SOCIAL MEDIA AND SMARTPHONE USAGE IN COLLEGE STUDENTS: ASSOCIATIONS WITH PERCEIVED RELATIONSHIP QUALITY, DEPRESSIVE COGNITION, MOOD, AND WELL-BEING

by

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ABSTRACT

In the past decade, there has been an explosion of smartphone utilization and social media usage, particularly among young adults. Both in popular culture and among researchers, there have been concerns about the effects of social media use on psychological well-being and mental health outcomes. This study included both passive and active longitudinal data collection to assess the links between social interaction variables and mental health variables. Participants were 113 college students who installed a monitoring application on their smartphones, completed daily surveys, and allowed the app to collect relevant passive data over a two-week period. Concurrent hierarchical correlations and regressions suggested that neither the frequency of electronic communication nor social media use were associated with daily mental health variables. However, when individuals reported experiencing positive social interactions, they also reported greater well-being and positive affect and less depressive cognition and negative affect on the same day. Hierarchical cross-lagged regressions revealed that none of the social interaction variables predicted next day mental health variables. However, increased negative affect on a given day predicted lower quality social interactions the next day, and increased well-being predicted higher quality social interactions and use of social media the next day. Finally, rumination (a known correlate of depression), moderated the relationship between perceived quality of social interactions and depressive cognition, such that high ruminators experienced more depressive cognition, even when experiencing positive interactions with others. Taken together, the results suggest that the context of interactions may matter much more than the frequency of electronic communication or social media use. Recommendations for future research in contextualizing social media use on smartphones and additional mental health and well-being factors are discussed.

Chapter 1

INTRODUCTION

Electronic devices have become an integral part of global culture. With improving technology and the advent of social media since the early 2000s, the world has, arguably, become much more connected and electronic-centric. Nearly 80% of Americans own a smartphone (compared to 35% in 2011), and approximately 70% report using at least one type of social media platform compared to 5% in 2005 (Smith, 2017). In 2018, as many as 88% of 18- to 29-year-old Americans use at least one form of social media, more than any other age bracket (Pew Research Center, 2018). With this cultural shift, many scientific disciplines have sought to examine the impact of this pervasive social media and smartphone usage. An emerging concern among these researchers is how social media and smartphone usage are associated with and may impact social functioning, mood, mental health, and well-being, the focus of the current study.

Public Health Concerns Related to Social Media Use

The ubiquity of social media and smartphone use is apparent among the U.S. population. A recent study of over 500,000 adolescents conducted between 2010 and 2015 concluded that social media and smartphone usage is associated with increased rates of suicide-related outcomes, including hopelessness, suicidal ideation, planning, and actual attempts (Twenge, Joiner, Rogers, & Martin, 2017). Further, these researchers reported a “dose-related effect,” whereby individuals who spent two or more hours using smartphones were more likely to endorse suicide-related outcomes compared to their counterparts who engaged in non-screen activities, such as in-person interactions, sports/exercise, religious activities, or job-related activities. It should be noted that effect sizes were small in this study, and it is premature to infer direct causality between social media or smartphone use and suicidality. However, this pattern of findings should not be ignored, as both rates of social media use and suicidality have been increasing in teenagers and young adults over the last 10 years (Centers for Disease Control and Prevention, 2017; Twenge et al., 2017). Other factors have been highlighted that may be associated with this trend, such as increased loneliness, which is a known predictor of suicidality (Van Orden et al., 2010) and has been shown to have physical and mental repercussions (Holt-Lunstad, 2018). Some researchers have posited that there is a strong connection between social media use and the drive to have meaningful connections, as well as the perception of current relationships (Ahn & Shin, 2013; Ryan, Allen, Gray & McInerney, 2017). Given that college-aged students are at increased risk for suicide and major depressive disorder (Cuijpers, et al., 2016; Kessler & Bromet, 2013; Klein, Glenn, Kosty, Seeley, Rohde, & Lewinsohn, 2013) and are the highest utilizers of social media (potentially to build close relationships), an examination of the impact of these types of social connections is warranted.

Mental Health Markers Negatively Affected by Social Media Use

To better understand the potential impact of social media usage (use of social networking platforms such as Facebook, Instagram, Twitter) and electronic communication (e.g. texting, emailing, phone calls, Skyping), researchers have evaluated several constructs, such as mood, mental health/well-being, and social connectedness using a variety of methods.

Mood

Mood is one of the most widely examined constructs, given its relationship to a variety of mental health disorders. Several studies have examined the effects of spending time on smartphones and social media sites on general mood. In a broad sample of participants in the United States, Sagioglou and Geitemeyer (2014) experimentally manipulated time spent on Facebook (20 minutes) compared to browsing the internet generally or no activity. Participants exposed to Facebook rated their mood as more negative, although they expected this online activity to make them feel better (i.e., faulty affective forecasting). The relationship between Facebook activity and mood was mediated by the perception of how meaningful the activity was, and lower levels of meaningful activity predicted more negative mood (Sagioglou & Geitemeyer, 2014). Other correlational and experimental studies suggest that exposure to positive or negative content on Facebook can even influence the valence of wall-posting behaviors of an individual and his or her friends (Coviello et al., 2014; Kramer, Guillory, & Hancock, 2014).

Mental Health/Well-being

Given that college-aged students are estimated to spend approximately two hours or more on social media a day (GlobalWebIndex, 2017), the cumulative effect of these experiences might contribute to reduced well-being or even mental health problems. Several cross-sectional studies have investigated the links between how social media is used and depression (Lin et al., 2016; Pantic, 2014; Primack, Shensa, Escobar-Viera, et al., 2017; Tromholt, 2016), anxiety (Dobrean & Păsărelu, 2016; McCord, Rodebaugh, & Levinson, 2014), and general well-being (Brooks, 2015; Satici & Uysal, 2015; Shakya & Christakis, 2017).

Depression and anxiety

In a cross-sectional study of U.S. adults (aged 19-32), participants were asked to rate their depression and their typical social media usage (total time per day, which social media platforms they used, and number of times a participant visited a social media site). Individuals in the highest quartiles for time spent on social media and frequency of accessing the sites were approximately three times more likely than those in the lowest quartile to report high levels of depression (Lin et al., 2016). This suggests that patterns of social media use might be associated with depression symptoms. Although duration of time on social media appears to be an important correlate of depression, other researchers have examined whether engagement with a larger number of social media platforms predicts mental health outcomes. Primack and colleagues (Primack, Shensa, Escobar-Viera, et al., 2017) investigated this among young adults using an up-to-date collection of social media platforms (i.e., Facebook, Twitter, Google+, YouTube, LinkedIn, Instagram, Pinterest, Tumblr, Vine, Snapchat, and Reddit). Results indicated that participants who were engaged on more social media platforms tended to have elevated scores on measures of depression and anxiety than individuals who used between zero and two social media platforms.

Self-esteem

Another area related to both mental health and well-being is self-esteem, a component of Ryff and Keyes's six-factor model of psychological well-being (Ryff & Keyes, 1995). With influential factors like cyberbullying (Brewer & Kerslake, 2015; Patchin & Hinduja, 2010), pressures to portray a perfect lifestyle (Gangadharbatla, 2008), and comparisons with others (Jan Anwwer Soomro, & Ahmad, 2017; Nesi & Prinstein, 2015), social media is a potentially powerful medium to inflate or deflate individuals' self-worth. For example, in a study of college students, researchers found that for every hour an individual spends on Facebook, they report a significant decrease in self-esteem due to comparisons with others (Jan et al., 2017). Other studies have found that online feedback (positive or negative) from others is associated not only with corresponding increases or decreases in self-esteem, but also with overall well-being (Valkenburg, Peter, & Schouten, 2006).

Well-being

In addition to studies that highlight increased depression and anxiety among social media users, researchers have investigated the effect of social media on psychological well-being more broadly. In one of the few experience-sampling studies among young adults, Kross and colleagues (2013) captured moment-to-moment affect ("How do you feel right now?") and Facebook use ("How much have you used Facebook since the last time we asked?"). Participants were texted five times per day to complete brief online surveys. Time-lagged analyses revealed that Facebook use significantly predicted decreased mood at the next time point, but the reverse pathway (affect predicting Facebook use) was not significant. Further, the more participants used Facebook over a two-week period, the more self-reported life satisfaction decreased over time. Longitudinal studies like this can help to establish the temporal precedence of social media usage and its effects on mood and mental health variables.

Individual factors

Researchers have also explored individual characteristics related to increased social media use. One group of researchers examined the moderating factors of depressive rumination and co-rumination (i.e., tendency to have persistent negative thoughts or discuss negative thoughts repetitively with others) on social media use, perceived quality of online relationships, and depressive symptoms (Davila, et al., 2012). Undergraduate students in the two-part study reported spending between 45 minutes and four hours on social networking sites (i.e., Facebook and MySpace), instant messaging, and texting. Unsurprisingly, when participants rated their online interactions as negative, their self-reported depression scores increased following the interactions. However, time spent on social media sites did not predict later depressive symptoms. An interesting nuance was that depressive rumination moderated the relationship between perceived quality of interactions on social media and depressive symptoms, such that high ruminators tended to experience more depressive symptoms when they rated their interactions on social media as negative. This finding is interesting, as it suggests that, compared to total amount of time spent on a variety of social media, individual differences in rumination (i.e., higher rumination) may contribute to depressive symptoms and perceiving social interactions negatively (Davila et al., 2012).

