AN EXAMINATION OF POTENTIAL MEDIATORS AND MODERATORS OF THE RELATIONSHIP BETWEEN SOCIAL MEDIA USE AND DEPRESSION SYMPTOMS

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BETWEEN SOCIAL MEDIA USE AND DEPRESSION

SYMPTOMS

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Title of Study: AN EXAMINATION OF POTENTIAL MEDIATORS AND MODERATORS OF THE RELATIONSHIP BETWEEN SOCIAL MEDIA USE AND DEPRESSION SYMPTOMS

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Abstract: Rates of depressive episodes are highest among emerging adults (aged 18-25) and the incidence of a major depressive episode has increased by 46%, 122%, 59%, and 39% for individuals aged 18-19, 20-21, 22-23, and 24-25, respectively, from 2009 to 2017 (Twenge, 2019). Because the rates of depression have been increasing over the same period as increases in the use of social media, social media has been implicated as a potential contributor to depression among emerging adults. Prior research has demonstrated an association between social media (SM) use and depression, but fewer studies examine the relationships between specific SM platforms despite potential differences in how these platforms affect mental health. The current study collected usage data for two SM platforms – Instagram and Twitter – directly from participants' smartphones and collected self-reported depression symptoms. Self-report measures of potential mediators and moderators of the relationship between SM and depression symptoms (social comparison, pessimism, negative SM experiences, and negative mood following SM use) were also administered. Participants also engaged in a manipulation and were assigned to one of four groups, either using Twitter for 5 minutes or 30 minutes or using Instagram for 5 minutes or 30 minutes. Results revealed no direct associations between Instagram use or Twitter use and depressive symptoms. However, there was a significant indirect effect of Instagram use on depressive symptoms through social comparison as well as a significant indirect effect of Twitter use on depressive symptoms through pessimism. Unexpectedly, 5 minutes of in-lab Instagram use resulted in lower social comparison scores. There were no significant findings regarding state angry mood, state sad mood, and state pessimism before and after Twitter use. The current study was the first to compare Instagram and Twitter use with our unique methodology. Our results suggest that increased Twitter use may be associated with increased depressive symptoms through increased pessimism, whereas Instagram may be associated with increased depressive symptoms through increased social comparison. Results emphasize the importance of examining social media platforms separately and investigating potential mediators of social media use and mental health symptoms.

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CHAPTER I

INTRODUCTION

Depression and Social Media

Depression is a common, recurrent disorder with 17.3 million U.S. adults experiencing at least one major depressive episode, and 11 million U.S. adults experiencing severe impairment due to a major depressive episode, at some point in their lifetime (NIMH, 2017). According to the most recent data, rates of depressive episodes are highest among emerging adults (aged 18-25) with 13.1% reporting a depressive episode (NIMH, 2017). Further, recent research suggests that the incidence of a major depressive episodes has increased exponentially in emerging adults from 2009 to 2017 (Twenge, 2019). Given the prevalence and seriousness of depression in emerging adults, it is important to identify potential causes and maintaining factors for these problems.

Although there are many possible explanations for the increases in depression among emerging adults, because rates of depression have increased over the same period as in increases in the use of social media (especially among emerging adults), social media has been implicated as a potential contributor (e.g. Twenge et al., 2019). Emerging adults are the most avid users of social media with 88% of emerging adults using some type of social media (SM; Pew Research Center, 2018). Among social media sites, Instagram and Twitter are frequently used by emerging adults and their use has been associated with depression (Pew Research Center, 21018; Twenge et al., 2019).

Thus far, meta-analyses have demonstrated a general association between increased SM use and increased symptoms of depression. Such studies revealed a small, but positive relationship (*r*s = .10 – .165) between SM use and self-reported depressive symptoms (Vahedi & Zannella, 2019; Yoon et al., 2019). However, these meta-analyses combined all social media applications and websites into a single overarching construct. Doing so assumes that all social media have similar effects on users and obscures potential differences between platforms. As such, it would be more valuable to examine the effects of specific social media platforms to better understand their unique contributions to mental health.

