passively use social media to view uplifting videos, improving one’s mood, but one could also passively use social media to view the supposed accomplishments of others, decreasing one’s mood due to social upward comparison or envy. Likewise, using social media actively may improve mood through positive interactions with others, but it may also decrease mood if one engages in arguments or is the target of cyberbullying (Kross et al., 2020). Thus, the ASMU and PSMU dichotomy does not accurately portray the various ways of *how* people can use social media and should thus be refined.

By applying a network approach, the present study shows that SMU shares unique correlations with individual symptoms of depression, underlining the importance of considering individual symptoms and contributing to the few studies that have used a similar approach (Aalbers et al., 2019; Rodriguez et al., 2021). Also, it underlines the importance of considering external yet related factors to the individual symptoms of the disorder, such as stress and loneliness, as these factors may influence the relationship between SMU and symptoms of depression. The present study could therefore inform future research to not simply consider depression as one construct but rather as a collection of individual symptoms that share unique relations with other factors.

While the present study does not offer any applied clinical implications due to the cross-sectional nature of the data, the findings could inform future clinical studies to explore the direction of the positive associations between social media usage and specific symptoms of depression by using longitudinal data. After all, it is important to know, for example, whether ASMU increases depressive mood or vice versa, especially among young age cohorts who are avid users of social media. The present study may therefore be a stepping stone for further research to determine whether social media usage is a potential risk factor for specific symptoms of depression.

Strengths and Limitations

To our knowledge, the present study is the first to include personality in a network approach to the relationship between SMU and individual symptoms of depression. It therefore builds on previous studies that asses the relationship between SMU and symptoms of depression using a network approach (Aalbers et al., 2019; Rodriguez et al., 2021). Furthermore, the present study considers the potential influence of external factors which have been proven to be related to depression, such as stress and loneliness, but are generally overlooked in the literature (Fried, 2015; Erzen & Çikrikci, 2018).

The present study is not without limitations. Namely, due to cross-sectional nature of the data no conclusions can be made about the direction of the associations and thus making causal inferences impossible. Of course, in the case of personality measures which are relatively stable over time, careful assumptions can be made. For example, since extraversion is strongly negatively associated with loneliness, it can be logically assumed that high extraversion leads to feeling less lonely rather than that feeling less lonely leading to high extraversion. However, this does not account for confounding variables. Also, since cross-sectional data only offers a snapshot in time, the results may not be representative. This is further affected by potential recall bias as participants were asked to report on their recent feelings of depression, stress, and loneliness as well as their typical daily usage of social media. Participants may thus have over- or underreported measures depending on their personal situation at the time of measurement. Lastly, in terms of data, as data was measured at the group level (i.e., between-subjects), individual differences remain obscured.

Another limitation concerns the sample size in relation to the EBICglasso estimation. Since the sensitivity (i.e., detecting true positives, in contrast to specificity which detects true negatives) with EBICglasso increases with sample size to only up to 80% at a sample size of over 1000, the sample size of 430 is relatively small. The presence of large partial correlations further reduces the sensitivity performance. As mentioned before, this issue is mostly a concern with the male and female network as these networks were based on a relatively very small sample size of 66 each and had some relatively large partial correlations. However, a silver lining is that low sensitivity reduces the chance of false positives, meaning the detected edges are likely to be true edges in the population (Wysocki & Rhemtulla, 2019). It must also be noted that the sample size is limited to only 430 participants as data was taken during the data collection phase of the original WARN-D research project, which aims to include 2000 participants.

The sample itself is an additional limitation as the sample is not representative of the population due to the relatively large percentage of females (84.7%) included in the study. Considering that women, on average, spend more time on social media and are more extraverted and neurotic than men, the results could be biased and can therefore not be generalized to the population (Gray et al., 2012; Twenge & Martin, 2020). Furthermore, since the present study only includes people aged between 18 and 30 years old, the results cannot be generalized to other age cohorts.

Recommendations

Based on the present study, it is recommended that the influence of user specific characteristics on the relationship between SMU and symptoms of depression is further researched, preferably using within-subjects designs to estimate temporal networks and thus allow for causal inference. It is further recommended that networks are also estimated at the individual level, so called idiographic networks, to reveal individual differences. By doing so, more conclusive answers can be found on whether social media use causes symptoms of depression or whether symptoms of depression lead to more social media use. To further explore the influence of user specific characteristics, it is important to move beyond the simplicity of the ASMU and PSMU dichotomy by more accurately measuring the individual difference in *how* social media is used. After all, *how* social media is used is likely for a large part dependent on *who* uses it. Future research should thus consider people’s motivations for using social media (e.g., socializing, information seeking, entertainment), what exact activities people engage in (e.g., scrolling, liking, commenting, creating content), which social media platform people use as well as its functionality, and to what extent people experience their social media use as positive or negative independent of their overall well-being. While the present study included stress and loneliness as external factors, future studies could also include other external factors that are mentioned in the literature, such as self-esteem in terms of accomplishments or body image. By exploring these user specific characteristics, we may discover how social media use can alleviate symptoms of depression in some individuals yet worsen symptoms of depression in others.

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Appendices

Appendix A: Questionnaire per Measure

Depression

Adapted version of the PHQ-9 (Kroenke et al., 2001).