Social media and social connectedness

Are relationships fostered or harmed by social media, and what impact might this have on well-being? Perhaps the type of relationship (electronic or in-person) is less important than the quality of the relationship. These questions have been at the forefront of the discussion related to social media (Ahn & Shin, 2013; Primack, Shensa, Sidani, et al., 2017; Ryan et al., 2017) and have important implications for well-being. Overall, research suggests that social media use and electronic communication may facilitate social isolation or connectedness, with each influencing well-being.

Perceived relationship quality

There is a well-established body of literature to suggest that developing quality relationships with others can be a strong protective factor against mental health concerns and can promote psychological well-being (Kawachi & Berkman, 2001; Ryff & Singer, 1998; Santini, Koyanagi, Tyrovolas, Mason, & Haro, 2015). However, there is some debate about whether social media use is a substitute for quality relationships, or a potential barrier to connecting with others, which could impact perceived quality of relationships. For example, a recent study indicated that both face-to-face and social media interactions relate to increased well-being, if an individual's sense of connectedness is fulfilled. However, only face-to-face interactions satisfy a deeper evolutionary drive to avoid social isolation (Ahn & Shin, 2013), which may be a context in which relationships develop more deeply.

Social isolation

Perceptions of social isolation (feeling avoided, excluded, or disconnected from others) could be a potential barrier to developing quality relationships or could color the perceived quality of existing relationships. Primack and colleagues (Primack, Shensa, Sidani, et al., 2017) collected self-report data from U.S. young adults to examine the relationship between perceived social isolation and social media usage (frequency and time duration). Their cross-sectional results suggest that individuals in the highest quartiles of social media usage also tend to rate themselves highly on social isolation. Conversely, individuals who were in the lowest quartile reported feeling less socially isolated.

Connectedness

In a review of the literature on social media and its effect on social behavior and connectedness, Ryan et al. (2017) highlight several studies with contrasting views on how social media use facilitates connectedness or loneliness and impacts well-being. The authors highlight examples of social media platforms providing a sense of belongingness to a community (Gruzd, Wellman, & Takhteyev, 2011), a central component of well-being (Diener, 2006; Ryff & Singer, 1998). Corroborating data suggest that social media usage may protect against loneliness (große Deters & Mehl, 2013; Lou, Yan, Nickerson, & McMorris, 2012). However, other studies have countered that users of MySpace and Facebook reported using these sites to communicate without a deep sense of community with others (Reich, 2010), and more time spent on social media is associated with less perceived connectedness and lower life satisfaction (Primack, Shensa, Sidani, et al., 2017, Stepanikova, Nie, & He, 2010).

Taken together, there is solid, although not conclusive, evidence to suggest that social media use has an effect on perceived connectedness and loneliness, which can affect well-being. Equally possible is that social media usage serves to increase superficial connectedness, but not to decrease feelings of social isolation (Ahn & Shin, 2013), which may lead lower perceived quality of relationships.

Mental Health Markers Positively Affected by Social Media Use

Most of the research on social media usage has focused on the negative consequences, and less is known about the potential links with positive outcomes, such as well-being and the ability to build/maintain relationships, boost self-esteem, and facilitate direct support from others. Several studies have reported associations between relationships on social media and mental health and psychological well-being outcomes (Burke, Marlow, & Lento, 2010; Grieve, Indian, Witteveen, Tolan, & Marrington, 2013; Valkenburg, Peter, & Schouten, 2006; Wang, Yang, & Haigh, 2017). For instance, Grieve and colleagues (2013) conducted a cross-sectional self-report study on 344 young adults, measuring perceptions of social connection of both on Facebook and in-person relationships. They found that Facebook social connectedness was positively correlated with subjective well-being and negatively correlated with self-reported depressive and anxiety symptoms (Grieve et al., 2013).

Researchers have also found that individuals benefit from social resources or support from relationships maintained on social media platforms such as Facebook. Benefits from greater Facebook use include more attempts to integrate into a community, particularly for students who reported lower life satisfaction and self-esteem (Ellison, Steinfield, & Lampe 2007).

Another benefit of social media use on well-being is the ability to receive direct feedback from a supportive network. Expressive writing on online forums is associated with benefits such as increases in perceived social support, subjective well-being, improved self-esteem, and decreases in depressive symptoms (Valkenburg, 2017). In addition, receiving positive responses to an online social media profile can boost self-esteem and well-being (Valkenburg et al., 2006).

While most studies have relied on self-report measures, one study examined social network activity and social well-being (i.e., social capital) using passively collected data, which included activity on Facebook (e.g., posting, viewing posts, feed story clicks, photo-tagging, text exchanges, and number of distinct profiles viewed; Burke, et al., 2010). When participants felt they used Facebook to bond better with preexisting relationships, they tended to report more life satisfaction and less loneliness. Further, direct communication (e.g., posting to others' walls, photo-tagging, "liking" statuses) was associated with more bonding and less loneliness, whereas passive "consumption" was associated with increased loneliness (Burke et al., 2010). These results suggest that specific social media behaviors may promote or attenuate well-being.

In summary, the answer to the question, "Does social media affect its users?" appears to be undoubtedly, yes. However, the degree and direction of that effect is complex and conditional on the purpose, type, duration, and function of using social media platforms.

The Current Study

Current research on the effect of social media and electronic communication on mental health and well-being is mixed, and there have been a number of methodological limitations in studies exploring these relationships. Research has predominantly focused on cross-sectional analyses with young adults and has surveyed a limited scope of social media platforms. In the majority of studies reviewed, there has been a call for longitudinal data to ascertain directionality of the effects of social media or electronic communication on mental health outcomes (Kross et al., 2013; Lin et al., 2016; Ryan et al., 2017).

Unlike previous studies, the current project included a range of social interaction variables including electronic communication (text messages, email, and phone calls), a broader range of social media sites, and self-reported perceptions of the quality of social interactions, well-being, and mental health outcomes. In addition, social media and electronic communication usage (frequency and duration) were gathered passively by the smartphone rather than relying on self-report, which can be biased. Variables were assessed daily across a 14-day assessment period. There have been few other multi-day longitudinal studies (Burke et al., 2010; Davila et al., 2012; Kross et al., 2013; Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017). Longitudinal designs allow for examination of temporal precedence, a necessary component of causal interpretations. The current study has the following aims:

Aim 1: Examine concurrent correlations between social interaction variables and mental health outcomes each day across 14 days.

While much of the previous literature suggests a direct link with social media usage and negative outcomes in cross-sectional contexts, fewer studies have examined this relationship with repeated measures over time. As such, the current study will examine concurrent multilevel correlations (i.e., how variables covary on the same day but examined over time, within- and between-subjects) of social interaction variables and mental health outcomes.

Hypothesis 1. Concurrent data will suggest significant correlations between social media usage, electronic communication (email, text, phone calls), and perceived quality of social interactions (PQSI), and the mental health outcome variables (depressive cognition, mood, psychological well-being) at the within-and between-person levels. Specifically, more social media usage and electronic communication will be negatively associated with self-reported psychological well-being (PWB) and positive affect (PA) and positively correlated with depressive cognition (DC) and negative affect (NA). PQSI will be positively associated with PWB and PA and negatively associated with DC and NA.

Aim 2: Examine social interaction variables as predictors of next day mental health outcomes.

Using cross-lagged analyses, Aim 2 seeks to examine the impact of frequency of the social interaction variables on depressive cognition, mood, and PWB, as well as the reverse effect of mental health outcomes as predictors of the social interaction variables.

Hypothesis 2a. Better PQSI will predict lower next day DC and NA and higher PWB scores and PA. All analyses of reverse causality (outcome variables predicting social interaction variables) are exploratory.

Hypothesis 2b. More electronic communication will predict higher next day DC and NA and lower PA and PWB.

Hypothesis 2c. More social media usage will predict higher next day DC and NA and lower PA and PWB.

Aim 3: Examine baseline rumination as a moderator of the relationships between social interaction variables and mental health outcomes.

Akin to the study conducted by Davila et al. (2012), the current study examined the relationship between rumination, a known predictor of depression and of poorer perceived quality of relationships. As Davila and colleagues collapsed measures of electronic communication and social media use in their study, the current study examined the relationship between newer forms of social media and depressive cognition and well-being and did not include the electronic communication variable.

Hypothesis 3a. Baseline levels of rumination will moderate the relationship between PQSI and two outcome variables (DC and PWB), such that those with higher baseline rumination will show a stronger negative relationship between PQSI and DC. Similarly, those with higher baseline rumination will show a weaker positive relationship between PQSI and PWB.