Although there is a general dearth of research that have examined the relationship between specific SM platforms (i.e. Instagram and Twitter) and depression, a few studies have found associations between Instagram use and depression both with cross-sectional (Sherlock & Wagstaff, 2018; Lup et al., 2015) and longitudinal data (Frisson & Eggermont, 2017). We are aware of only one study that has specifically examined the relationship between Twitter use and depression, which found that individuals experiencing depression were almost twice as likely to use Twitter over other SM sites such as Instagram and Facebook (Jeri-Yabar et al., 2019). This emerging research has found an association between social media use and depression but it is not yet clear *why* there is such a relationship. Thus, there is a need to examine the potential moderators and mediators of social media use and depression.

Negative SM Experiences

Recent research indicates that the quality of experiences on SM also has consequences for depressive symptoms. Specifically, a recent meta-analysis revealed that the frequency of negative experiences on SM moderated the relationship between SM and severity of depression such that, the frequency of SM use had a stronger association with depression when participants reported higher instances of negative SM experiences, but the relationship was weaker when participants reported lower instances of negative SM experiences (Vahedi & Zannella, 2019). These results suggest that the quality of interactions and experiences on SM sites may moderate the relationship between the amount of time spent using an SM site and depression symptoms.

Social Comparison

Upward social comparison involves the natural inclination to compare the self to other individuals who are higher in status. SM provides a rich stream of information about individuals that the user is "following" and against whom the user could compare themselves. Although upward social comparison can be adaptive by allowing the individual to self-motivate, this process can also become maladaptive by creating an attentional bias to more successful individuals which encourages more negative self-talk (Blease, 2015). While also detrimental in the "real world", social comparison is especially pernicious in online settings due to the meticulous nature of user self-presentation.

Social comparison has primarily been examined as a mediator between Instagram use and depression due to the highly visual nature of Instagram. A recent study found that social comparison demonstrated partially mediated the relationship between Instagram use and depressive symptoms in a sample of young adult women (Sherlock & Wagstaff, 2018). Although limited, research suggests that social comparison potentially plays a role in the relationship between Instagram use and depression.

Twitter, State Mood, and Pessimism

Although research regarding Twitter and depression is limited, there is some evidence to suggest that exposure to negative news through the app may lead to negative mood states. News information is spread widely throughout Twitter and is generally able to permeate deeply through Twitter networks, thus allowing for widespread coverage of news events (Lerman & Ghosh, 2010), and it has been noted that Twitter displays the most negatively-worded news in comparison to other SM sites (Pew Research Center, 2015).

In general, exposure to negative news stories often results in sad mood (Johnston & Davey, 2011; Pfua et al., 2006). Exposure to negative news stories on Twitter, specifically, results in increased anger (Park, 2016). Reactivity of sad and angry mood has been implicated in depression and depression vulnerability (e.g., Ellis et al., 2013; van Rijsbergen et al., 2013). Furthermore, exposure to negative news increases feelings of pessimism (McNaughton-Cassill, 2001). Given the existing research on state negative mood, pessimism, and depression (Johnston & Davey, 2011; Pfua et al., 2006; Park, 2016; Ellis et al., 2013; van Rijsbergen et al., 2013) sad and/or angry mood and pessimism may mediate the relationship between Twitter use and depression.

The Current Study

In summary, emerging research has demonstrated an association between Instagram use and depression (Frison & Eggermont, 2017; Lup et al., 2015; Sherlock & Wagstaff, 2018) and between depression and Twitter use (Jeri-Yabar et al., 2019). In addition, factors such as social comparison, pessimism, negative SM experiences, and state mood may mediate or moderate these relationships (Sherlock & Wagstaff, 2018; Vahedi & Zannella, 2019; McNaughton-Cassill, 2001). Given these findings, we evaluated the following hypotheses in a sample of emerging adults:

SM Use and Depression Symptoms

H1: Increased Instagram use would be associated with increased symptoms of depression.

H2: Increased Twitter use would be associated with increased symptoms of depression.

Mediators and Moderators of SM Use and Depression Symptoms

H3: Social comparison would mediate the relationship between Instagram use and depression symptoms with more Instagram use associated with increased upward social comparison, which would be associated with increased symptoms of depression. Social comparison has not been evaluated in the context of Twitter, so no specific hypothesis was made for social comparison and Twitter.