Over the past two weeks, how often have you been bothered by the following problems?

	Not at all (0)	Several Days (1)	More Than Half the Days (2)	Nearly Every Day (3)
Little interest or pleasure in doing things (PHQ_1)	○	○	○	○
Feeling down or depressed (PHQ_2)	○	○	○	○
Feeling hopeless (PHQ_3)	○	○	○	○
Trouble falling asleep or staying asleep (PHQ_4)	○	○	○	○
Sleeping too much (PHQ_5)	○	○	○	○
Feeling tired or having little energy (PHQ_6)	○	○	○	○
Poor appetite (PHQ_7)	○	○	○	○
Overeating (PHQ_8)	○	○	○	○
Feeling bad about yourself – or that you’re a failure or have let yourself or your family down (PHQ_9)	○	○	○	○
Trouble concentrating on things, such as reading or watching television (PHQ_10)	○	○	○	○

Moving or speaking so slowly that other people could have noticed (PHQ_11)	○	○	○	○
Being so fidgety or restless that you have been moving around a lot more than usual (PHQ_12)	○	○	○	○
Thoughts that you would be better off dead or of hurting yourself in some way (PHQ_13)	○	○	○	○
Little interest in sex (PHQ_14)	○	○	○	○

Loneliness

UCLA Loneliness Scale (Russel et al., 1978).

Indicate how often each of the statements below is descriptive of you.

	Hardly ever (1)	Some of the time (2)	Often (3)
How often do you feel that you lack companionship? (1)	○	○	○
How often do you feel left out? (2)	○	○	○
How often do you feel isolated from others? (3)	○	○	○

Social Media Use

Adapted measure of the Caring Universities questionnaire (Caring Universities, 2022)

Type of SMU

On a typical day, approximately how much time do you spend using social media (e.g. Facebook, Twitter, Instagram, Snapchat, TikTok)? We are interested in public social media use, not time spent writing e.g. private messages.

- ○ I don't use social media (1)
- ○ Less than half an hour (2)
- ○ Half an hour to an hour (3)
- ○ 1-2 hours (4)
- ○ 3-4 hours (5)
- ○ 5-6 hours (6)
- ○ More than 6 hours (7)

Time Spent on Social Media

Only displayed if participant indicated in previous question that he or she uses social media.

One can use social media <u>actively</u> (e.g., liking, up-/downvoting, sharing, commenting, posting), or <u>passively</u> (e.g., scrolling/browsing social media feeds/pages, reading/watching content). What percentage of your social media use is <u>active</u>?

	Only passive	%	Only active
	0 10 20 30 40 50 60 70 80 90 100		
()			

Neuroticism and Extraversion

BFI (John et al., 1991) and shortened BFI-10 (Rammstedt & John, 2007).

I see myself as someone who...

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
… is reserved (BFI_E_1)	○	○	○	○	○
… is generally trusting (BFI_A_1)	○	○	○	○	○
… tends to be lazy (BFI_C_1)	○	○	○	○	○
… has few artistic interests (BFI_O_1)	○	○	○	○	○
… is outgoing, sociable (BFI_E_2)	○	○	○	○	○
… tends to find fault with others (BFI_A_2)	○	○	○	○	○
… does a thorough job (BFI_C_2)	○	○	○	○	○
… has an active imagination (BFI_O_2)	○	○	○	○	○
... is depressed, blue (BFI_N_1)	○	○	○	○	○
...is relaxed, handles stress well (BFI_N_2)	○	○	○	○	○
... can be tense (BFI_N_3)	○	○	○	○	○
... worries a lot (BFI_N_4)	○	○	○	○	○
... is emotionally stable, not easily	○	○	○	○	○

upset (BFI_N_5)					
... can be moody (BFI_N_6)	○	○	○	○	○
... remains calm in tense situations (BFI_N_7)	○	○	○	○	○
... gets nervous easily (BFI_N_8)	○	○	○	○	○

Stress

Adapted version of the PSS-10 (Cohen et al., 1983)

The questions in this scale ask you about your feelings and thoughts during the last 2 weeks.

Please indicate how often you felt or thought a certain way.

In the last 2 weeks...

	Never (0)	Almost never (1)	Sometimes (2)	Fairly often (3)	Very often (4)
How often have you been upset because of something that happened unexpectedly? (PSS_1)	○	○	○	○	○
How often have you felt that you were unable to control the important things in your life? (PSS_2)	○	○	○	○	○
How often have you felt nervous and stressed? (PSS_3)	○	○	○	○	○

How often have you felt confident about your ability to handle your personal problems? (PSS_4)	○	○	○	○	○
How often have you felt that things were going your way? (PSS_5)	○	○	○	○	○
How often have you found that you could not cope with all the things that you had to do? (PSS_6)	○	○	○	○	○
How often have you been able to control irritations in your life? (PSS_7)	○	○	○	○	○
How often have you felt that you were on top of things? (PSS_8)	○	○	○	○	○
How often have you been angered because of things that were outside of your control? (PSS_9)	○	○	○	○	○
How often have you felt difficulties were piling up so high that you could not overcome them? (PSS_10)	○	○	○	○	○

Appendix B: Formula for Network Parameters Calculation

a: Number of nodes in the network

p: Number of parameters estimated in the network

$p = (a * (a – 1)) / 2$ (formula only applies to undirected networks)