Hypothesis 3b. Those with higher baseline rumination will show a stronger positive relationship between social media use and DC. Similarly, those with higher baseline rumination will show a weaker negative relationship between social media use and PWB.

Chapter 2

METHODS

Participants

One hundred and fifteen participants were recruited from the University of Delaware's (UD) undergraduate research subject pool system, as well as from other psychology courses at UD (Psychopathology, Abnormal Psychology, and Social Psychology). Students were recruited from January 2014 through December 2014. They were compensated for their time with extra credit or research participation course credit. One student withdrew from the study citing privacy concerns. The data from one participant were not included because of significant complications with the application, which resulted in nonconsecutive days of data collection. After these adjustments, 113 participants were included in the current analyses. Participant flow is presented in Figure 1.

Eligibility criteria for the Health and Wellness UDTracker Android Application study included being at least 18 years old, currently enrolled in course work at UD, owning a personal Android smartphone, and having access to Wi-Fi at least once daily. The sample was 57.5% female and 42.5% male and relatively racially diverse (57.5% Caucasian, 16.8% Asian, 13.3% Black/African American, 1.8% American Indian or Alaskan Native, and 10.6% mixed/other). Approximately 8% of participants identified as being ethnically Hispanic or Latino/Latina but not all Hispanic/Latino/Latina people fell into the same racial category. The mean age of participants was 19.27 years (*SD* = 2.03; range = 18 to 31). Most participants were in their freshman year (55.8%).

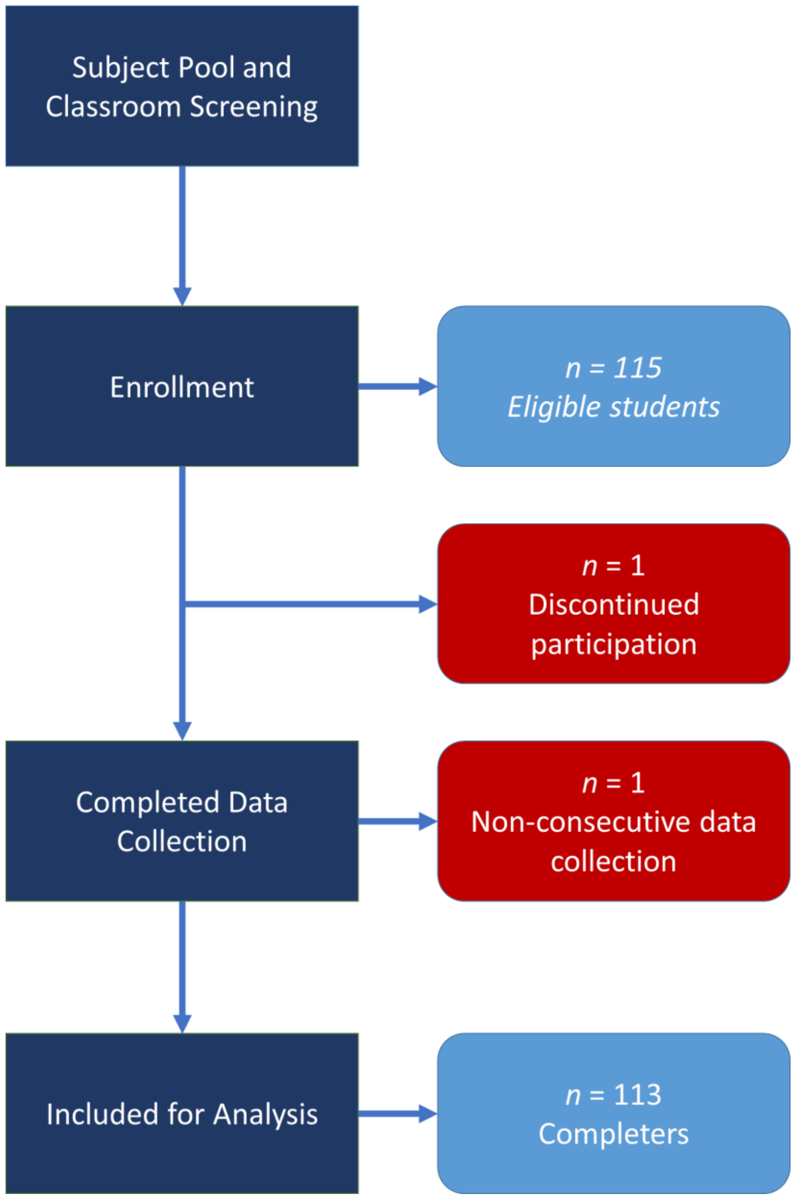

Figure 1 Participant flow. Flow of participants through each stage of the UDTracker study. Red blocks indicate participants not included in the final analyses.

Phases of Study

The Health and Wellness UDTracker app study was divided into three phases. *Phase I* (Baseline) was an in-person visit that included the consent procedures, completion of baseline measurements, and installation of the app with a tutorial on how to use it. *Phase II* (Data Collection Period) began the day after the baseline visit. The data collection period lasted 24 hours a day, or as long as the participants' phones were on, for a total of 14 days. *Phase III* (Termination) was an in-person visit scheduled as close to the last day of the data collection as possible. During the termination visit, students were asked to complete a written feedback form, while the researchers uninstalled the application. Participants were debriefed about the aims of the study and received an explanation of the hypothesized connections between passive and active data collection. The application was removed, and the phone was reconfigured to the previous functionalities.

Smartphones

Students with any manufacturer or model of Android smartphone were invited to participate in the study. Android, compared to Apple (iOS) platforms, allowed the application's developer more flexibility in developing the application and its functionality. While previous studies of smartphone applications have been constrained to a singular model of an Android device (Lane et al., 2014; Wang et al., 2014), our program is versatile and has been tested with a variety of Android smartphones and individualized settings. The most common model of smartphone used in the current study was the Samsung Galaxy S4 (27.4%), and almost all phones were owned by participants for two years or less (99.1%). See Table 1 for a total listing of phone models used in the study.

Table 1 Android Phone Models Used by Study Participants

Blu	LG- Volt
HTC- Droid DNA	Motorola- Droid HD Maxxx
HTC- Droid Incredible	Motorola- Droid Razr
HTC- Droid Incredible 2	Motorola- Moto X
HTC- One	MyTouch
HTC- One M7	MyTouch Slide
HTC- One M8	Samsung- Avant
HTC- One X	Samsung- Galaxy Light
HTC- Resound	Samsung- Galaxy Note 2
LG- Flex	Samsung- Galaxy Note 3
LG- G3	Samsung- Galaxy S2
LG- Lucid	Samsung- Galaxy S3
LG- Nexus 4	Samsung- Galaxy S4
LG- Nexus 5	Samsung- Galaxy S4 mini
LG- Optimus	Samsung- Galaxy S5
LG- Optimus 3	Samsung- Stratosphere
LG- Optimus F6	ZTE- Awe
LG- Optimus G	

UD Health and Wellness App "UDTracker"

The application (app) is designed to capture data entered by participants (active data), as well as data recorded passively through the smartphones automated functions (passive data). The active data collection included three separate surveys administered on the smartphone. The application is easy to access and navigate. Located under the

“Apps” feature on Android phones, the app has an icon-driven graphical user interface (GUI), which allows students to complete daily, sleep, or weekly surveys. The GUI also allows participants to access the passive data toggling features. The toggling feature enables students to turn off tracking of specific types of data collection (e.g., SMS, Call Recording, Sensors, Location) for specified intervals of time ranging from 15 minutes to six hours. The app consisted of three questionnaires, the *daily, sleep,* and *weekly questionnaires.* The current study included only data from the *daily questionnaire*. The *daily questionnaire* is 28-item measure assessing multiple domains of wellness (e.g., exercise, eating habits, social interaction, and mood). Questions were presented with radio buttons or slider style response formats. Students received a pop-up reminder on their smartphones at 8:00PM EST and were instructed to complete the survey as close to that time as possible. It should be noted that although students were prompted to complete the survey at 8:00 PM, they could complete the survey at any point within a given day. On average, participants completed 11 of 14 surveys, indicating a 78.57% compliance rate.

While participants could access the surveys manually through the GUI, a pop-up reminder feature allowed them to link directly into each type of survey. To navigate the surveys, participants are required to swipe from screen to screen, answering questions with radio button, slider, text box, and audio recording response formats. The app was equipped with an automatic updating system that allowed for real time bug repair.

Mental Health Variables

Depressive cognition and mood

The Beck Depression Inventory-II (BDI-II; Beck, Steer, & Brown 1996) is a widely used and validated 21-item self-report measure of the frequency and intensity of depression symptoms experienced over a two-week period. Individual items measure a variety of symptoms consistent with depression symptoms (e.g., mood, appetite, anhedonia) on a 0-4 scale. A subset of BDI-II items was used to assess daily depressive cognition (i.e., within the last 24 hours). The four items included relate to one's view of self and future (*self-criticism, pessimism, worthlessness,* and *self-dislike*). A composite score of this 4-item measure was calculated for each student on each of the 14 days.