H4: Given the past research linking negative news and pessimism (McNaughton-Cassill, 2001) and Twitter and negative news (Park, 2016), it was hypothesized that pessimism about the world would mediate the relationship between Twitter use and symptoms of depression with more Twitter use associated with increased pessimism, which would be associated with increased symptoms of depression. There is less evidence for a potential relationship between Instagram and pessimism, so no specific hypothesis was made regarding their relationship.

CHAPTER II

METHODOLOGY

Participants

As part of a larger, preregistered, ongoing lab study we recruited participants who were 18 years of age or older from the Oklahoma State University psychology student participant pool. Participants who indicated on prescreening that they use Instagram, Twitter, or both, were invited to participate. This larger study is recruiting participants until the longitudinal phase of the study (not reported here) reaches 200 participants with complete data. Data from 595 participants were available for the current study. An a priori power analysis (G*Power; Faul et al., 2009), using an effect size of $r = .11$ for the relationship between SM use and depression symptoms (Vahedi & Zannella, 2019) indicated that 286 participants would be needed to detect an effect of this size with a power of .8 and an alpha of .05. Thus, we were overpowered to detect our main effects.

Materials

Patient Health Questionnaire – 9 (PHQ-9): The PHQ-9 (Kroenke et al., 2001) is a 9-item self-report measure that is a depression-specific module from the Patient Health Questionnaire (PHQ). Each item on the PHQ-9 was designed to align with its respective core symptom of depression according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV). Participants are asked to rate each item by the frequency of which they are experiencing the item in the past two weeks. The PHQ-9 has demonstrated with test-retest reliability of .84 (Kroenke et al., 2001). The internal consistency (Cronbach's α) was .86 in the current study.

Social Comparative Evaluation Scale (SCES): The SCES was modified from the Iowa-Netherlands Comparison Orientation Scale (INCOM; Gibbons & Buunk, 1999). The frequency subscale evaluates the frequency with which the participant compares themselves to others. Examples of items on this measure include: "I compare my social life with others' social lives" and "I check my social media to see what others are doing in their everyday lives". The frequency subscale is scored on a scale of 0 to 4 with 0 being "never", 1 being "once per week or less", 2 being "several times per week", 3 being "nearly every day", and 4 being "multiple times per day". The severity subscale assesses the degree to which participants engage in negative social comparison. Examples of severity items include: "Other people have better lives than me" and "Other people have more accomplishments than me" with response options from 0 (disagree strongly) to 4 (agree strongly). In line with prior literature, (e.g. Yoon et al., 2019) frequency of social comparison was used in the primary analyses and severity of social comparison was examined in the exploratory analyses. The internal consistency of the frequency subscale was .85 and the severity subscale was .87.

The Pessimism Scale (PS): The PS was created specifically for this study to evaluate negative perceptions of the world and other people. The PS includes 18 items and is scored from 1 (strongly disagree) to 5 (strongly agree). Examples of items measuring world pessimism include: “At times, the future seems unclear to me” and “Things in the world are getting worse.” Examples of items measuring pessimism about others include: “People are mostly selfish and unkind” and “People will exploit your emotions to hurt you” (See Appendix for the full measure). In line with current literature, “pessimism about the state of the world” was used in the primary statistical analyses and the other subscales (pessimism about other people) was examined in exploratory analyses. The internal consistency of the world pessimism subscale was .78, the people pessimism subscale was .70, and the internal consistency for the entire scale was .82.

Negative Social Media Experiences: Negative experiences on SM was measured via a visual analogue scale ranging from 0 being “0% of experiences are negative in nature” and 100 being “100% of experiences are negative in nature”. The question presents as follows: “Thinking about your social media usage generally, what percentage of your social media experiences are NEGATIVE?”.

Demographic Data: Participants reported age, gender, race/ethnicity, and sexual orientation. Rather than asking participants to provide labels regarding their sexual orientation (heterosexual, gay, etc.) participants were asked to indicate their romantic and/or sexual attraction to women and men.

Social Media Usage Data

The overwhelming majority of emerging adults with access to the internet use their SM accounts through mobile smartphones (Villanti et al., 2017). Smartphones often record a substantial amount of information about the owner of the phone including the amount of time and percentage of battery the user spends on each application. This feature on smartphones offers an objective way to measure SM use rather than relying on self-report.