For the aggregate network: $(12 * (12 – 1)) / 2 = 66$ parameters

For the male and female network: $(6 * (6 – 1)) / 2 = 15$ parameters

Appendix C: Supplementary Results of the Aggregate Network

Table C1

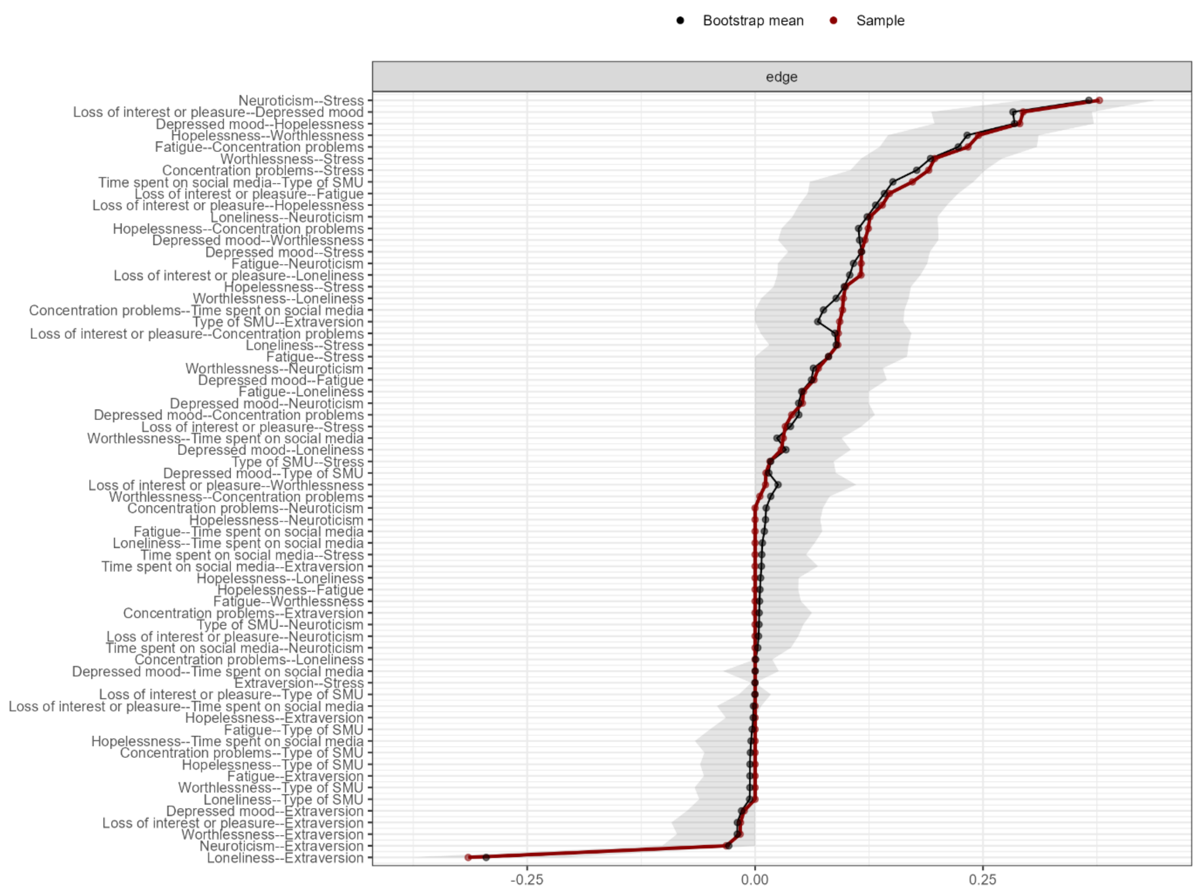
Pearson Correlations of Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Los.												
2. Dep.	.589**											
3. Hop.	.506**	.616**										
4. Fat.	.428**	.409**	.337**									
5. Wor.	.397**	.504**	.546**	.300**								
6. Con.	.414**	.424**	.438**	.465**	.356**							
7. Lon.	.374**	.360**	.304**	.310**	.370**	.234**						
8. TSSM	.043	.059	.032	.097*	.117*	.171**	.066					
9. TSMU	-.001	.066	-.019	-.008	-.017	-.010	-.043	.244**				
10. Neu.	.334**	.424**	.378**	.397**	.425**	.350**	.401**	.072	.031			
11. Ext.	-.200**	-.198**	-.150*	-.144*	-.200**	-.082	-.418**	.028	.132*	-.220**		
12. Str.	.452**	.539**	.518**	.444**	.543**	.496**	.420**	.110*	.068	.625**	-.166**	

Note. *N = 430* $^{*}p < .05$ $^{**}p < .001$; Los. = Loss of interest or pleasure, Dep. = Depressed mood, Hop. = Hopelessness, Fat. = Fatigue, Wor. = Worthlessness, Con. = Concentration problems, Lon = Loneliness, TSSM = Time spent on social media, TSMU = Type of social media use, Neu. = Neuroticism, Ext. = Extraversion, Str. = Stress.

