A Network Analysis of Facebook Use and Well-being in Relation to Key Psychological Variables: Replication and Extension

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Abstract

Studies exploring the relationship between Facebook use and well-being have yielded inconsistent findings. Investigating the intermediate mechanisms seems to be of crucial importance to gain insight into the positive and negative consequences of Facebook use. A recent study illustrated the importance of taking into account social comparison and self- esteem, since these constructs are central to theories about the link between Facebook use and risk for affective disorders. Extending these findings will be key to increase our knowledge on possible risk and/or protective intermediate mechanisms. Therefore, we conducted a cross-sectional study (*n* = 459) to investigate the position of attention control and social capital in this previously reported network. Our results provide a conceptual replication of Faelens et al. (2019). In addition, our findings suggest that attentional control does not play a central role in the relationship between Facebook use and well-being. However, (bridging) social capital uniquely connected the variables related to Facebook use with our indicators of vulnerability for affective disorders via social comparison and contingent self-esteem. Possible explanations are discussed.

Introduction

In modern society, social network sites (SNS) such as Facebook are highly popular. This has generated a lively debate regarding the positive and negative effects of SNS use on general well-being. More specifically, systematic reviews and meta-analyses found conflicting results regarding the direction and strength of the relationship. For example, while some meta-analyses and reviews reported a small, but negative relationship between SNS use and well-being (e.g., Huang, 2017; McCrae et al., 2017; Yoon et al., 2019), other reviews also pointed towards positive associations (e.g., Frost & Rickwood, 2017; Verduyn et al. 2017). Verduyn and colleagues (2017) argued that two factors may be important to explain these inconsistent findings, namely (1) type of SNS use and (2) psychological processes that may be involved in the relationship between SNS use and well-being.

Type of Use

Previous research findings suggest that it may be important to examine the effects of different kinds of SNS utilization (e.g., Verduyn et al., 2017). For example, Frison and Eggermont (2015) made a distinction between three types of Facebook usage: active public Facebook use, active private Facebook use and passive Facebook use. First, active public Facebook use can be defined as activities that enhance direct interactions between users in a public setting (e.g., posting status updates/pictures). Second, active private Facebook use refers to activities that facilitate private interactions between users (e.g., instant messaging). Third, passive Facebook use is characterized by the passive consumption of content of other users, without direct exchanges between users (Frison & Eggermont, 2015). Prior research findings illustrated that passive Facebook use seems to be linked with decreased well-being (e.g., Verduyn et al., 2015). In contrast, active private Facebook use seems to have more beneficial effects (e.g. Frison & Eggermont, 2016; Verduyn et al., 2017). The effects of active public Facebook use on well-being are inconsistent (Frison & Eggermont, 2016).

A possible explanation for these findings is that different usage patterns activate different underlying mechanisms (e.g., Verduyn et al., 2017), which in turn may lead to increases/decreases in well-being and the other way around. In the next paragraphs, we will discuss different psychological processes that may be important factors in the relationship between SNS use and well-being and therefore make an attempt to explain these inconsistent results.

Psychological Processes

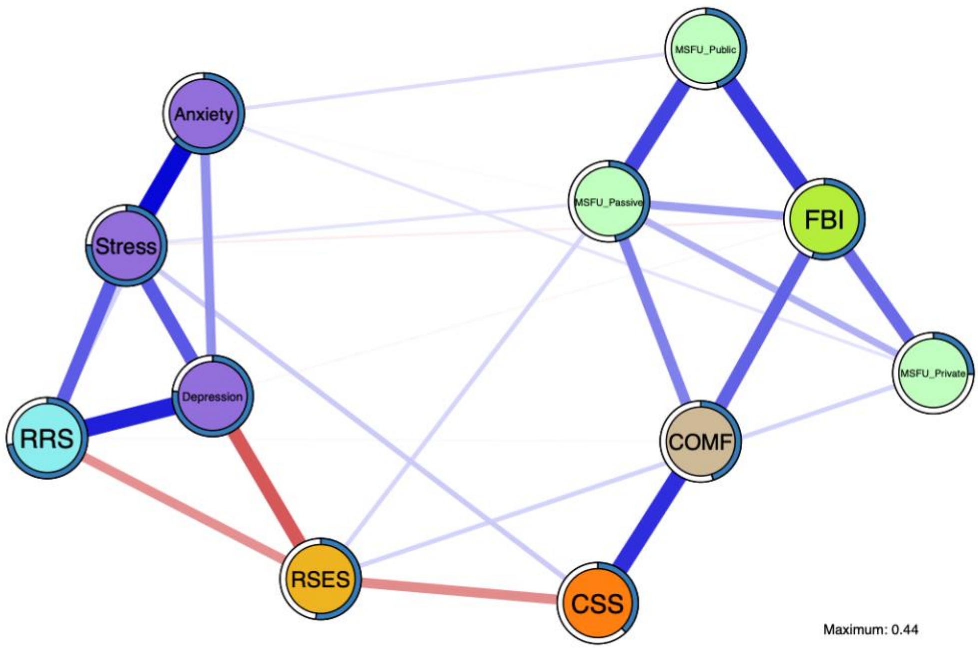
Social Comparison and Self-Esteem

Previous research findings suggest that constructs such as social comparison and self-esteem may be involved in the relationship between SNS use and well-being (e.g., Faelens et al., 2019). In that study, network analysis was used to examine the association between Facebook use, well-being and a variety of psychological constructs. The results of this study are depicted in Figure 1. This study found associations between Facebook use and psychological constructs such as self-esteem and social comparison which seems plausible. In particular, it has been suggested that on Facebook strategically presented content could trigger social comparison and induce negative self-evaluations in the viewer (Vogel et al., 2014; Vogel & Rose, 2016). Repeated exposure to such content could over time decrease global self-esteem and eventually foster more detrimental psychopathological processes (Sowislo & Orth, 2013; Wouters et al., 2013). However, due to the undirected nature of the network of Faelens et al. (2019), the opposite pattern is also possible. For example, participants with higher depression, anxiety, or stress levels generally report lower self-esteem and higher social comparison tendencies (e.g., Gibbons & Buunk, 1999), which may affect their Facebook use (e.g., Aalbers et al., 2018; Scherr et al., 2019).