Mood was assessed by the Positive and Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988), which measures a participant's identification with affect descriptors (e.g., enthusiastic, angry, excited). PANAS items were measured daily. Participants were asked to, "*Indicate to what extent you feel [insert mood] RIGHT NOW*." Responses were captured on a five-point scale (0 = *Not at all or very slightly,* 1 = *A little,* 2 = *Moderately,* 3 = *Quite a bit,* 4 = *Extremely*). Three positive ("happy", "enthusiastic", and "calm") and three negative ("nervous", "angry", and "sad") items were summed in their respective categories to create daily positive affect (PA) and daily negative affect (NA) composites. These composites were calculated for each of the 14 days for each student.

Psychological well-being

Three items from the 80-item Psychological Well-being Scale (PWB; Ryff, 1989; Ryff & Keyes 1995) were used to create a well-being variable. The full scale has been shown to have high internal consistency and test-retest reliability (Ryff, 1989). The three-item composite score included the participants' self-reported ability to handle situations in life (Environmental Mastery), sense of confidence/positive view of self (Self-acceptance), and a sense of direction or purpose (Purpose in Life) over the last 24 hours. Statements such as "*In the past 24 hours, I have felt that I can handle situations in my life*" were rated on a five-point scale from 0-*Strongly disagree* to 4-*Strongly agree*. Again, this variable was computed as a daily composite for each participant.

Rumination

The Rumination Responses Scale, short form (RRS-SF*;* Nolen-Hoeksema & Morrow, 1991) was used to assess overall depressive rumination (as distinct from more general rumination). The RRS-SF was collected at baseline. The RRS-SF contains 10-items that respondents rate on a four-point scale (1-*almost never*; 2-*sometimes*; 3-*often*; 4-*almost always*), indicating the degree to which they typically engage in cognitive reactions when they, "feel down, sad, or depressed." Total scores range from 10 to 40 with higher scores indicating greater rumination. Example items include: "*I think to myself, 'Why do I always react this way*?'" or "*I think about a recent situation, wishing it had gone better*." The RRS-SF consists of two subscales, *brooding* and *reflection. Brooding* is more strongly associated with depression. These subscales represent an individual's tendency to perseverate or be preoccupied versus reflect without complete immersion, respectively. The measure has been found to have good internal validity (α = .90; Treynor, Gonzalez, & Nolen-Hoeksema, 2003).

Social Interaction Variables

Social interaction variables include variables that were used for descriptive purposes and those that were included in the concurrent or lagged regression analyses.

Social interaction and perceived quality

Participants were asked to indicate the extent of social interaction on two items in the *daily questionnaire.* Items related to length of time interacting with others ("*How much time did you spend interacting with other people?*"; five-point scale, 0 = *None,* 1= *Less than 30 minutes,* 2 *= 30-60 minutes,* 3 *= 1-2 hours,* 4 = *More than 2 hours*) and whether those interactions were positive or negative (*"Overall, how positive or negative were these interactions with other people?";* seven-point scale, 0 = *Very negative* to 6 = *Very positive*). Given that a number of studies have indicated that young adults tend to spend at least two hours on social media a day (not including in-person interactions; Davila et al., 2012; GlobalWebIndex, 2017), responses to our variable of time spent with others were likely to be inflated and insensitive. Indeed, every day of the 14-day assessment period participants' modal responses indicated that they spent more than two hours with others. This response pattern, taken together with a robust literature on perceived quality of social interaction, led us to choose perceived quality of social interactions (PQSI) as the primary variable included in the analyses.

Electronic communication

Electronic communications were assessed passively each day. These data represent all electronic communication from 12:00AM-11:59PM within a given day. The electronic communication variable is measured in three ways: overall frequency (total number of texts, emails, or phone calls made), unique addresses to which communication was made (total number of unique phone numbers dialed/texted or email addresses emailed), and duration of phone calls (seconds). Each of these variables was captured for each individual for each day of the 14-day assessment. Although electronic communication was captured in three ways, overall frequency of electronic communication was the primary variable included in the analyses, as the duration variable is unique to phone calls and unique addresses contacted is not necessarily representative of how much someone may be communicating with others.

Social media applications

Data on social media application usage were collected continuously from installation at baseline and through the data collection period. Data collection concluded at the termination visit when the app was uninstalled. Data on the frequency and duration of social media application usage was time stamped (i.e., the application collected the time and date when social media apps were accessed). A variety of applications (n = 675) were used by our participants, however this study prioritized applications that are considered "social apps." Social apps are those designed to access social media sites/platforms and are not exclusively used for communication (i.e., texting or video-chat services such as WhatsApp or Skype). In 2016, applications were categorized into one of 27 different application types (e.g., social, communication, shopping, sports, transportation, entertainment, games), using app identification tags on the Google Play Store. This resulted in 39 independent "social applications" (see Table 2).

Table 2 Social Media Applications Accessed by Participants over a 14-day Assessment Period

Badoo	Seeking Arrangement
Couple- The App for Two	Shapegram (Instagram feature)
Date my school	Snapchat
DeviantArt	Swarm by Foursquare
Facebook	Tango
FireChat	Tapatalk
Followers+ for Instagram	Timehop (Facebook feature)
Get followers on Twitter	Tinder
Get likes on Instagram	Tumblr
Google +	Twitter
Hot or Not App	uMentioned
Instafollow (Instagram feature)	Unfollowers (Twitter/Instagram feature)
Instagram	Unseen- campus community
LinkedIn	Vine
MeetMe	We Heart It
OkCupid	Weibo
ooVoo	WeLove
Pinterest	Xiao Enai
Plenty of Fish	Yik Yak
QQ Messenger	

It is important to note that applications ranged from widely used social media platforms such as Twitter, Facebook, and Instagram, to less common and currently discontinued applications (e.g., Yik Yak). Further, “dating apps” were also classified by Google Play Store as social apps. While most applications were English-based, a subset of applications were Chinese (e.g., Weibo, QQ Messenger, Xiao Enai). Because the latter were classified as social media by Google Play, these apps were included in the current study. The social media variable was measured by both access frequency (the number of times a participant accessed the application on their phone) and duration, measured in minutes. The duration variable is more susceptible to measurement error, given that some phone models indicate that applications are being “used” even if running in the background of the phone instead of actively used. For this reason, the frequency variable was included in the analyses.

Chapter 3

RESULTS

Preliminary and Descriptive Analyses

Analyses included all 113 participants in the sample over the 14-day data collection period. An intercorrelation matrix and descriptive statistics for relevant variables are presented in Table 3. These longitudinal data were comprised of both within-person (i.e., repeated daily observations within a participant) and between-person (i.e., average levels of each variable over the 14-day period, across participants) observations. Two considerations are addressed here, given the longitudinal nature of the data and the use of a subset of items from the original full-length self-report measures (e.g., BDI-II). Second, while the reliability and validity of the measures selected for this study have been evaluated for the full measures, assuming reliability of a selected subsets of items from total measures and with altered time frames (i.e., “In the last 24 hours” vs. “Over the last two weeks”) can be problematic. To estimate reliability of longitudinal data of variables derived from full measures, methodologists recommend the use of the hierarchical omega coefficient (Cranford et al., 2006; Dunn, Baguley, & Brunsden, 2014). Omega was estimated for the daily self-report measures derived from full scales. These included the four-item depressive cognition (referred to as *daily DC*), three-item negative affect (*daily NA*), three-item positive affect (*daily PA*), and three-item psychological well-being (*daily PWB*) composites.

Table 3 Intercorrelations and Descriptive Statistics for Mental Health Variables and Social Interaction Variables Averaged over the 14-Day Data Collection

	1	2	3	4	5	6	7
1. Daily Depressive Cognition	---						
2. Daily Negative Affect	.60***	---					
3. Daily Positive Affect	-.44***	-.33***	---				
4. Daily Psychological Well-being	-.46***	.32**	.51***	---			
5. Daily Perceived Quality of Social Interactions	-.29**	.29**	.54***	.51***	---		
6. Electronic Communication	.07	.14	-.07	-.04	.02	---	
7. Social Media Use Frequency	.03	-.03	-.04	-.11	.09	.30**	---
M	0.98	1.43	5.72	7.48	4.65	39.88	16.81
Within-person *SD*	1.36	1.48	2.00	1.77	0.79	24.68	11.93
Between-person *SD*	1.29	1.26	1.65	2.24	0.72	36.10	16.57

Note. Mean (*M*) and standard deviation (*SD*) values reported for all variables across the 14-day data collection period. Both within- and between-level standard deviations are reported in the final two rows. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Reliabilities are reported at the within- (ω_w) and between- (ω_b) levels. Daily DC ($\omega_w = .85$, $p < .001$; $\omega_b = .92$, $p < .001$), PA ($\omega_w = .75$, $p < .001$; $\omega_b = .82$, $p < .001$), and PWB ($\omega_w = .90$, $p < .001$; $\omega_b = .95$, $p < .001$) all showed acceptable reliability, suggesting that responses to items for a specific composite variable tended to be answered similarly. Daily NA showed good reliability at the between level ($\omega_b = .83$, $p < .001$) but somewhat lower within-person reliability ($\omega_w = .66$, $p < .001$). An argument could be made to examine the NA items separately instead of using the composite with lower within-person reliability. However, this would increase the number of analyses being run and parameters estimated, which would reduce power for analyses with this relatively small sample. It could also potentially increase the probability of Type I errors. Therefore, the more parsimonious daily NA composite was included in the main analyses as a composite score.