In order to collect objective measures of social media use, participants were asked to allow the research assistant to collect “usage times and percentages” from the “Settings” application in the participants’ phones. In total, we collected four measures of SM usage per social media application (Twitter and Instagram): time spent on the application in the last 24 hours, time spent on the application for the past 7 or 10 days, percentage of battery life spent on the application in the last 24 hours, and percentage of battery life spent on the application over the past 7 or 10 days. Prior to iOS 12.0 iPhones recorded time and battery life spent on applications over the prior 7 days. After the release of iOS 12.0 on September 17th, 2018, iPhones recorded time and battery life over the prior 10 days. All units of time collected were converted into minutes in order to standardize the measurements. Time spent from the past 7 or 10 days were averaged by the number of days in order to create a measure of “average daily usage” for each application. Although four measures of SM application use were collected from participants’ phones, average daily usage was used as the primary independent variable measuring participants’ SM use. All other measures of application use were evaluated in exploratory analyses.

SM Manipulation

During the SM manipulation, participants were assigned to one of four groups, either using Twitter for 5 minutes or 30 minutes or using Instagram for 5 minutes or 30 minutes. A randomization schedule was created using the “RAND()” randomization feature in Microsoft Excel. The randomized list was then used by the researchers to manually assign participants identification numbers as they attended the research sessions. The SM manipulation occurred between the first and second survey (see “Procedure” below for a detailed description of the entire study). When the SM manipulation occurred, participants are told to “use the application in their normal manner” and not to exit the application. The researcher then set a timer for five or thirty minutes and monitored the participant periodically to ensure that they participant did not exit the application. For the group that was assigned to a five-minute condition, they completed a word search as a filler task during the remaining 25 minutes in order to control for time spent in the lab, cognitive effort, etc. between conditions.

Procedure

Participants who indicated on the SONA pre-screener that they use Instagram or Twitter “once or twice” per week or more frequently were invited to participate in the study. All data collection took place in 023 and 024 North Murray on the Oklahoma State University – Stillwater campus. Upon arrival, all participants completed informed consent procedures. Participants were seated at a computer in the laboratory and completed questionnaires through Qualtrics.

After completion of questionnaires, a research assistant collected social media application usage data from the "Settings" feature of the participant's cell phone. Twitter and Instagram use were collected as noted above.

Following the collection of social media data, each participant was assigned to the SM manipulation condition according to the randomization schedule. Participants then used their assigned SM application for their assigned length of time. Immediately following the SM use manipulation, participants completed Profile of Mood States/Positive and Negative Affect Schedule (POMS/PANAS), the Pessimism Scale (PS), and the Social Comparative Evaluation Scale (SCES). After completing the study, participants were debriefed and were given a list of local psychological resources as well as the contact information for the two principle investigators.

Analytic Plan

We used zero order correlations to test hypotheses 1 and 2 (that increased Instagram and Twitter use, respectively, would be associated with depressive symptoms). To test the hypotheses regarding mediation (3 and 4) and moderation (5a and 5b), we used bias-corrected bootstrapping, which involves resampling with replacement from the original sample, with 5000 resamples using the SPSS PROCESS macro (Hayes, 2012). In order to bootstrap an indirect effect, an approximation of the sampling distribution of the product of the *a* and *b* paths is generated from the resampling with replacement which is then used to calculate *ab**, which is the indirect effect of the single resample. Significance is determined based on the absence of zero in the confidence interval which is generated by sorting the resamples from low to high (in this case, 5000) and more accurate confidence intervals are derived from bias-correction.

To evaluate the acute effects of Instagram on social comparison (hypothesis 6) and Twitter on state sad mood, state angry mood, and pessimism (hypotheses 7a, 7b, and 7c, respectively), we used a 2 (Condition: 30-minutes or 5-minutes) X 2 (Time: Pre, Post) repeated measures ANOVA. We used t-tests to examine significant interaction effects.