Although these initial findings offer interesting insights into the relation between Facebook use and well-being, extending this network model with cognitive and social parameters will be key to further improve our understanding of this complex relationship. Therefore, the goal of the current study was to investigate the role of attentional control and social capital in relation to Facebook use, social comparison, (contingent) self-esteem, and risk for affective disorders (rumination, stress, depressive- and anxiety symptoms). In particular, we modeled the impact of these variables on the network structure that was previously obtained by Faelens et al. (2019; Figure 1). The choice for these constructs was based on the following arguments.

Figure 1

Regularized Partial Correlation Network Faelens et al. (2019)



Note: FBI = Facebook intensity; MSFU_Private = active private Facebook use; MSFU_Public = active public Facebook use; MSFU_Passive = passive Facebook use; COMF = social comparison; CSS = contingent self-esteem; RSES = global self-esteem; RRS = ruminative tendency; Stress = stress; Anxiety= anxiety; Depression = depression. The strength of the association between constructs is represented by the thickness of the edges. While blue lines represent positive associations, red lines represent negative associations.

Attentional Control

As human information processing capacity is limited, attentional control is very important. Within the current paper attentional control is defined as the top-down cognitive process that allows to focus on a relevant task set and suppress irrelevant distractions (Broadbent, 1971; Shiffrin & Schneider, 1977). There are multiple ways in which attentional control could be linked to SNS use and well-being. For example, previous studies suggest that highly frequent use of social media, and the extent to which this relies on multitasking, could also be connected to the ability to control our attention. Specifically, it has been suggested that people who often engage in social media multitasking may be more susceptible to interference of irrelevant information due to the continuous stream of social information (Bermúdez, 2017). In particular, Ophir et al. (2009) showed that heavy social media multitaskers performed worse on a switching task than low social media multitaskers. These results suggest that heavy social media multitaskers are more likely to experience difficulties to block out distractions and focus their attention on a single task. This is in accordance with the counterintuitive notion that people who are not capable of multitasking efficiently are in fact the people who are most likely to engage in multiple tasks simultaneously (Sanbonmatsu et al., 2013). Hence, people who have lower attentional control capacities are more likely to become heavy social media multitaskers as they are easily distracted by social media cues (Ophir et al., 2009).

In addition to the influence of attentional control as a more stable trait, it is also important to consider the direct impact of social media multitasking on academic performance given that attentional control plays a crucial role in learning. Indeed, previous studies suggest that people who spent more time using social media while attending classes, studying and doing homework, had lower comprehension of the lecture material and lower grades (Junco & Cotton, 2011; Junco & Cotton, 2012; Kirschner & Karpinski, 2010; Gupta & Irwin, 2016; Rosen et al., 2013). The disadvantageous impact of chronic social media use on academic performance and attentional control is likely mediated by multitasking (Chen & Yan, 2016; Junco, 2015). However, note that the negative influence of social media multitasking on attentional control also seems to depend on task difficulty. The negative influence of social media multitasking on attentional control mainly seems to hold for complex tasks (Min, 2017). Although using social media while doing schoolwork, might harm academic performance, this does not necessarily mean that social media use is detrimental to attentional control. It could just mean that social media is distracting students in-the-moment.

Furthermore, ample studies suggest that attentional control deficits may put one at risk for developing depressive symptomatology (for reviews, see De Raedt & Koster, 2010; Joormann et al., 2007; Joormann & Gotlib, 2010). In particular, depressed individuals seem to have difficulties focusing their attention towards positive information and relocating their attention away from negative towards positive information (Armstrong & Olatunji, 2012). Moreover, these deficits in attentional control have been linked to emotion regulation difficulties, which are known to impact the onset and maintenance of depressive symptoms (Joormann & Stanton, 2016). Together, these findings point towards the importance of extending previous network models with attentional control in an attempt to further unravel relationships between social media use and self-reported psychopathology (e.g., depressive, anxiety, and stress symptoms). A second variable that would be worthwhile investigating in this context, is social capital.

Social Capital

The desire to form and maintain interpersonal relationships is a fundamental human motivation (Baumeister & Leary, 1995). Not surprisingly, research has shown that having positive relationships increases our well-being and vice versa (Lyubomirsky et al., 2005). For example, Saherman et al. (2006) illustrated that participants who had harmonious relationships with their family and friends (warm relationships with little conflict) reported lower loneliness and higher self-esteem scores. Furthermore, Sousa-Poza and Sousa- Poza (2000) suggested that having a good relationship with your colleagues and managers is an important determinant of job satisfaction. Indeed, social networks are important for people, since users derive numerous benefits from their social relations or connections, which are often described as ‘social capital’. Putnam (2000) makes a distinction between ‘bonding social capital’ and ‘bridging social capital’. Bonding social capital is typically provided by emotionally close relationships, such as family members and good friends. These individuals tend to share similar backgrounds and usually provide emotional/social support, trust and companionship to each other. Alternatively, having a large amount of ‘weak ties’ or acquaintances, which are casual connections between individuals who travel in different circles, provides bridging social capital. These connections give individuals access to novel information and a broader worldview, since they are more likely to add non-redundant information and new perspectives, not possessed by the individual’s family or friends. Consequently, such relations do not necessarily provide emotional support.