Aim 1

Data analytic strategy

Correlational methods are commonly used to describe aggregate data across participants, whereas repeated measures data offer a more nuanced interpretation of the relationship between two variables for an individual across time. Given the goal of examining both within-person (repeated daily observations within a participant) and between-person (average levels of each variable over the 14-day period, across participants) levels of analysis in Aim 1, two types of analyses can be considered. The repeated measures correlation (rmcorr) or multilevel modeling (MLM) are recommended (Bakdash & Marusich, 2017). MLM allows for more sophisticated analyses than rmcorr alone. While both approaches can be used when the assumption of independent observations is violated, MLM more flexibly models both within- and between-individual variance, whereas rmcorr only considers intra-individual variance. Another advantage of the MLM approach is that it allows for the modeling of random or fixed slopes and intercepts (Bakdash & Marusich, 2017).

Because these data are multilevel, with observations nested within individuals, Aim 1 was addressed by conducting concurrent multilevel (i.e., hierarchical) correlational analyses. Analyses include within- and between-level correlations between the social interaction variables (perceived quality of social interactions, overall frequency of electronic communication, and frequency of social media use) and mental health variables (daily DC, NA, PA, and PWB scores), all of which were measured daily during the 14-day assessment period. Analyses were conducted in Mplus 7 (Muthén & Muthén, 1998-2012).

Results for Aim 1

When conducting longitudinal correlational analyses, methodologists recommend that researchers assess the percentage of the total variance of an outcome that may be due to mean differences between subjects or within subjects (Bolger & Laurenceau, 2013). To examine this, intraclass correlations (ICCs) were estimated. The ICCs for mental health variables tended to demonstrate greater within-person variability than between-person variability ($ICC_{daily\ DC} = .47$; $ICC_{daily\ NA} = .42$; $ICC_{daily\ PA} = .41$), with the exception of daily PWB ($ICC_{daily\ PWB} = .61$). ICCs for social interaction variables showed greater within-person variability on self-reported perceived quality of social interactions ($ICC_{PQSI} = .46$), whereas electronic communication and frequency of social media app usage showed greater between-person variability ($ICC_{totcomm} = .68$; $ICC_{socacc} = .66$, respectively). These results confirm the need for multilevel modeling, as the ICCs of all variables point to substantial dependency among observations.

The between- and within-level concurrent correlations over the 14-day period are presented in Table 4. Contrary to predictions, electronic communication and social media access were not correlated with mental health variables at the within- or between-levels, with the exception of a weak between-level correlation between electronic communication and daily NA (r = .214, p < .05). However, as predicted, PQSI had medium and large associations with mental health variables at the within- and between-levels in the expected directions. Specifically, more positive perceived social interactions were associated with lower daily DC and NA and higher daily PWB and PA at both the between- and within-levels. These within-person relationships suggest that *on a day* that a person rates interactions with others as more positive, they tend to also rate their mood as better (lower NA and higher PA), DC as lower (i.e., less depressive cognition endorsed), and well-being as higher on that same day. The between-person relationships suggest that on average, *people* who tend to rate PQSI as more positive across the 14 days also tend to rate their PWB and PA higher, while rating DC and NA lower during that same period.

Table 4 Concurrent Correlations for Mental Health Variables and Social Interaction Variables over 14-Day Data Collection Period

	PQSI	Electronic Communication	Social Media Use Frequency
Within-person correlation			
Daily DC	-.25***	-.02	.02
Daily NA	-.32***	.03	.01
Daily PA	.35***	.03	-.03
Daily PWB	.34***	-.02	.02
Between-person correlation			
Daily DC	-.29*	.12	-.05
Daily NA	-.27*	.21*	-.10
Daily PA	.60***	-.12	.08
Daily PWB	.51***	-.06	.05

Note. Daily DC = Daily depressive cognition, Daily NA = Daily negative affect, Daily PA = Daily positive Affect, Daily PWB = Daily psychological well-being, PQSI = Daily perceived quality of social interactions. *p < .05. **p < .01. ***p < .001.

Aim 2

Data analytic strategy

Aim 2 was designed to examine daily social interaction variables as predictors of next day mental health outcomes. To have a useful comparison between the predictive capabilities of our variables concurrently and the next day, we first evaluated whether social interaction variables predicted mental health variables on the same day using concurrent multilevel regression analyses prior to the cross-lagged regressions. Relationships between variables in concurrent regression analyses were predicted to mirror the hypotheses of Aim 1. Then, using methods similar to Kross et al. (2013), multilevel cross-lagged regression analyses were conducted. Social interaction variables were examined as predictors of next day mental health outcomes, and in secondary analyses, the lag was reversed and mental health outcomes were examined as predictors of social interaction variables. Within-level associations were of particular interest, as few studies have examined the relationship among these variables at the individual level. To put this in context, cross-lagged analyses examined the effect of a predictor on an outcome variable (e.g., daily frequency of social media use predicting next day PWB), using predictor data from one day (T) and outcome data from the next day (T+1) across the 14-day period. Second, the predictor and outcome variables were reversed to examine the effects of mental health variables on the next-day social interaction variables. In all cross-lagged analyses, time and same-day level of the (next-day) outcome variable were included as within-person covariates. All estimates in the current study are reported as unstandardized estimates. A graphical representation of this one-day cross-lag model is included in Figure 2. Level-1 predictors were group-mean-centered, and intercepts were allowed to vary.

Two outcome variables (daily DC and NA) had positively skewed distributions with a large proportion of zero scores and were therefore modeled using zero-inflated Poisson regression to account for these count distributions (Atkins, Baldwin, Zheng, Gallop, & Neighbors, 2013).

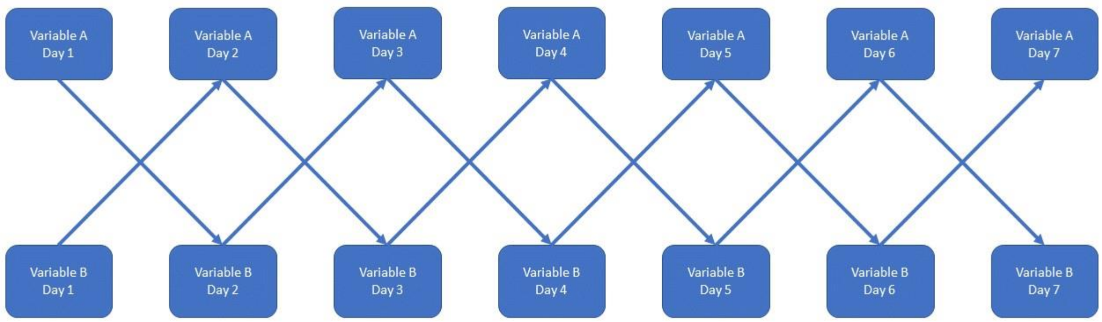

Figure 2 Example of cross-lagged analysis. The cross-lagged analyses are conducted with a predictor and outcome variable, which can be represented by either Variable A or B. For illustrative purposes, the figure above is an example of one week of data collection with lags across each day for a given participant. The current study included a 14-day assessment period. Analyses were conducted at the within- and between-levels.

Results for Aim 2

Prior to estimating directionality between mental health and social interaction variables, the concurrent (i.e., same-day) associations were examined including time as a covariate. Predictors were group-mean centered at the within-level. Twelve unidirectional regressions were conducted where mental health variables were regressed on same-day social interaction variables (see Table 5). Results suggest that PQSI was a strong predictor of all mental health variables (daily DC, NA, PA, and

PWB). Specifically, on a day when a participant perceives social interactions as more positive compared to what is typical for that person, they also report less depressive cognition and NA and more PA and PWB on that same day.