CHAPTER III

FINDINGS

Descriptive Statistics

Five hundred and ninety-five participants from a large, Midwestern university completed the study. Participants had a mean age of 19.08 (*SD* = 1.23) and the sample was 76.3% female, 23.4% male, and .2% transgender. Participants were primarily Caucasian (77.5%), and 6.8% of the sample were Native American or Alaskan Native, 6.6% of the sample were Black or African American, 4.4% identified with multiple races, 1.7% of the sample were Asian, and < 1% of the sample identified as Native Hawaiian or other Pacific Islander. Additionally, 11% of the sample identified as being Hispanic. In the sample, 95% of women reported being “only or primarily attracted to men”, 2.1% of women reported being “only or primarily attracted to women”, and 2.9% of women reported being “equally attracted to men and women”. In men, 90.7% reported being “only or primarily attracted to women”, 7.1% reported being “only or primarily attracted to men”, and 2.2% reported being “equally attracted to men and women”.

Hypothesized Results

Instagram use was not significantly associated with depressive symptoms (*p* = .67). Twitter use was also not significantly associated with depressive symptoms (*p* = .92). See Table 1 for correlations between all primary study variables.

Table 1. Means, standard deviations, and correlations between variables.

Measure	1.	2.	3.	4.	5.	6.	7.	8.
1. Instagram	-							
2. Twitter	.007	-						
3. Neg. Exp.	-.053	.003	-					
4. PHQ-9	**-.018**	**-.004**	$.257^{***}$	-				
5. SCES	$.087^{*}$	-.082	$.335^{***}$	$.206^{***}$	-			
6. World PS	-.061	$.104^{*}$	$.236^{***}$	$.308^{***}$	$.091^{*}$	-		
7. Sad Mood	.000	-.023	$.142^{**}$	$.506^{***}$	$.106^{**}$	$.165^{***}$	-	
8. Angry Mood	.031	-.050	$.012^{**}$	$.207^{***}$	.080	$.113^{**}$	$.556^{***}$	-
Mean	37.90	20.41	26.37	5.80	9.37	14.05	.98	.92
SD	24.39	22.30	17.35	5.00	4.46	3.16	1.88	1.75

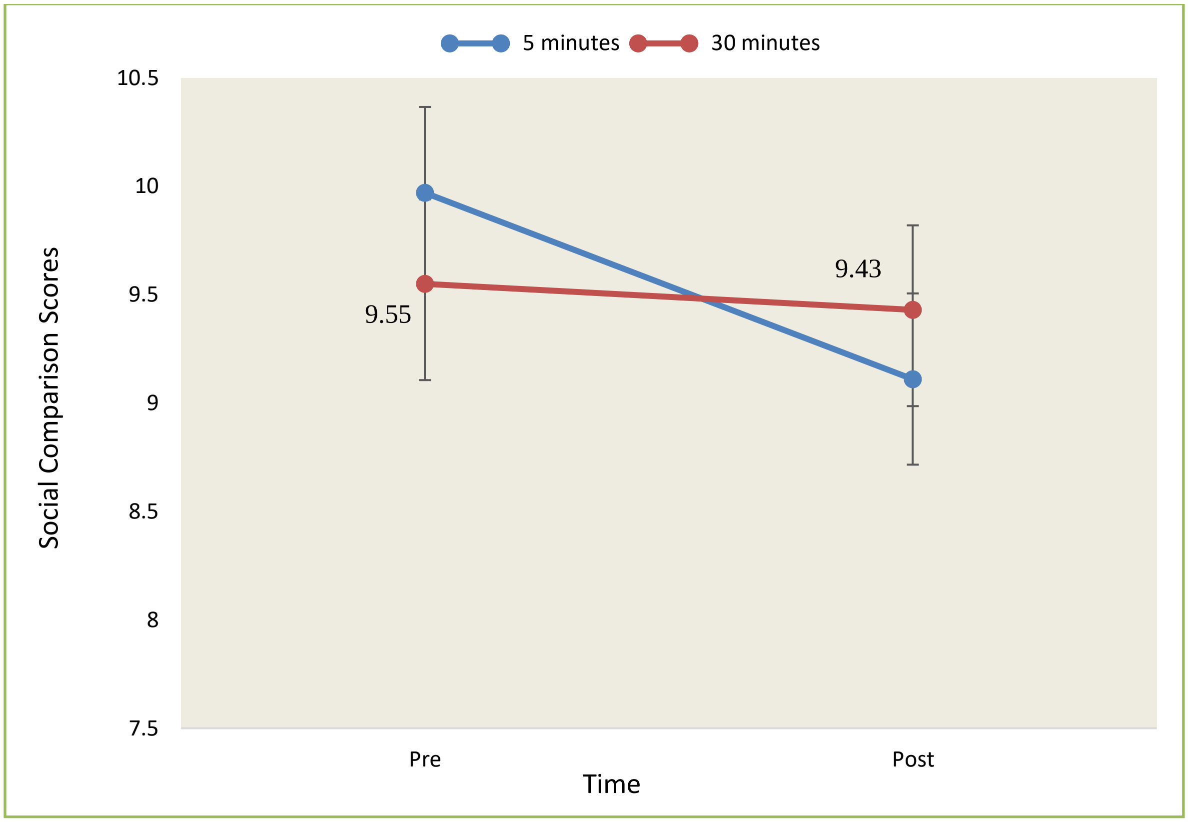
Note. $^{***} = p < .001$; $^{**} = p < .01$; $^{*} = p < .05$; Instagram = Average Instagram Usage; Twitter = Average Twitter Usage; Neg. Exp. = Negative Social Media Experiences; PHQ-9 = depressive symptoms; SCES = Social Comparison Frequency subscale; World PS = Pessimism Scale World Pessimism subscale; sad mood = POMS State sad mood items; angry mood= POMS State angry mood items. Hypothesized relationships are in **bold**.