SNS such as Facebook have the potential to foster communication with our close and weak connections. Indeed, SNS are particularly well-suited to maintain existing relationships, and to keep up to date with Facebook friends and therefore provide social capital benefits (Ellison et al., 2007). For example, Phua & Jin (2011) highlighted that intensity of Facebook use contributed to bonding social capital, which could in turn lead to improved well-being (Burke & Kraut, 2013; Verduyn et al., 2017). Next, it is also plausible that individuals’ mental health influences the amount of social support they receive (e.g., Billedo et al., 2019), which could in turn affect how they use Facebook. However, this warrants further (longitudinal) investigation. Based on these findings, we wanted to investigate if bonding social capital could possibly serve as intermediate mechanism in the relationship between Facebook use and well-being.

In addition, SNS provide users the opportunity to activate latent ties into weak or bridging ties. This gives users the chance to maintain connections that would otherwise disappear, allowing (intensive) users to maintain larger and more heterogeneous networks (Brandtzaeg, 2012; Ellison et al., 2007). More specifically, these networks provide access to novel information and diverse viewpoints (e.g., novel information via status updates/photo updates … ; Burke et al., 2010). Furthermore, individuals who use Facebook at least partly for information seeking, reported higher scores on bridging social capital. Information seekers were also more likely to agree with the fact that they use this channel to 'check out' someone they met in a social environment, to learn more about them. In this way, Facebook can facilitate (offline) social interactions and potentially lead to positive consequences (Burke et al., 2011). However, at the same time these individuals will be exposed to strategically presented information of individuals they don't know (well), which may induce upward comparison and negative self-evaluations (Vogel, et. al. 2014; Vogel & Rose, 2016). Therefore, we wanted to explore whether bridging social capital would operate as intermediate mechanism in the relationship between Facebook and well-being.

Current study

The current study aims to investigate the impact of attentional control and social capital (bonding, bridging) on the network structure obtained by Faelens et al. (2019). This network showed complex associations between social media use, social comparison, self-esteem and indicators of risk for affective disorders. In particular, to improve our understanding of the complex relationship between Facebook use and risk for internalizing psychopathology, we added two additional constructs: social capital and attentional control. As such, our goal was threefold:

1. to replicate the network structure obtained by Faelens et al. (2019)
2. to investigate the role of attentional control within this network
3. to investigate the possible protective role of bonding social capital (3A) and bridging social capital within this network (3B)

Methods

Recruitment

We recruited our participants via Prolific, a recently developed crowdsourcing platform designed for research purposes (https://www.prolific.co). This platform has been extensively used in several research domains (e.g., Effron & Raj, 2019; Frimer & Skitka, 2018; Simmonds et al., 2018) and has several advantages over other crowdsourcing platforms such as (1) a customer support team with scientific expertise (2) anonymous communication with participants (if needed) (3) ethical rewards: defined minimum payments for participants (https://www.prolific.co/prolific-vs-mturk/). Nevertheless, crowdsourcing platforms such as prolific also have some drawbacks which include the use of a nonnaïve worker pool: participants who repeatedly complete (psychological) studies may become somewhat familiar with some questionnaires or tasks, which may reduce the effect sizes (for more information see: Chandler et al., 2015; Miller et al., 2017). However, due to the fact that Prolific is a rather new platform, which is less known, this problem may be significantly smaller as compared to well-known platforms such as Mturk (Peer et al., 2017).

Participants

Participants needed to have a Facebook profile and had to be between 18-35 years old, since young adults are the most active Facebook users (Pew Research Center, 2019; Van den Driessche & De Marez, 2019). Based on the power-analysis of Faelens et al. (2019), we aimed to recruit around 500 participants. Five hundred and nine participants started the study. Fifty participants were excluded as they failed to answer one of the three reading check items correctly (e.g., “As a reading check could you please select the answer 'I disagree strongly’ '”), resulting in a final sample of 459 participants. Participants provided informed consent prior to completing the survey**.** This study was approved by the local institutional review board.

Measures

Facebook Related Constructs

Facebook Use. The Multidimensional Scale of Facebook Use (MSFU; Frison & Eggermont, 2015) consists of 10 items, each rated on a 7-point Likert scale ranging from 1 (“never”) to 7 (“several times per day”). This instrument measures three types of Facebook activities: *passive Facebook use* (MSFU.PA, e.g. “How often do you look at photos of a Facebook friend?), *active private Facebook use* (MSFU. PR; e.g., “How often do you send a private message?”), and *active public Facebook use* (MSFU.PU; e.g., “How often do you post a status update?”). However in line with previous research, we decided to exclude one item of the passive Facebook use subscale (“How often do you read your newsfeed?”) because this item loaded highly on another subscale (i.e., active private Facebook use; Faelens et al., 2019; Frison & Eggermont, 2015). The internal consistency of the three subscales in the current study was as follows: *passive Facebook use* (α = .90), *active private Facebook use* (α = .90), and *active public Facebook use* (α = .91).