It is important to note that regression coefficients for zero-inflated outcomes and continuous outcomes are interpreted differently. Count regression coefficients are interpreted as the predicted percentage increase or decrease in an outcome variable using rate ratios, which are calculated through exponentiation of the estimate. Once the rate ratio is calculated, that value is subtracted from one, yielding an interpretable percentage of change. For example, examining the rate ratio for the effect of PQSI on DC ($\gamma = -.34$, $p < .001$, rate ratio = 0.71), indicates that a one unit increase (more positive) in PQSI predicts a 29% (1.00-0.71) lower daily DC score on the same day. Outcomes that are continuous (such as daily PWB or PA) are interpreted using the estimates themselves. For example, on a day where a participant has a one-unit increase in perceived social interactions compared to what is typical for them, they are predicted to report increased daily PA on that same day by 0.90 units ($\gamma = .90$, $p < .001$). Neither frequency of electronic communication nor social media usage were significant predictors of any of the same-day mental health outcome variables. A total of 12 bidirectional hierarchical cross-lagged regressions, three for each mental health outcome variable, were conducted. All predictors were group-mean centered at the within-person level. Predictors and outcomes were assessed for linear trends (i.e., linear increases or decreases in a given variable over the data collection period). Only one variable demonstrated a significant linear decrease, daily PA, suggesting that individuals tended to report less positive affect over the course of the 14-day data collection period ($\gamma = -.04$, $p = .008$). Daily DC and NA were, again, modeled using zero-inflated Poisson regression to treat these outcomes as count variables. Results of primary cross-lagged analyses (i.e., social interaction variables predicting mental health outcomes) are shown in Table 6, and secondary reverse lagged analyses (mental health variables predicting social interaction variable outcomes) are shown in Table 7.

Table 5 Hierarchical Regression Analyses of Concurrent Associations between Social Interaction Variables and Mental Health Outcomes

Effect	*n*	Estimate	SE	Est./SE	Rate Ratio[b]	*p*
Outcome: Daily Depressive Cognition[a]						
PQSI	113	-0.34***	0.07	-5.17	0.71	.000
Electronic communication	113	0.00	0.00	-0.16	1.00	.877
Social media use frequency	109	0.00	0.00	-0.27	1.00	.791
Outcome: Daily Negative Affect[a]						
PQSI	113	-0.35***	0.05	-6.51	0.70	.000
Electronic communication	113	0.00	0.00	0.40	1.00	.692
Social media use frequency	109	0.00	0.00	0.13	1.00	.895
Outcome: Daily Positive Affect						
PQSI	113	0.90***	0.09	10.12	-	.000
Electronic communication	113	0.00	0.00	0.83	-	.407
Social media use frequency	109	0.00	0.00	-1.07	-	.284
Outcome: Daily Psychological Well-being						
PQSI	113	0.76***	0.10	7.91	-	.000
Electronic communication	113	0.00	0.00	-0.23	-	.815
Social media use frequency	109	0.00	0.00	0.27	-	.784

Note. PQSI = Daily perceived quality of social interactions. Total *n* reported in table represents cluster size (i.e., number of participants included in the analysis) compared to total observations. Estimates are unstandardized. [a]Outcome variables examined with zero-inflated Poisson. [b]Estimates are exponentiated for interpretation as rate ratios. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 6 Hierarchical Cross-lagged Regression Analyses of Mental Health Outcomes on Next Day Social Interaction Variable Predictors (Main Analyses, within-person)

Effect	*n*	Estimate	SE	Est./SE	Rate Ratio[b]	*p*
Outcome: Daily Depressive Cognition[a]						
PQSI	113	-0.05	0.07	-0.73	0.95	.465
Electronic communication	113	0.00	0.00	-1.04	1.00	.297
Social media use frequency	109	0.01	0.01	0.85	1.01	.395
Outcome: Daily Negative Affect[a]						
PQSI	113	0.04	0.05	0.70	1.04	.483
Electronic communication	113	0.00	0.00	0.44	1.00	.430
Social media use frequency	109	0.00	0.06	-0.45	1.00	.656
Outcome: Daily Positive Affect						
PQSI	113	0.01	0.05	0.23	-	.818
Electronic communication	113	0.00	0.00	-0.21	-	.836
Social media use frequency	109	0.00	0.01	0.40	-	.692
Outcome: Daily Psychological Well-being						
PQSI	113	0.00	0.04	0.09	-	.932
Electronic communication	113	0.00	0.00	0.80	-	.421
Social media use frequency	109	0.00	0.01	-0.16	-	.871

Note. PQSI = Daily perceived quality of social interactions. Total *n* reported in table represents cluster size (i.e., number of participants included in the analysis) compared to total observations. Estimates are unstandardized. [a]Outcome variables examined with zero-inflated Poisson. [b]Estimates are exponentiated for interpretation as rate ratios. *p < .05. **p < .01. ***p < .001.

Table 7 Hierarchical Cross-lagged Regression Analyses of Social Interaction Variable Outcomes on Next Day Mental Health Predictors (Secondary Analyses, within-person)

Effect	*n*	Estimate	*SE*	*Est./SE*	*p*
Outcome: PQSI					
Daily DC	113	-0.04	0.02	-1.80	.072
Daily NA	113	-0.05*	0.02	-2.20	.028
Daily PA	113	0.03	0.02	1.70	.088
Daily PWB	113	0.05*	0.02	2.54	.011
Outcome: Electronic Communication					
Daily DC	113	-0.57	0.49	-1.17	.243
Daily NA	113	0.39	0.69	0.57	.570
Daily PA	113	0.13	0.48	0.27	.788
Daily PWB	113	-0.16	0.50	-0.33	.743
Outcome: Social Media Use Frequency					
Daily DC	109	-0.29	0.19	-1.56	.118
Daily NA	109	-0.12	0.25	-0.50	.617
Daily PA	109	0.05	0.17	0.31	.760
Daily PWB	109	0.36*	0.17	2.08	.037

Note. PQSI = Daily perceived quality of social interactions, Daily DC = Daily depressive cognition, Daily NA = Daily negative affect, Daily PA = Daily positive affect, Daily PWB = Daily psychological well-being. Total *n* reported in table represents cluster size (i.e., number of participants included in the analysis) compared to total observations. Estimates are unstandardized. *$p < .05$. **$p < .01$. ***$p < .001$.

Hypothesis 2a. PQSI was not a significant predictor of any hypothesized next-day mental health outcomes, including DC (γ = -.05, p = .465), NA (γ = .04, p = .483), PA (γ = -.08, p = .05), or PWB (γ = .01, p = .818). However, secondary reverse lagged analyses did yield significant findings (see Table 7). Daily NA and PWB were both significant predictors of next day perceived quality of social interactions (NA: γ = -.05, p = .028; PWB: γ = .05, p = .011) above and beyond the previous day's PQSI. This suggests that, on a day that an individual rates negative affect as higher or PWB as lower, compared to what is typical for them, that individual would report experiencing more negative social interactions the following day. Daily DC and PA were both only marginally significant predictors of next day PQSI (DC: γ = -.04, p = .072; PA: γ = .03, p = .088).

Hypothesis 2b. Contrary to our hypothesis, electronic communication was not a significant predictor of any next-day mental health outcomes. Similarly, none of the mental health variables were significant predictors of next-day electronic communication.

Hypothesis 2c. Social media use, measured by the frequency of accessing social media applications on one's smartphone, was not a significant predictor of any next-day mental health outcome variables. However, secondary analyses revealed that higher ratings of PWB did predict more next-day social media use (γ = .36, p = .037). Thus, on a day when an individual rated greater PWB than what is typical for them, it is expected that their social media use would increase the following day.

Aim 3

Data analytic strategy

Inspired by Davila and colleagues' (2012) examination of rumination and co-rumination as moderators of the relationship between social media use (and perception of interactions on social media) and depressive symptoms, this study extended this research by: 1) assessing whether the relationship between perceived quality of social interactions and depressive cognition or PWB is moderated by baseline rumination, and 2) whether the relationship between frequency of social media use and daily depressive cognition or well-being is moderated by baseline rumination. To assess moderation, multilevel regression modeling was used to estimate cross-level interactions, which occur when a between-level variable (rumination) moderates a within-level relationship (relationship between depressive cognition and social media use).

Results for Aim 3

Following the Davila and colleagues' (2012) analytic strategy, four multilevel regressions were conducted. For each regression, time and the two within-person predictor variables (perceived quality of daily interactions or daily social media use frequency) were entered as covariates at the within-level. Each model also included a cross-level interaction term representing moderation and two separate outcome variables (depressive cognition and well-being). Daily depressive cognition was modeled as zero-inflated Poisson and was treated as a count variable, which is interpreted using rate ratios.

Model 1- Daily DC and PQSI. As predicted, the relationship between PQSI and DC was moderated by baseline rumination (γ = .03, p = .001). Results suggest that for people with average levels of rumination (in sample, $M = 18.14$, $SD = 5.34$), on a day that they rate their social interactions as one unit more positive, they are predicted to have a 44% lower DC that same day ($\gamma = -.57$, $p < .001$, rate ratio = 0.580). However, for people who report baseline rumination as one unit *higher*, on a day that they rate their social interactions as one unit more positive, they are predicted to have a 42% lower DC that same day, compared to days on which they had average levels of social interaction.

To help contextualize these findings, the results were transformed to a standard deviation metric. As such, for people who report baseline rumination as one standard deviation higher than the sample average, on a day that they rate their social interactions as one unit more positive, they are predicted to have a 32% lower DC that same day. Conversely, individuals who rate their baseline rumination as one standard deviation lower than average, and who also rate social interaction as one unit more positively, are predicted to have 52% lower DC that same day. Said another way, when people ruminate more, positive social interactions may not be as helpful at buffering depressive cognition from day to day.