Bootstrap analysis revealed a significant indirect effect of Instagram use on depressive symptoms through social comparison as indicated by the absence of zero in the confidence interval (β = .005, *95%CI* = .0002, .0093).). Specifically, higher rates of

Instagram use were associated with more frequent social comparison which was associated with higher depressive symptoms. Similarly, there was a significant indirect effect of Twitter use on depressive symptoms through pessimism about the world as indicated by the absence of zero in the confidence interval (β = .007, *95%CI* = .0014, .0133). Specifically, higher rates of Twitter use were associated with increased world pessimism which was associated with increased depressive symptoms. However, negative SM experiences did not moderate the relationship between Instagram and depressive symptoms (M = .0002, SE = .0005, t = .33, p = .75, *95%CI*[-.0009, .0012]) or the relationship between Twitter and depressive symptoms (M = .0002, SE = .0005, t = .42, p = .68, *95%CI*[-.0008, .0012]).

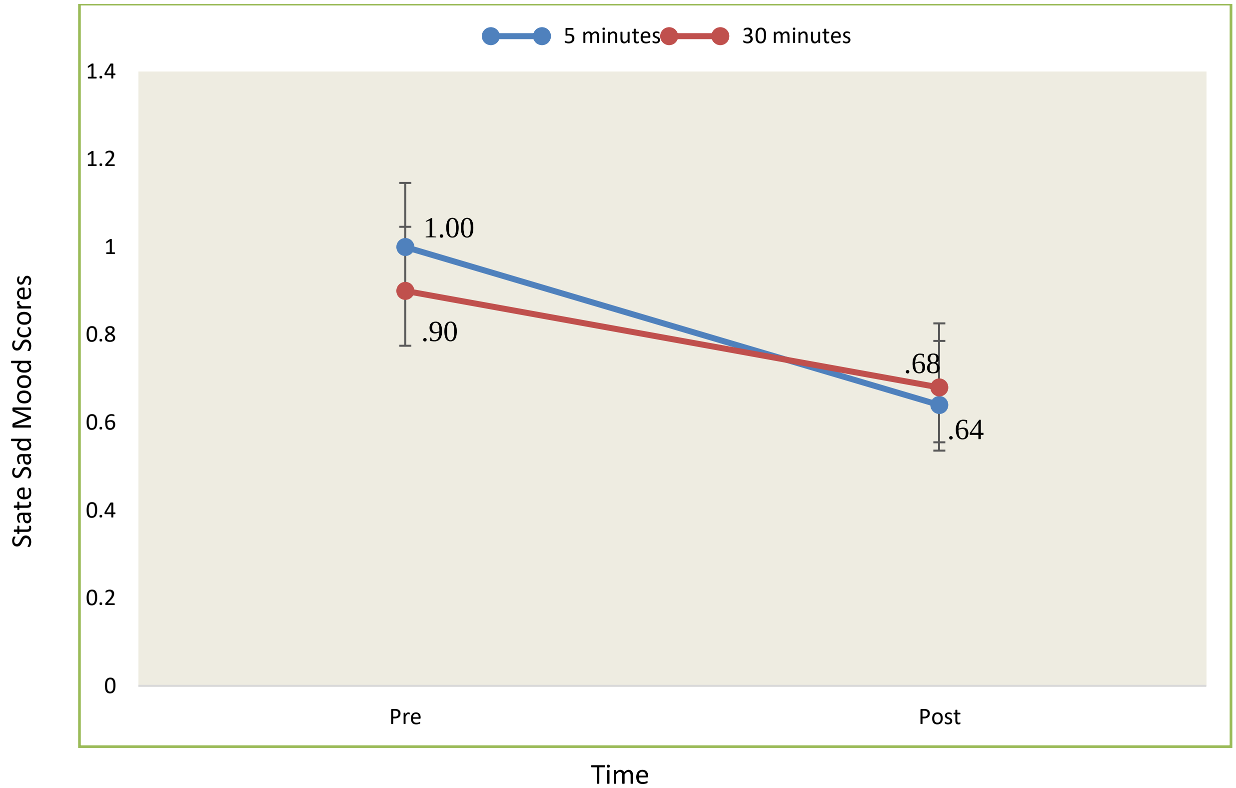
There was a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Instagram* use on *social comparison*, $F(1, 288) = 7.11$, $p = .008$, $\eta^2 = .024$. See Figure 1. There was not a significant main effect for condition, $F(1, 288) = .01$, $p = .92$, $\eta^2 = .000$. However, there was a significant main effect for time, $F(1, 288) = 12.49$, $p < .001$, $\eta^2 = .042$, with higher social comparison scores