Facebook Intensity. The Facebook Intensity Scale (FBI; Ellison et al., 2007) assesses people’s emotional connection to Facebook and its integration in people’s daily lives. In this study, we only used the six attitudinal items, rated on a 5-point Likert scale (e.g., “Facebook has become part of my daily routine”). The scale showed good internal reliability (Cronbach’s α = .88).

Intermediate Psychological Constructs

Facebook-specific Bridging and Bonding Social Capital. The Facebook-specific social capital measure (Su & Chan, 2017) was adapted from Ellison and colleagues (2014). The Facebook-specific bridging social capital subscale (BRSC) consists of seven items and measures the degree to which people perceive bridging benefits (e.g., information that triggers new interests) from interaction with their Facebook friends (e.g., “Interacting with Facebook friends makes me interested in things that happen outside of my city”, α = .89). In contrast, the Facebook-specific bonding social capital subscale (BOSC) assesses the extent to which individuals report to experience bonding social capital benefits as emotional support and mutual trust via their Facebook friends (e.g., “There are several Facebook friends I trust to help solve my problems”, α = .88). Both subscales are rated on a 5-point Likert scale ranging from 1 (“strongly disagree) to 5 (“strongly agree).

Social Comparison on Facebook. Social comparison on Facebook was measured with the Comparison Orientation Measure-Facebook (Steers et al., 2014). The COM-F consists of 11 items and is an adaptation of the well-established Iowa-Netherlands Comparison Orientation Measure (Gibbons & Buunk, 1999). All items were rated on a 5-point Likert scale (e.g., “When I am on Facebook, I try to find out what others think who face similar problems as I face”, α = .88).

Contingent Self-esteem. The Contingent Self-Esteem Scale (CSS; Paradise & Kernis, 1999) is a measure of global self-esteem contingency. The 15-item instrument consists of 15 items each rated on a 5-point Likert scale ranging from 1 ("not at all like me") to 5 ("very much like me"; e.g., "An important measure of my worth is how physically attractive I am.") and has a good reliability (α = .83).

Global Self-esteem. The Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965) is a widely used measure of global feelings of self-worth and shows good reliability (α = .90). The 10-item instrument instructs participants to rate how much they agree with each statement (e.g., "I take a positive attitude toward myself", range 0-30), using a 4-point Likert scale ranging from 1 ("strongly disagree") to 4 ("strongly agree").

Attentional Control. We used the attentional control subscale of the Adult temperament questionnaire to assess attentional control as a stable trait (ATC; Evans & Rothbart, 2007). This questionnaire consists of 5 items measured on a 7-point Likert scale ranging from 1 ("extremely untrue of you") to 7 ("extremely true of you"; e.g., "It's often hard for me to alternate between two different tasks", α = .68). Participants could also choose the option 'Not applicable' if the item was not applicable to them.

Rumination. The Ruminative Responses Scale (RRS; Treynor et al., 2003) is a 22-item instrument that measures trait rumination and indicates how often participants generally engage in repetitive negative thinking (α = .94). Responses are scored on a four-point Likert scale ranging from 1 ("almost never") to 4 ("almost always").

Psychopathology Symptoms

Negative Emotional States of Depression, Anxiety, and Stress. The Depression, Anxiety and Stress Scales (Lovibond & Lovibond, 1995) is a self-report questionnaire designed to measure psychological distress on three 7-item dimensions. Participants are instructed to report the extent to which they experience depressive- (DEPR; e.g., “I found it difficult to work up the initiative to do things”, α = .92), anxiety- (ANX; e.g., “I was worried about situations in which I might panic and make a fool of myself”, α = .86), and stress symptoms (STRESS; e.g., “I felt that I was using a lot of nervous energy; α = .87) with response options ranging from 0 (“Did not apply to me at all”) to 3 (“Applied to me very much, or most of the time”).

Data Analyses

Data analysis was conducted in R version 3.5.0 (see supplemental material for R-packages used and version information). After detecting skew in the data, we conducted a nonparanormal transformation using the *huge* package (Zhao et al., 2015) to improve normality. Subsequently, we estimated a Gaussian Graphical Model (GGM; Epskamp & Fried, 2018) using *qgraph* (Epskamp et al., 2012). Network models consist of edges and nodes, where nodes refer to the variables included in the model, while an edge represents the relationship between two given nodes. We relied on partial correlations to model the unique shared variance between the nodes, using regularization to remove spurious edges. In particular, we implemented regularization based on the Graphical Least Absolute Shrinkage and Selection Operator (gLASSO; Friedman et al., 2014) with Extended Bayesian Information Criterion model selection (EBIC). In line with Faelens et al. (2019), we set the EBIC hyperparameter γ at 0.5, erring on the side of parsimony (Epskamp & Fried, 2018). In particular, we used thresholded EBIC gLASSO (cf. Epskamp, 2018) to maximize model specificity (for a non-thresholded version of the network, see supplemental Figure 1), resulting in a model that is less likely to contain false positive edges. We then estimated node predictability – the percentage of variance of each node that is explained by its neighboring nodes in the network – with *mgm* (Haslbeck & Waldorp, 2016), and proceeded with bootstrapping procedures to assess the reliability of the obtained network model. In particular, *bootnet* (Epskamp & Fried, 2017; Epskamp et al., 2018) was used to compute the accuracy of the edge weights, where we provided 95% confidence intervals for all edges in the model. In addition, we plotted significant differences between edges, and estimated the stability of strength centrality. Node strength centrality provides an estimate of the sum of absolute edge weights connected to each node. As such, node strength reflects strength of connectivity for a given node (Costantini et al., 2015). We standardized this centrality measure to facilitate interpretation. Stability of the order of node strength within subsets of the data was established using a case-dropping subset bootstrap. In order to be considered stable, the resulting correlation stability coefficient should not be below 0.25 and preferably exceed 0.50 (Epskamp et al., 2018). To visualize the network model, we relied on a modification of the Fruchterman-Reingold's algorithm (Fruchterman & Reingold, 1991), which aims to position nodes more central in the model based on their level of connectivity (but see Jones et al., 2018). The unique associations between two given nodes are represented by edges, where (a) the thickness of the edge reflects the strength, and (b) the type of line used and color of the edge reflect the valence of this association (blue / full line = positive, red / dashed line = negative). Finally, node predictability was plotted as a pie chart in the outer ring of each node (Haslbeck & Fried, 2017).