Model 2- Daily DC and social media use frequency. Contrary to our hypothesis, depressive cognition and social media use were not associated on a daily level, and rumination did not moderate this within-level relationship.

Model 3- Daily PWB and PQSI. There was support for the hypothesis that PWB and PQSI would relate to one another. The within-level association between PWB and PQSI was positive and significant at average levels of rumination ($\gamma = .77$, $p < .001$). However, this relationship was not moderated by baseline rumination ($\gamma = .01$,

p = .433). In other words, the positive relationship between PWB and PQSI did not significantly vary across different levels of baseline rumination.

Model 4- Daily PWB and social media use frequency. Contrary to our hypothesis, the relationship between PWB and social media use was not significant, and this relationship was not moderated by baseline rumination.

Chapter 4

DISCUSSION

Social media and electronic communication use are among the fastest growing tools that young adults use to interact with others. Given research highlighting the possible connection between these methods of communication and increased risk for perceived isolation (Primack, Shensa, Sidani, et al., 2017), loneliness (Holt-Lunstad, 2018), and suicide risk factors (Twenge et al., 2017), a deeper look at the relationship between the types of communication and mental health factors is warranted.

Overall, the findings about positive and negative contributions of social media use are mixed. Research has indicated that social media use is related to negative mood (Sagioglou & Geitemeyer, 2014), depression and anxiety (Lin et al., 2016; Pantic, 2014; Tromholt, 2016), reduced global well-being (Brooks, 2015; Satici & Uysal, 2015; Shakya & Christakis, 2017), and feelings of isolation (Primack, Shensa, Sidani et al., 2017). However, other research suggests benefits of social media usage, such as facilitating the development and maintenance of relationships (Ellison et al., 2007) and well-being (Valkenburg et al., 2006).

The goal of the current study was to extend the research on the relationships between social media and electronic communication use, perceived quality of social interactions, and mental health and psychological well-being. Unlike many previous studies, this study 1) included longitudinal data to examine temporal precedence of the social interaction variables relative to the mental health outcome variables and 2) examined both actively and passively collected data.

Overall, the results of the current study indicate that examining how often students communicate with smartphones or engage on social media may not be as robust a correlate of mental health variables as previous studies have suggested. An unexpected finding was that neither frequency of electronic communication (texts/emails/phone calls) nor the amount of times individuals accessed social media were correlated with any self-reported mental health or well-being variables on a given day for an individual or across participants. Similarly, hierarchical regressions and cross-lagged regressions revealed that the frequency of electronic and social media usage were poor predictors of same-day and next-day mental health and well-being outcomes.

Given that cross-sectional studies, highlighted earlier, indicate that there should be *some relationship* between these passively collected social interaction variables and self-reported mental health or well-being variables, it is surprising that we found no such associations in the current study. However, it is important to note that Davila and colleagues (2012) also found no associations between frequency of social media use and depressive symptoms on the same day or three weeks later. Perhaps our mental health variables were too broad to detect social media usage effects, and other measures might be more relevant, such as perceived isolation (Primack, Shensa, Sidani, et al., 2017), loneliness (Burke et al., 2010), and comparisons with others (Jan Anwwer Soomro, & Ahmad, 2017; Nesi & Prinstein, 2015).

Unlike the passively collected frequency of social interactions, the self-report measure of students' perceptions of the quality of their interactions was a moderate to strong correlate of mental health variables, both across within and across participants, as predicted. Students who reported having better quality interactions on a given day also tended to report higher positive mood and well-being and lower negative moods and depressive cognition. The same-day regression analyses showed the same pattern of findings. Given the extensive literature on positive relationships and perceived social support as protective factors against mental health problems (Santini et al., 2015), these findings are not surprising. However, it is interesting that neither electronic communication nor social media use were significant predictors of any of the mental health variables that same day. This may suggest that the sheer amount of contact that someone has with others is not what is associated with well-being, but rather it is the quality interactions (electronic or not) that may be more meaningful (Sagioglou & Geitemeyer, 2014).

We also examined whether social interaction variables predicted next day changes in mental health variables. While social interaction variables were hypothesized to predict mental health variables at the next day, none did. However, the reverse cross-lagged regressions (i.e., mental health variables predicting later social interaction variables revealed that both negative affect and well-being appeared to have a carry-over effects into the next day, even after accounting for the previous day's reported quality of social interactions. Specifically, when individuals experienced more negative affect or well-being on one day than what is typical for them, it may dampen or heighten their ability to enjoy social interactions, skew negative of positive their perceptions of the interactions, or actually influence the interactions.

One possible explanation of this carry-over effect of negative affect may be the "negative downward spiral" phenomenon, which is an accumulation of negative experiences that narrows one's thinking (potentially skewing thinking and attention towards negativity) and can impact one's ability to enjoy future experiences (Garland et al., 2010). Daily well-being had an opposite effect, where individuals who reported more well-being than was typical for them also reported more positive interactions with others the next day, and they engaged more frequently on social media. Because positive relations with others is a key component of Ryff and Keyes's (1995) six-factor model of psychological well-being, it is possible that more reported well-being might also be associated with and predict higher perceived quality of interactions with others. The well-being carry-over effect might also reflect the "upward spiral" phenomenon (Fredrickson, 2001), which unlike the downward spiral, reflects when positive emotions foster adaptive and broadening scopes of attention and cognition and expand one's behavioral and coping repertoires. This, in turn, feeds back to perpetuate positive emotion, which over time contributes to the building of personal resources, such as a positive view of self and relationships, adaptive coping, and healthy lifestyle behaviors. This broadening and building of personal resources is viewed as a gateway for building resilience to negative emotions and life events, as well as increasing overall life satisfaction and well-being (Fredrickson, 2001).

It was also interesting that well-being on one day predicted more engagement with social media on the next day. Although it cannot be assumed from the results of this study, students might be seeking to capitalize or maintain these positive gains by interacting on social media (Sagioglou & Geitemeyer's, 2014). Consistent with this idea, previous research has suggested that receiving feedback online can help to promote well-being and continue to consolidate existing social relations (Valkenburg et al., 2006).

The final aim of the current study was to examine the potential moderating effects of a known correlate of depression, rumination, on the relationship between social interaction variables and mental health variables. It was hypothesized that baseline rumination (between-level predictor) would moderate the relationship between social media use/social interaction quality and depressive cognition/PWB (within-person outcome). Consistent with findings of Davila and colleagues (2012), we found that rumination did moderate the relationship between daily depressive cognition and perceived social interaction quality, such that individuals with a tendency to perseverate on negative information (possibly related to social interactions) appeared unable to benefit from positive social interactions and reported more depressive cognition compared to their low ruminator counterparts. Additionally, the relationship between well-being and perceived quality of relationships was significant at all levels of rumination. The current study examined these relationships over a longer period of observation than in the Davila et al. study, which further suggests that rumination is an important factor in how relationships are perceived.

Taken together, the results of this study highlight the importance of perceptions of one's relationships with others might be a more useful predictor of mental health outcomes than overall frequencies of social media and electronic communication, which has been the focus of much of the previous research. However, it will be important to investigate in a broader context how students experience social interactions (on and off of these types of media).

Strengths and Limitations

This study had a number of strengths: unique data collection methods, the inclusion of a wide range and number of social applications, good completion rate of daily collected measures, and the measurement of mental health/well-being factors and a variety of social interaction variables across time. Further, these data were examined at the typical aggregate group level but also, and more importantly, at the individual level. This allows for interpretations not only about the hypothesized population, but also how individuals may behave on a given day within that population. Investigating social interaction and mental health variables at the within-person level is also critical to the development of the UDTracker application as a potential individualized intervention tool.

The collection of both passive and active data was a strength, particularly for the electronic communication and social media usage. Although previous research suggests that self-reported social media use is often comparable to observed activity on social media sites (Scharkow, 2016), passively collected information helps to reduce participant-based bias in reporting electronic communication or social media use. Another strength of the monitoring application itself was its flexibility to run on any Android device, where previous research has been limited by a need to control the type of phone used by participants (Lane et al., 2014).

Despite these strengths, a number of limitations in the current study are important to consider. Although a strength of the study was to include any type of Android smartphone, a phone's technology and ability to capture and transmit data may vary from phone to phone. We attempted to ameliorate the effects of measurement error by selecting variables likely resistant to phone-specific factors, such as electronic communication and social interaction frequency, but fully understanding how phone-specific effects may influence results is a complicated endeavor and outside the scope of the current project. In order to take advantage of all aspects of the passive data collection, training periods are common to establish standardizations for these variables among a variety of phones, or “training data” (Lane et al., 2014; Lu et al., 2010; Ravi, Dandekar, Mysore, & Littman, 2005). This allows researchers to assess whether collected or lost data are related to phone functionalities.