Figure C1

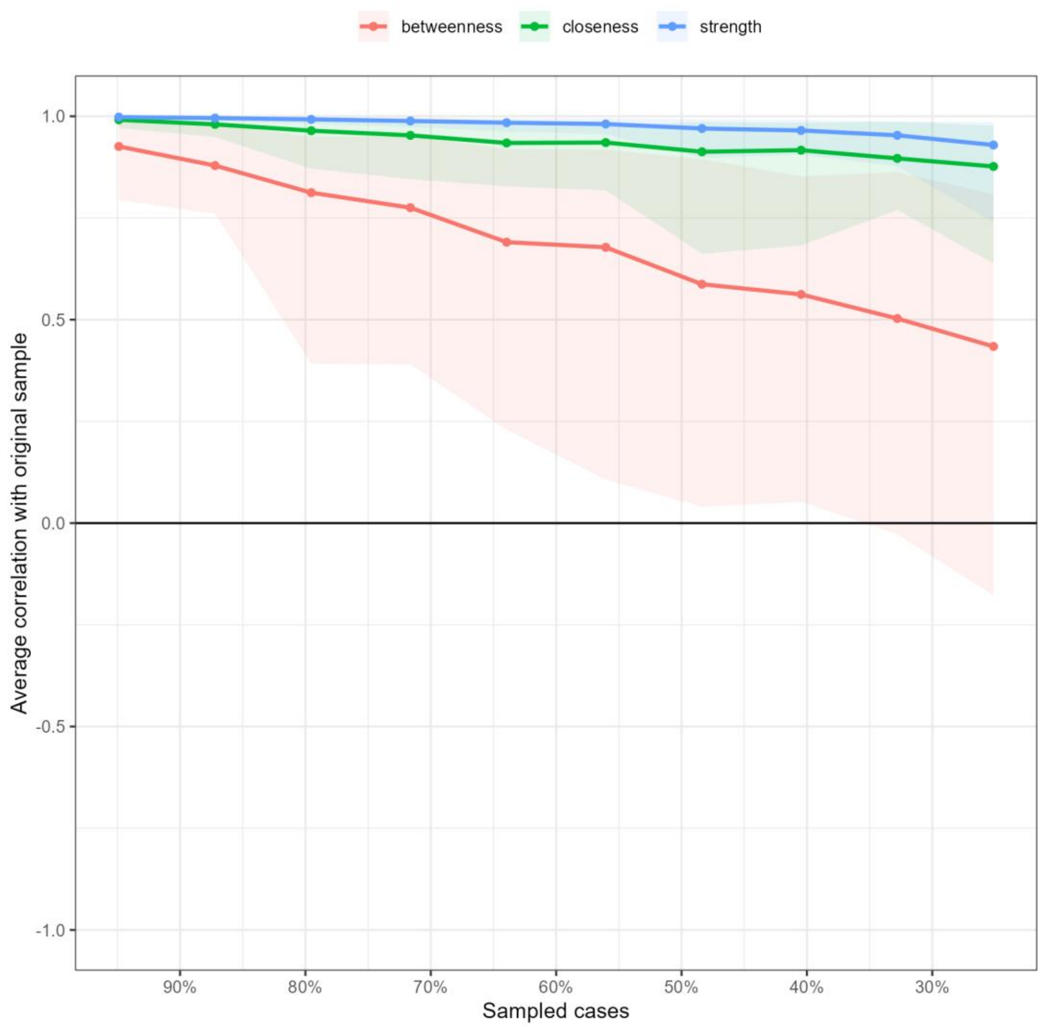
Edge Weight Accuracy of Aggregate Network



Note. Accuracy of the estimated edge-weights of the aggregate network as illustrated by bootstrapped confidence intervals. The red dots indicate the sample values, the black dots indicate bootstrapped mean values, and the grey area indicates the bootstrapped confidence intervals. The horizontal lines each correspond to one specific edge weight within the network, ordered from the highest edge-weight to the lowest edge-weight (top to bottom). The nonparametric bootstrap plotted the bootstrapped mean value and confidence interval (CI) of each estimated edge-weight. The CIs were relatively narrow for the negative edge-weights as well as for the smaller and greater positive edge-weights, suggesting little variation in the bootstrapped values and thus indicating relatively high accuracy of the estimated edge-weights. The moderate positive edge-weights, the CIs were relatively moderate in size, suggesting more variation in the bootstrapped values and lesser accuracy of the estimated edge-weights compared to other edge-weights. However, the order of the moderate positive edge-weights can still be safely interpreted.

Figure C2

Centrality Stability of Aggregate Network



Note. Average correlations between the centrality indices of the original sample and bootstrapped samples from which cases were dropped. The dotted lines indicate the mean values, and the colored areas indicate the range from the 2.5th quantile to the 97.5th quantile. The case-dropping bootstrap plotted the average correlations between the centrality indices of the original sample and bootstrapped samples from which cases were dropped, as can be seen in Figure C2 in Appendix C. The strength and closeness centrality estimates were relatively stable upon visual inspection of the plot, unlike the betweenness centrality estimate which showed a steep decline in stability. The CS-coefficients confirmed this notion as strength (CS(cor = 0.7) = 0.672) and closeness (CS(cor = 0.7) = 0.516) had values exceeding the preferred 0.5 cutoff value for CS-coefficients to indicate stability, whereas betweenness (CS(cor = 0.7) = .128) had a value well below the minimum 0.25 cutoff value, indicating instability (Epskamp et al., 2017). In other words, 67.2% of cases could be dropped to say with 95% probability that the correlation between the strength centrality estimates of the original dataset and that of the case-dropped subset of the data are 0.7 or higher. Due to the low stability of the betweenness centrality estimates the order of betweenness should be interpreted with extreme caution.