Results

Descriptive statistics of the variables of interest are reported in Table 1. Figure 2 depicts the GGM, which is a regularized partial correlation network. Each edge depicts the unique associations between two nodes while controlling for all other nodes in the network. The obtained network depicts two conceptual clusters related to use of Facebook (Facebook intensity (FBI), active public, passive and active private Facebook use (MSFU-PU/MSFU-PA/MSFU- PR), bonding social capital (BOSC) and bridging social capital (BRSC) and emotional vulnerability (rumination (RRS), depression (DEPR), stress (STRESS), anxiety (ANX), attentional control (ATC)). These clusters are indirectly linked via indicators of social comparison (COMF) and (contingent) self-esteem (CSS). Within the cluster related to Facebook use, bridging social capital (BRSC) emerged as a bridging construct, being connected to most indicators of Facebook use and social comparison (COMF). Within the cluster of emotional vulnerability, attentional control (ATC) showed unique negative associations with stress and rumination. The latter emerged as the most strongly connected node in the model, closely followed by stress (STRESS), depression (DEPR), Facebook intensity (FBI) and bridging social capital (BRSC). Based on node strength, attentional control (ATC) was the least central node in the model (Figure 2 and 3). This was also reflected in terms of node predictability, which is visualized as a pie chart around each node. For instance, only 22% percent of variability in attentional control was predicted by its surrounding nodes, whereas 64 - 71% of variance in the indicators of symptomatology was explained by neighboring nodes. For the corresponding weight matrix and indicators of node predictability, see supplemental Tables 1 and 2.[1]

The obtained model showed acceptable accuracy and stability, as indicated by the bootstrapped 95% confidence intervals around the edge weights (Supplemental Figure 2) and the obtained correlation stability coefficient for Strength centrality (.60). That is, with a 95% probability, a maximum of 60% of the original sample could be dropped while remaining a correlation ≥.70 for Strength centrality between the original sample and the obtained samples following the case-dropping subset bootstrapping procedure (Supplemental Figure 3). Significant differences between edge weights are plotted in Supplemental Figure 4.

[1] Note: The GGM was obtained via qgraph, which relies on inversion of the covariance matrix, whereas predictability was obtained via mgm, relying on a node-wise regression approach. Importantly, both methods yielded similar results, where we observed a correlation of r = .71 between the two obtained adjacency matrices.