Another limitation was the selection of self-report items. Although the items showed good internal consistency (omega coefficient), the four-item BDI composites used to asses depressive cognition (*self-criticism*, *pessimism*, *worthlessness*, and *self-dislike*) did not include all symptoms of depression. A potential solution to this would be to include full BDI, but this also increases participant burden. We were most interested in the depressive thoughts that could come up day-to-day, rather than the full constellation of symptoms of depression, which are usually assessed over a two-week period.

The self-reported perceived quality of social interactions item could have been more specific. As written, it is not clear whether this refers to in-person interactions, online/electronic interactions with others, or both. However, there is a benefit in collecting information about all types of interactions. Future research may consider distinguishing perceptions of in-person vs. electronic interactions, as research has suggested that connectedness from offline relationships differs from connectedness on Facebook relationships (Grieve et al., 2013).

A clear strength of this study is the inclusion of a wide range of social media applications. However, a potential limitation in including this number of social media platforms is that we do not have information on how our participants used those applications, and whether the types of apps included are relevant to mental health and psychological well-being. For example, although Facebook and the OkCupid dating site are both considered social media applications, the experiences on the platforms can be vastly different, with different expectations from its users. Thus, collapsing across such a range of apps could obscure the unique contributions of individualized social media apps and even weaken the associations between the social media variables and mental health outcomes.

While selection of our participants was purposefully broad to increase ecological validity, sample characteristics could be another limitation. Most participants reported relatively low daily depressive cognition and negative affect and higher psychological well-being and positive affect, which can make it difficult to detect effects. Perhaps with more diversity of negative symptoms, the findings would differ at the extreme ends of the psychological health spectrum.

Finally, it is important that studies on social media usage consider the changes in social media platforms from year to year. For instance, when Facebook began in 2004, this service was used to connect individuals with others using content created by those individuals. Today, Facebook is an amalgam of advertising, personal stories, news, content from other websites, sales, and information sharing. It is important to consider that how an individual interacts with a given social media platform may drastically change over the years, we have to consider what applications like Vine, Snapchat, and Facebook looked like in 2014, not 2018.

Future Directions

This study suggest several exciting directions for future research.

Adding context

The literature on electronic communication and social media use suggests that even broad use of these modalities is associated both positive and negative effects. While those findings were not replicated in the current study, it stands to reason that understanding the context in which social media or electronic communication use occurs is important. For example, an important contextual factor and mediator of the relationship between social media use and mood can be the perceived meaningfulness of online interactions (Sagioglou & Geitemeyer, 2014). The UDTracker App is uniquely designed so that it could be modified to capture other contextual factors, such as daily events that may directly impact mood or well-being. As part of a weekly questionnaire, students were asked to reflect on the best and worst event that occurred over the last week. These responses were collected through brief narratives or audio recordings. Modifying these items to occur daily and with more specificity around social media interactions may yield a more contextually rich picture of daily events that impact mental health and well-being.

Another suggestion to deepen context in future research is to expand the use of passively collected data. Other authors have already suggested the use of "sensing data" such as GPS, WiFi, accelerometer, proximity to others, size of social network, and others as potential proxies for behavioral data (Eagle, Pentland, & Lazer, 2009; Harari et al., 2017, Lane et al., 2014), which can fit into the current framework of the UDTracker App.

The current study was limited in its ability to contextualize how social media was used by participants. Other studies have sought to close this gap by assessing language used on social media sites (Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017; Luhmann, 2017), or broader activity on Facebook or Twitter, such as posts, comments, and hashtag use (Burke et al., 2010; Lee, Efstratiou, & Bai, 2016). Continuing to explore sentiment analysis (i.e., how individuals express themselves on social media) and logging activity on social media are useful passive tools to consider linking with self-report measures.

Examining other factors related to mental health

The current study examined measures of mental health and psychological well-being. Other indirect constructs that could be collected passively (i.e., not using self-report) could also be useful. For example, social media use might be associated with other factors such as sleep, activity level, or other known correlates of mental health issues. Some literature has suggested that individuals who engage in higher social media use were at greater risk for disturbed sleep (Levenson, Shensa, Sidani, Colditz, & Primack, 2016). Another study showed that social network platforms can be beneficial for improving physical activity and continued adherence to increased activity over several months (Althoff, Jindal, & Leskovec, 2017). Both sleep and activity level have been examined using passively collected data (Althoff et al., 2017; Lane et al., 2014) and could continue to be modified and assessed concomitantly with mental health variables.

Functionality of social behavior on social media

Examining other mediators and moderators of social media use and mental health and well-being is essential to continue to contextualize the relationship between these variables. Future studies should examine promising constructs among social media users, including social comparison and feedback-seeking behaviors as they relate to self-esteem (Jan et al., 2017) and depression (Nesi & Prinstein, 2015). Nesi and Prinstein (2015) note that social comparison with other adolescents and seeking interpersonal feedback are a strong predictors of concurrently reported depression, regardless of the frequency of technology use (cell phones, Facebook, or Instagram). Another construct that seems putatively linked to social media use is loneliness/connectedness, which has also been shown to be linked to well-being (Grieve et al., 2013). Currently there are few studies that examine the size and quality of an individual's social network to estimate how connected an individual may be. Existing studies tend to prioritize physical proximity to others and communication between network individuals to approximate how close a given relationship might be (Eagle et al., 2009).

More experimental manipulation

The current study examined temporal precedence of social interaction and mental health variables over a 14-day assessment period. However, directionality is only one component suggesting a potential causal relationship. Experimental manipulation or careful contextual analysis, as mentioned above, could more precisely examine the impact of a person's social media usage on mood and mental health factors. There have been a few attempts at manipulating the social media experience (Kramer et al., 2014), time spent on social media (Sagioglou & Geitemeyer, 2014), or feedback received on one's personal profile on a social media platform (Valkenburg at el., 2006). Combined with sensing data, future studies could examine the daily impact of naturally occurring positive and negative experiences on and offline. Alternatively, using longitudinal data and an ABAB designed study with the conditions (A) using social media and (B) restricting social media use could be a useful manipulation to see how time on and away from social media impacts mental health and well-being.

Conclusion

The present study aimed to improve the understanding of the relationship between social media and other forms of electronic communication, perceived quality of interpersonal relationships, and mental health variables such as depressive cognition, psychological well-being, and momentary affect. Previous research has been mixed on the beneficial and detrimental effects of social media use and electronic communications, but most of these studies were limited by cross-sectional designs and self-reported measures of social interaction variables. The current study extends this literature by examining the aforementioned relationships longitudinally and with passively collected social media use and electronic communication data. Neither the frequency of social media use nor electronic communications was significantly associated with daily DC, NA, PA, or PWB. Further, these variables did not predict same-day or next-day mental health variables. What was interesting is that how individuals perceive their daily global social interactions (positively or negatively) was a strong correlate and predictor of same-day and next-day mental health variables within an individual. In addition, another cognitive variable, rumination, moderated the relationship between perceived quality of interactions and self-reported depressive cognition. Overall, these findings support the idea that the quality of interactions, online or otherwise, may be a more sensitive correlate and predictor of mental health and psychological well-being than the number of times social media or other forms of electronic communication were used. As such, continued development of this application and future research should strive to contextualize how and when social media and electronic communication are used and an individual’s perceptions of those experiences.

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Appendix

INSTITUTIONAL REVIEW BOARD APPROVAL LETTER

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE: April 24, 2014

TO: Adele Hayes, Ph. D.
FROM: University of Delaware IRB

STUDY TITLE: [375698-4] Daily cognitive, emotional, and behavioral patterns of undergraduates: A smartphone feasibility study

SUBMISSION TYPE: Amendment/Modification

** Amendment Request to reopen the feasibility study to run an additional 100 subjects*

ACTION: APPROVED
APPROVAL DATE: April 24, 2014
EXPIRATION DATE: January 15, 2015
REVIEW TYPE: Full Committee Review

Thank you for your submission of Amendment/Modification materials for this research study. The University of Delaware IRB has APPROVED your submission. This approval is based on an appropriate risk/benefit ratio and a study design wherein the risks have been minimized. All research must be conducted in accordance with this approved submission.

This submission has received Full Committee Review based on the applicable federal regulation.

Please remember that informed consent is a process beginning with a description of the study and insurance of participant understanding followed by a signed consent form. Informed consent must continue throughout the study via a dialogue between the researcher and research participant. Federal regulations require each participant receive a copy of the signed consent document.

Please note that any revision to previously approved materials must be approved by this office prior to initiation. Please use the appropriate revision forms for this procedure.

All SERIOUS and UNEXPECTED adverse events must be reported to this office. Please use the appropriate adverse event forms for this procedure. All sponsor reporting requirements should also be followed.

Please report all NON-COMPLIANCE issues or COMPLAINTS regarding this study to this office.

Please note that all research records must be retained for a minimum of three years.

Based on the risks, this project requires Continuing Review by this office on an annual basis. Please use the appropriate renewal forms for this procedure.

If you have any questions, please contact Nicole Farnese-McFarlane at (302) 831-1119 or nicolefm@udel.edu. Please include your study title and reference number in all correspondence with this office.