Table C2

Weights Matrix of Aggregate Network

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Los.												
2. Dep.	.294											
3. Hop.	.139	.290										
4. Fat.	.147	.065	.000									
5. Wor.	.011	.120	.245	.000								
6. Con.	.091	.040	.124	.234	.005							
7. Lon.	.116	.029	.000	.053	.097	.000						
8. TSSM	.000	.000	.000	.000	.031	.000	.000					
9. TSMU	.000	.012	.000	.000	.000	.096	.000	.173				
10. Neu.	.000	.052	.000	.116	.069	.000	.126	.000	.000			
11. Ext.	-.016	-.012	.000	.000	-.016	.000	-.315	.000	.093	-.032		
12. Str.	.033	.117	.099	.081	.197	.190	.091	.000	.016	.378	.000	

Note. $N = 430$; N = 406 for TSMU. Los. = Loss of interest or pleasure, Dep. = Depressed mood, Hop. = Hopelessness, Fat. = Fatigue, Wor. = Worthlessness, Con. = Concentration problems, Lon = Loneliness, TSSM = Time spent on social media, TSMU = Type of social media use, Neu. = Neuroticism, Ext. = Extraversion, Str. = Stress.

Appendix D: Supplementary Results of Male and Female Network

Table D1

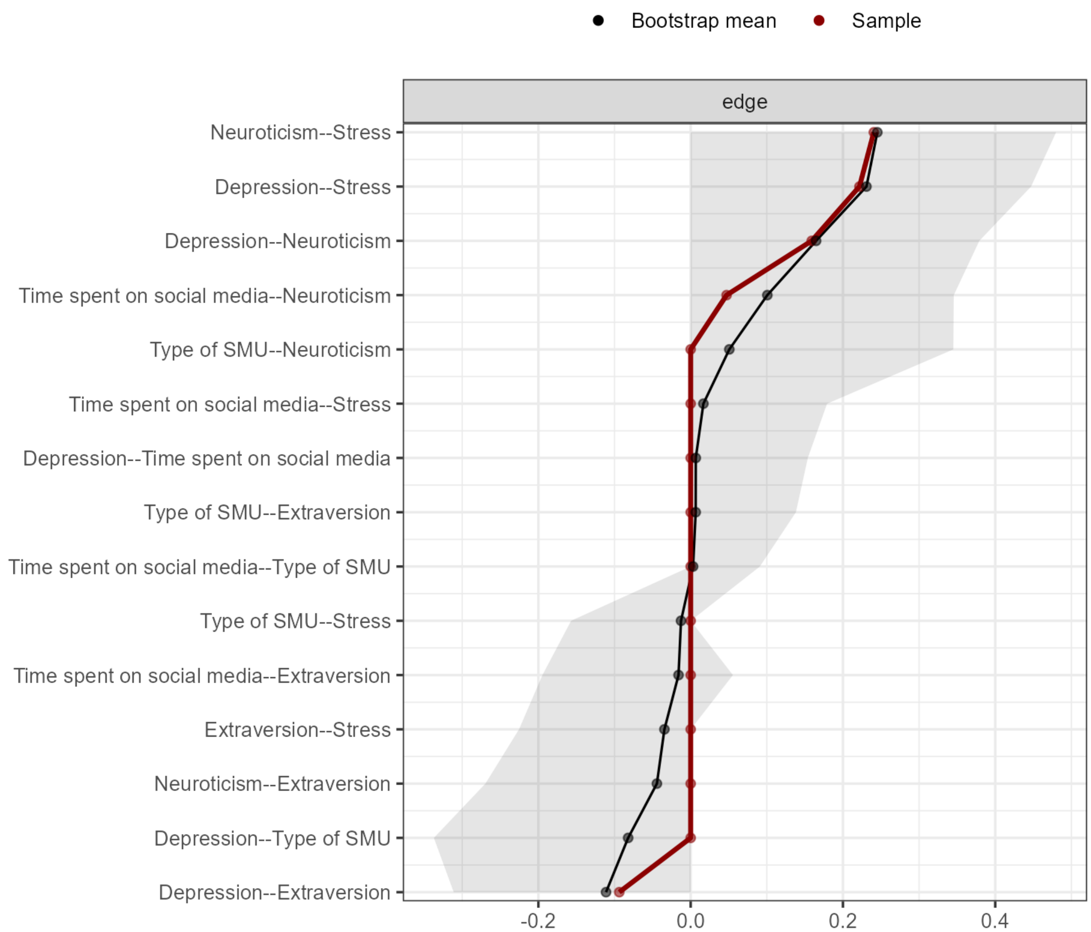
Weights matrix of Male and Female Network

Group	*Variable*	1. Dep.	2. TSSM	3. TSMU	4. Neu.	5. Ext.	6. Str.
Male	1. Dep.						
	2. TSSM	.000					
	3. TSMU	.000	.000				
	4. Neu.	.000	.047	.000			
	5. Ext.	.159	.000	.000	.000		
	6. Str.	.222	.000	.000	.241	.000	
Female	1. Dep.						
	2. TSSM	.000					
	3. TSMU	.000	.000				
	4. Neu.	.132	.000	.000			
	5. Ext.	.000	.000	.000	.000		
	6. Str.	.333	.000	.000	.314	.000	