Table 1

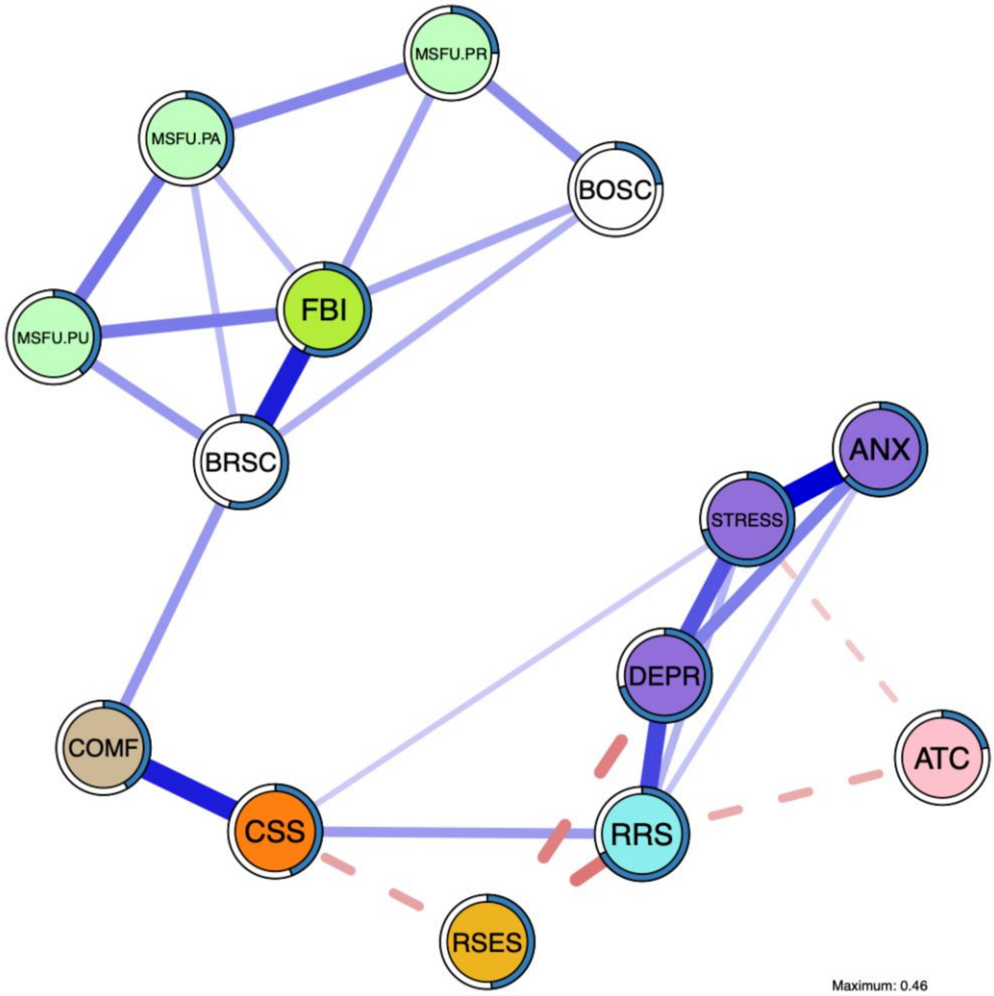
Sample Characteristics

	N = 459
Female: Male	232:227
Continent: North America: South America: Europe: Africa: Asia: Oceania: Antarctica	52: 2: 392: 0: 8: 4: 1
Age	26.20 (4.525)
Facebook intensity (FBI)	18.46 (5.73)
Social comparison (COMF)	33.63 (8.70), range 1-55
Global self-esteem (RSES)	17.46 (5.54), range 0-30
Ruminative tendency (RRS)	49.12 (14.02), range 22-88
Contingent self-esteem (CSS)	51.40 (8.13), range 15-75
Passive Facebook use (MSFU.PA)	13.69 (5.06), range 4-28
Active private Facebook use (MSFU.PR)	9.07 (3.80), range 2-14
Active public Facebook use (MSFU.PU)	7.09 (3.54), range 3-21
Stress (STRESS)	7.37 (4.84), range 0-21
Anxiety (ANX)	5.06 (4.65), range 0-21
Depression (DEPR)	6.39 (5.58), range 0-21
Attentional control (ATC)	3.99 (1.12), range 0-35
Bridging social capital (BRSC)	21.17 (5.85), range 7-35
Bonding social capital (BOSC)	17.54 (5.72), range 6-30

Note: Standard deviations are given in parentheses.