pre-SM manipulation (M = 9.76) compared to post-SM manipulation (M = 9.27). Contrary to our hypothesis, the interaction effect was driven by a significant decrease in social comparison scores in the 5-minutes condition from pre (M = 9.97) to post (M = 9.11). Follow-up paired samples t tests revealed that the difference between pre and post social comparison scores for the 5-minutes condition was significant $t(139) = 4.183$, $p < .001$, Cohen's d = .18. However, there was no significant change in social comparison scores from pre (M = 9.55) to post (M = 9.43) Instagram exposure in the 30-minute condition, $t(149) = .643$, $p = .521$, Cohen's d = .02.

Figure 1. Graphical representation of changes in social comparison between Instagram exposure conditions from pre- to post-exposure.



There was a non-significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Twitter* use on state *sad mood* scores, $F(1, 295) = 1.35$, $p = .25$, $\eta^2 = .005$. See Figure 2. There was also a non-significant main effect for condition, $F(1, 295) = .00$, $p = .99$, $\eta^2 = .000$. However, there was a significant main effect for time, $F(1, 295) = 14.61$, $p < .001$, $\eta^2 = .050$. Contrary to our hypothesis, the main effect for time was driven by a significant decrease in state sad mood scores from pre ($M = .95$) to post ($M = .64$).

Figure 2. Graphical representation of changes in state sad mood between the condition (5-minutes versus 30-minutes) and time points (Pre versus Post usage).