Note. N = 66, N = 60 for TSMU in male network and N = 59 for TSMU in female network; Dep. = Depression, TSSM = Time spent on social media, TSMU = Type of social media use, Neu. = Neuroticism, Ext. = Extraversion, Str. = Stress.
Note. N = *430*; Los. = Loss of interest or pleasure, Dep. = Depressed mood, Hop. = Hopelessness, Fat. = Fatigue, Wor. = Worthlessness, Con. = Concentration problems, Lon = Loneliness, TSSM = Time spent on social media, TSMU = Type of social media use, Neu. = Neuroticism, Ext. = Extraversion, Str. = Stress.

Figure D1

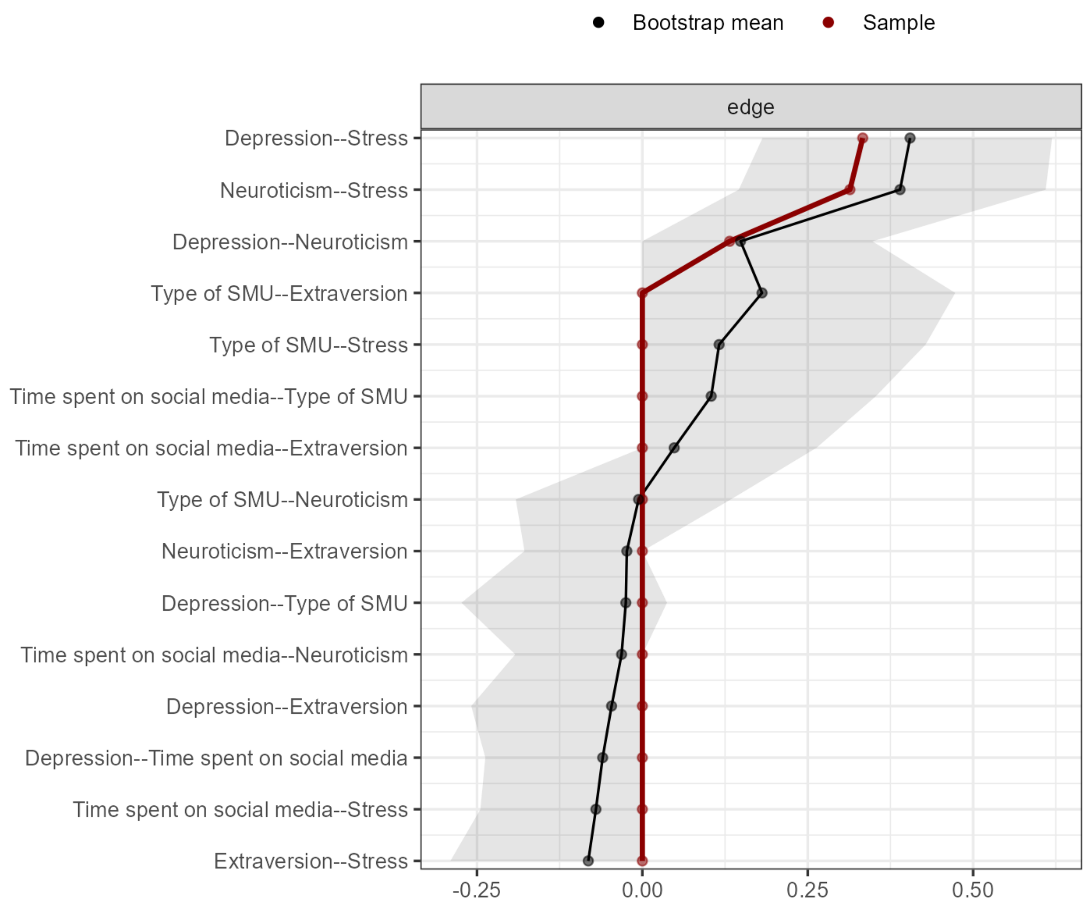
Edge Weight Accuracy of Male Network



Note. Accuracy of the estimated edge-weights of the male network as illustrated by bootstrapped confidence intervals. The red dots indicate the sample values, the black dots indicate bootstrapped mean values, and the grey area indicates the bootstrapped confidence intervals. The horizontal lines each correspond to one specific edge weight within the network, ordered from the highest edge-weight to the lowest edge-weight (top to bottom).