Figure 2

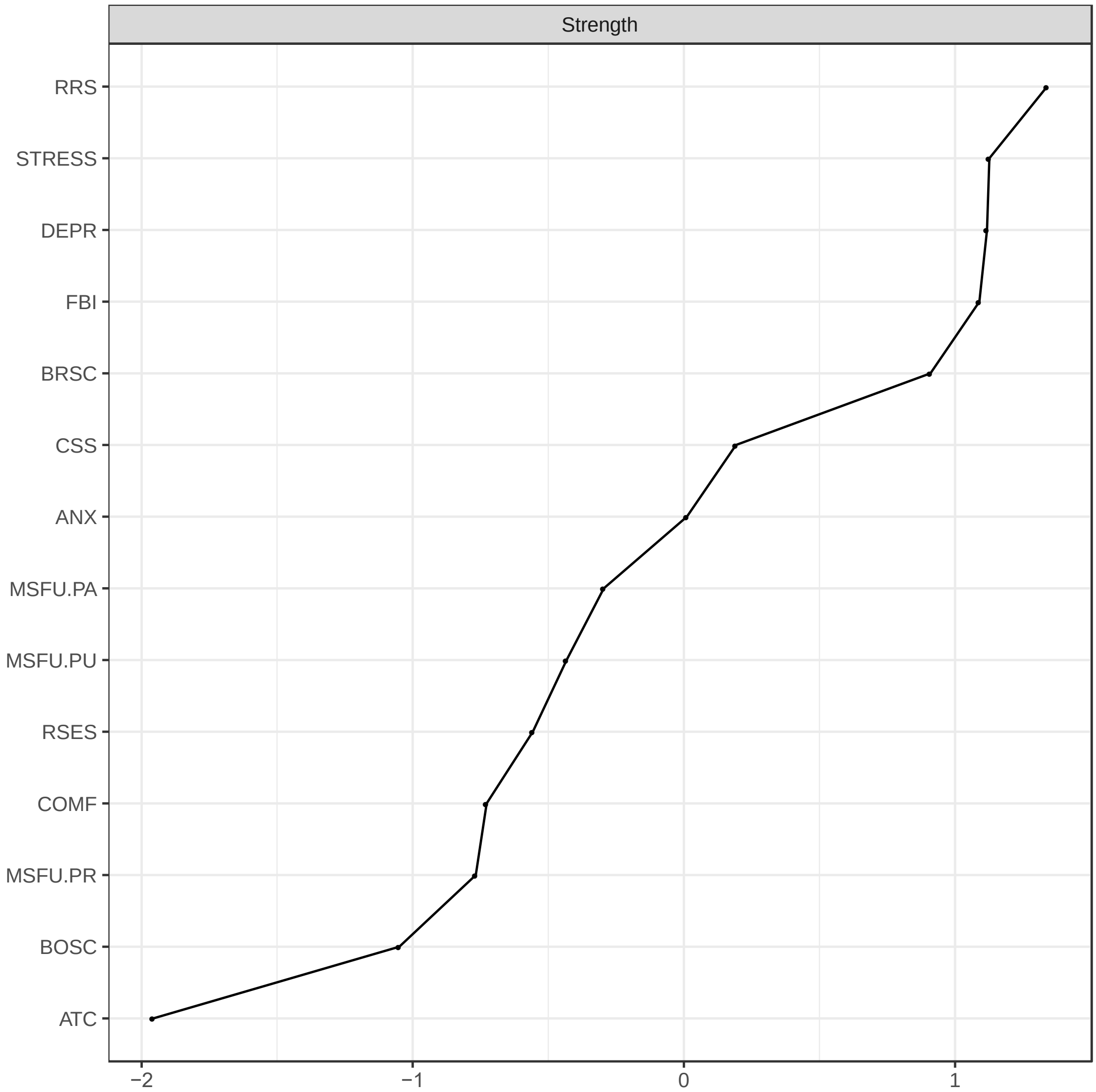
Regularized Partial Correlation Network



Note: Edges in the GGM represent the unique associations between each of the constructs of interest. Edge thickness reflects the strength of association, where strong associations are presented using thicker edges. Blue / Full edges represent positive associations, whereas red / dashed edges represent negative associations; The edge weights presented in the model can also be found in the edge weight matrix (Supplemental Table 1); FBI = Facebook intensity; MSFU.PR = active private Facebook use; MSFU.PU = active public Facebook use; MSFU.PA = passive Facebook use; BOSC = bonding social capital; BRSC = bridging social capital; COMF = social comparison; CSS = contingent self-esteem; RSES = global self-esteem; RRS = ruminative tendency; ATC = attentional control; STRESS = stress; ANX = anxiety; DEPR = depression.

Figure 3

Standardized Strength Centrality



Note: This figure ranks nodes included in the network model based on the extent to which these take a more central position in the network. In particular, nodes are ranked based on strength centrality, reflecting the level of connectedness of each of the nodes (i.e., the sum of absolute edge weights connected to each node). FBI = Facebook intensity; MSFU.PR = active private Facebook use; MSFU.PU = active public Facebook use; MSFU.PA = passive Facebook use; BOSC = bonding social capital; BRSC = bridging social capital; COMF = social comparison; CSS = contingent self-esteem; RSES = global self-esteem; RRS = ruminative tendency; ATC = attentional control; STRESS = stress; ANX = anxiety; DEPR = depression.

Discussion

The goal of the current study was to model the complex interrelations between Facebook use, social capital, social comparison, self-esteem, attentional control, and indicators of risk for affective disorders (level of rumination, stress-, anxiety-, and depressive symptomatology). In this context, we used network analysis to provide a comprehensive overview of the associations between these constructs, with a specific focus on attentional control and social capital in particular.

First, the results provide a conceptual replication of Faelens et al. (2019). More specifically, our results provide support for the importance of social comparison and self- esteem, connecting (passive) Facebook use with indicators of psychopathology. In line with our expectations, the obtained network structure is highly similar to the model obtained by Faelens et al. (2019). That is, the Facebook cluster was linked to social comparison and social comparison linked Facebook use with self-esteem. In turn, self-esteem connects the indicators of psychopathology with social comparison and indicators of Facebook use.

Due to the undirected nature of our network, we cannot make claims about the direction of the effects. For example, previous research has shown that users with elevated depression- anxiety- or stress symptoms report difficulties at the level of self-esteem and social comparison process (e.g., Appel et al., 2016). Consequently, they may use Facebook differently than healthy users (e.g., Aalbers et al., 2018; Scherr et al., 2019). However, the explanation that Facebook usage may induce social comparison, which may in turn lead to negative self-evaluations, repetitive negative thinking, and higher depression/anxiety or stress symptoms is equally plausible (e.g. Feinstein et al., 2013; Vogel et al., 2014) and seems to be better supported in the current literature (e.g. Appel et al., 2016; Kross et al., 2013; Verduyn et al., 2015).

Second, we found no direct link between Facebook use and attentional control as measured with the effortful control scale. Although attentional control was not involved in the relations between Facebook use and depression, it could still have an influence as indirect links emerged via rumination, self-esteem, and social comparison. That is, individuals showing poor attentional control may be more prone to ruminate, which increases the likelihood of experiencing depressive-, stress-, or anxiety symptoms (Koster et al., 2011).

Related to this, ruminators may report lower self-esteem and be more likely to compare themselves on Facebook. Vice versa, Facebook use may trigger social comparison, which can have a detrimental impact on self-esteem and may induce rumination, resulting in poor attentional control. This pathway provides evidence for the impulsivity pathway proposed by Billieux (2012). This pathway states that people who score high on the impulsivity personality trait are more likely to start ruminating when they are confronted with negative feelings due to reduced self-control. As a consequence, social media use might serve as a short-term avoidance strategy to deal with unpleasant emotions to get rid of the ruminative thoughts.

Furthermore, there are also several tentative explanations for the absence of direct links between attentional control and problematic effects of Facebook use. First, attentional control can fluctuate over time, but the ATQ only measures attention as a stable construct. Hence, important fluctuations in attention are not captured within the current approach. Second, individuals might not be able to give an accurate estimate of their attentional capacities in the face of distracting information. Therefore, in future studies, it would be very relevant to investigate attentional control through performance tasks that capture minor attentional control fluctuations. The use of an ecological momentary assessment design would additionally facilitate the monitoring of both the amount of social media use and the short term and long term influences on attentional control.

Third, in addition to extending the initial model with attentional control (cf. Faelens et al., 2019), we also examined the role of bonding and bridging social capital (Putnam, 2000). In line with previous research, both constructs are directly connected with Facebook intensity (Ellison et al., 2007), suggesting that people who feel strongly connected to this platform experience higher social capital outcomes. As expected by their different nature, both constructs show unique associations in the network. First, bonding social capital is uniquely associated with active private Facebook use, which is in line with previous research showing that one-on-one communication (e.g., via instant messaging) with friends is linked with social capital benefits as perceived social support (Frison & Eggermont, 2016).