Figure D2

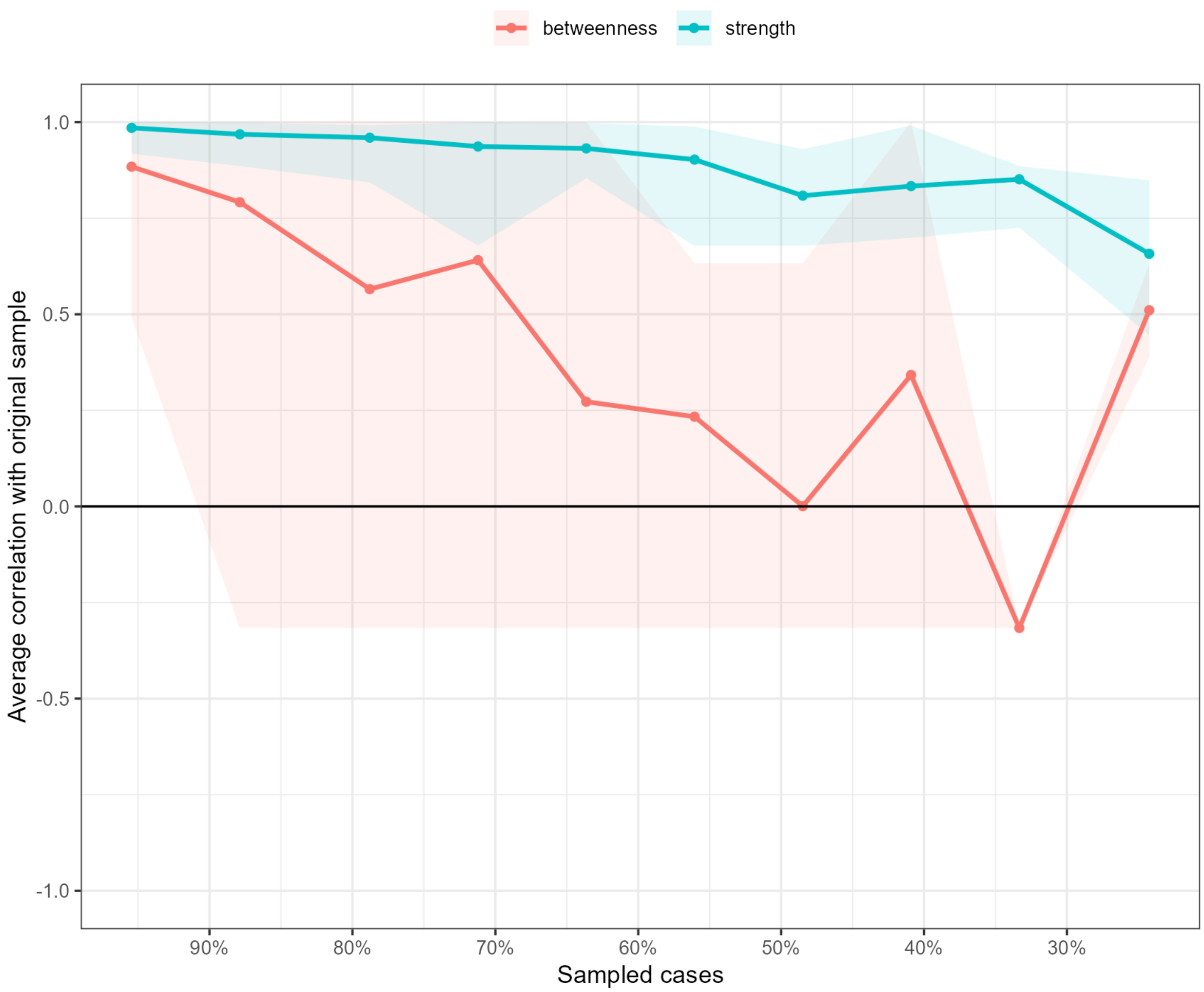
Edge Weight Accuracy of Female Network



Note. Accuracy of the estimated edge-weights of the female network as illustrated by bootstrapped confidence intervals. The red dots indicate the sample values, the black dots indicate bootstrapped mean values, and the grey area indicates the bootstrapped confidence intervals. The horizontal lines each correspond to one specific edge weight within the network, ordered from the highest edge-weight to the lowest edge-weight (top to bottom).