Next, we hypothesized that bonding social capital could function as an important intermediate mechanism in the relationship between Facebook use and well-being. In contrast to the pattern of results reported in the review of Verduyn et al. (2017), we found no direct link between bonding social capital and indicators of well-being. One possible explanation for this finding is that we mainly included negative outcome measures such as stress, anxiety and depressive symptoms. Previous research has shown that feelings of social support and relatedness are mainly linked to positive outcomes instead of negative outcomes (Reis et al., 2018). For example, Watson and Clark (1994) showed that positive affect is raised when people are socializing, whereas negative affect is primarily a function of stressful or aversive events. Another possible explanation is that we focused on Facebook-specific social capital and did not include a measure of offline social capital. Previous research has shown that computer-mediated support especially helps people who are unable to connect with others in an offline environment. As an illustration, for socially anxious individuals, online social support via Facebook provided an additional source of contact above offline social support, increasing subjective well-being. However, this beneficial effect of additional online social contacts did not contribute to well-being in the low anxiety group (Indian & Grieve, 2014). This may explain the absence of a direct connection between Facebook-specific bonding social capital and indicators of well-being in our healthy convenience sample.

In contrast, bridging social capital emerged as a key construct. That is, bridging social capital seems to connect (a) intensity of Facebook use, active public Facebook use, and passive Facebook use, with (b) social comparison, which provides support for the role of bridging social capital as a potential risk factor in a social media context. The network shows that users, who (1) engage in active interaction with their Facebook friends (e.g., by posting photos, status updates) and (2) are passively consuming to profile content of their connections, tend to have a higher bridging social capital. However, looking at the strategically presented content of others may facilitate the process of social comparison with their acquaintances. Although these users have access to a lot of new information due to their heterogeneous network, bridging social capital can have some unexpected downsides. As users with a higher bridging social capital may perceive more desirable content of others, this can be accompanied by negative self-evaluations when users rely on this extensive network to compare themselves to others, which may then induce psychopathology symptoms (Vogel & Rose, 2016). Vice versa, being in a negative state with low self-esteem may trigger more social comparison and bridging social capital.

The current study set out to model the unique associations between central indicators of Facebook use and vulnerability for affective disorders. An important strength of this study is that it examines the role of both social capital and social comparison in the relationship between Facebook use and indicators of well-being. Previous studies suggested that these constructs could be important factors in the relationship between Facebook use and well-being. For example, they reported that browsing on Facebook could cause distress, by inducing social comparison and envy (e.g., Verduyn et al., 2015), which could in turn lead to decreased self-evaluations and positive affect (e.g., Vogel et al., 2014). Again, research indicates that the opposite pattern may also be plausible (e.g., Aalbers et al., 2018; Scherr et al., 2019), but needs further investigation since the literature predominantly focused on the effects of SNS use on well-being instead of the reverse direction. Next, active communication with Facebook friends could increase people's social capital, which can result in a higher well-being and potentially also the other way around (Billedo, 2019; Frison & Eggermont, 2016).

However, in the current study, only social comparison seems to be involved in the (negative) relationship between Facebook use and well-being. With regard to the positive relationship, we did not find a direct link between social capital and indicators of psychopathology. Second, we were one of the first to model the unique associations of attentional control in the context of Facebook use and psychopathology. This is of particular interest given the well-established role of attentional control in emotion regulation processes (De Raedt & Koster, 2010; Joormann et al., 2007; Joormann & Gotlib, 2010; Joormann & Stanton, 2016) and previously reported inconsistencies pertaining the relation between social media use and attentional control (Chen & Yan, 2016; Junco, 2015; Min, 2017; Ophir et al., 2009).

The findings of the present study are limited in some respects. Due to the use of a convenience sample that we recruited via Prolific, the findings of this research should not be overgeneralized. Future research should extend this sample in order to map the relationships between Facebook use and indicators of psychopathology in a broader group of Facebook users in terms of age groups, ethnicity, etc. Second, the present study was limited by self-report measures. Previous research has shown that the correlation between retrospective self-report questionnaires and actual smartphone usage is weak (e.g. Ellis et al., 2019) Consequently, we should be cautious to make strong interpretations about the relationship between SNS use and well-being. Therefore, future research should use more objective measurements of Facebook intensity to extend the current insights about the impact of intensity of SNS use on well-being. Notably, a recent prospective study using objective assessment of Facebook use did confirm most of the associations observed in the current work (Faelens et al., 2020). Third, it should be noted that the obtained network model stems from cross-sectional data and is undirected. As such, no inferences can be made regarding causality and the direction of the observed relationships. Based on the existing literature – these findings likely represent bidirectional pathways. The key strength of this exploratory data-driven approach is that it allows to identify and model potential mechanisms across a broad range of constructs. However, the direction and causality should be further tested using prospective or experimental designs (e.g., Aalbers et al., 2018).

Conclusion

This study set-out to replicate and extend the network model obtained by Faelens et al. (2019) with two factors: (1) attentional control and (2) social capital. Our results provide a conceptual replication and extension of the original network model(s) obtained by Faelens et al. (2019). Interestingly, attentional control showed no direct associations with Facebook use, whereas bridging social capital emerged as a key variable in the network uniquely connecting indicators of (intensity of) Facebook use with indicators of risk for affective disorders via social comparison and self-esteem. These findings advance our understanding regarding the complex relation between Facebook use and psychological well-being.

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