Figure D3

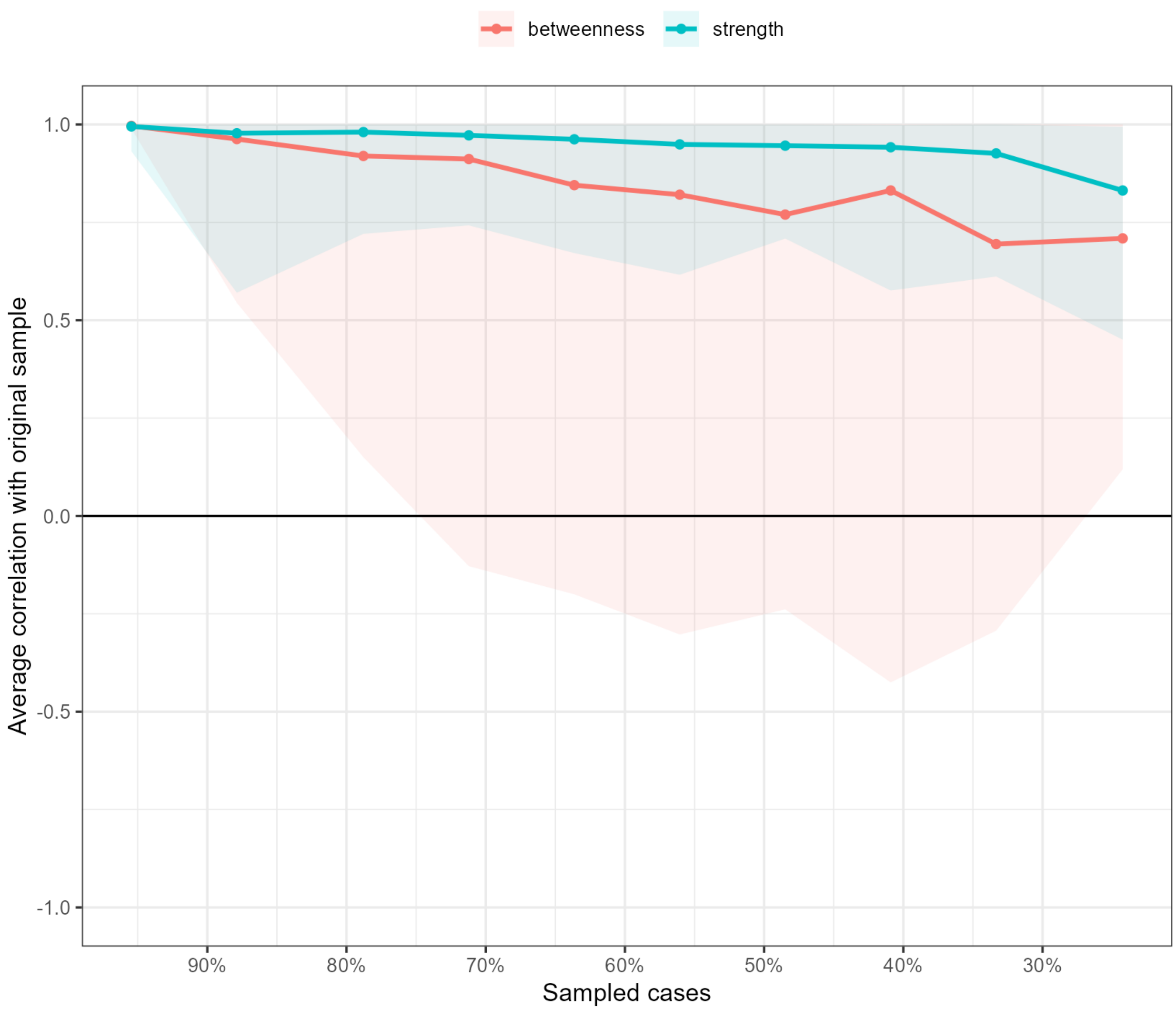
Centrality Stability of Male Network



Note. Average correlations between the centrality indices of the original sample and bootstrapped samples from which cases were dropped. The dotted lines indicate the mean values, and the colored areas indicate the range from the 2.5[th] quantile to the 97.5[th] quantile.

Figure D4

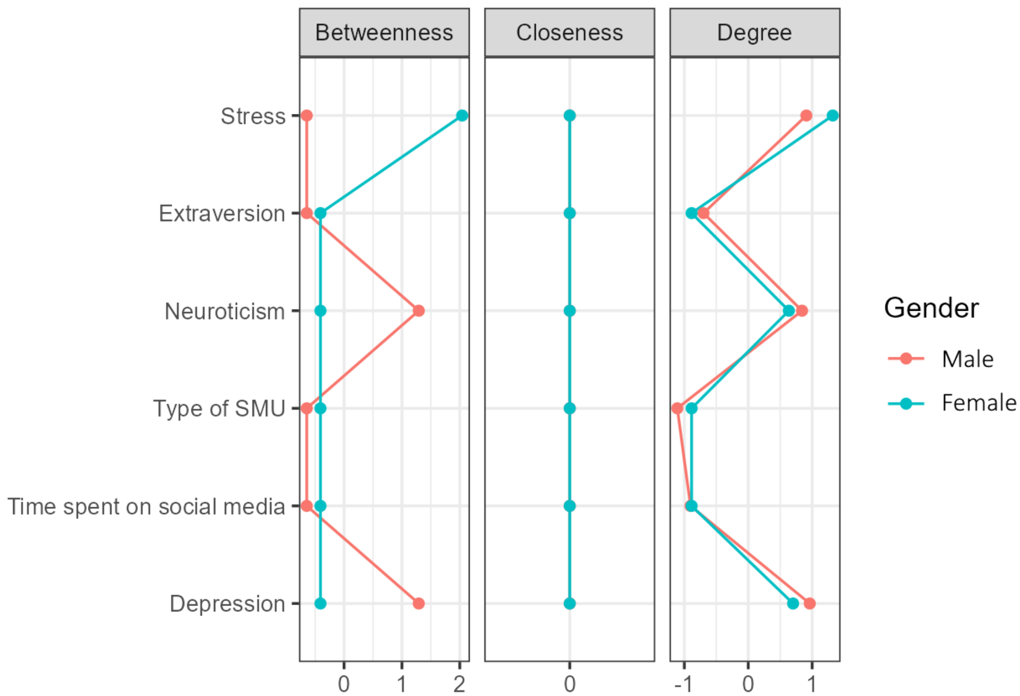
Centrality Stability of Female Network



Note. Average correlations between the centrality indices of the original sample and bootstrapped samples from which cases were dropped. The dotted lines indicate the mean values, and the colored areas indicate the range from the 2.5th quantile to the 97.5th quantile.

Figure D5

Centrality Measures of the Male and Female Network



Note. Betweenness, closeness, and degree (i.e., strength) centrality of the nodes in the male and female network. The x-axis represents standardized centrality scores.