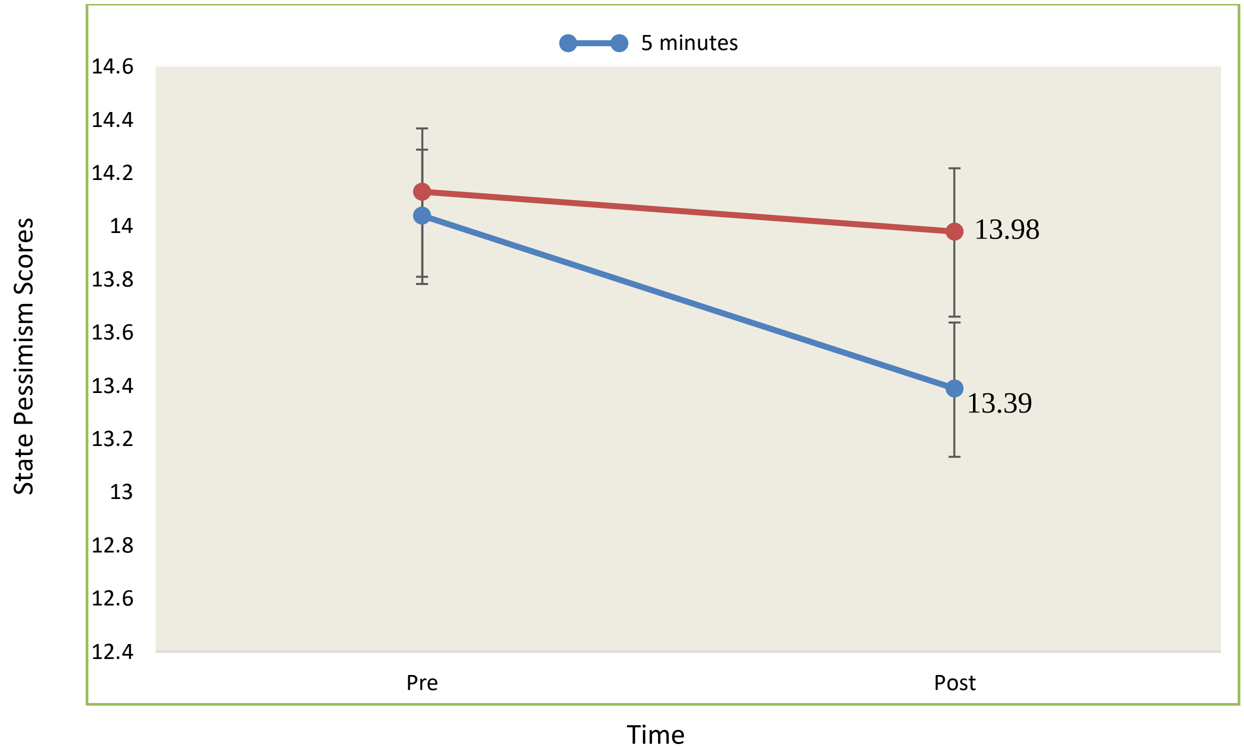


There was a non-significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Twitter* use on state *angry mood* scores, $F(1, 295) = 1.45$, $p = .23$, $\eta^2 = .010$. See Figure 3. There was also a non-significant main effect for condition, $F(1, 295) = .13$, $p = .72$, $\eta^2 = .000$. Additionally, there was non-significant main effect for time, $F(1, 295) = 1.61$, $p = .21$, $\eta^2 = .010$.

Figure 3. Graphical representation of changes in state angry mood between the condition (5-minutes versus 30-minutes) and time points (Pre versus Post usage).

There was a non-significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Twitter* use on *state pessimism* scores $F(1, 295) = .02$, $p = .88$, $\eta^2 = .000$. See Figure 4. There was also a non-significant main effect for condition, $F(1, 295) = .04$, $p = .84$, $\eta^2 = .000$. Additionally, there was non-significant main effect for time, $F(1, 295) = 1.30$, $p = .25$, $\eta^2 = .004$.

Figure 4. Graphical representation of changes in state pessimism between the condition (5-minutes versus 30-minutes) and time points (Pre versus Post usage).



Exploratory Analyses

Gender Differences

Examining gender differences in social media usage is important because previous literature has indicated that there may be differences in the types of interactions and activities that users engage in based on gender, and the effects from social media might differ based on gender (Corea et al., 2010).

Correlations

A Fisher r-to-z transformation did not indicate a significant difference between women (r = -.043, p = .378) and men (r = .033, p = .713) in the association between Instagram and depressive symptoms, z = -.075, p = .453. Similarly, there was no significant difference between women (r = .055, p = .261) and men (r = -.080, p = .373) in the association between Twitter and depressive symptoms, z = 1.31, p = .190. In addition, all other associations where the difference between the r values between men and women were greater than .1 were evaluated and the only significant difference between women (r = .550, p < .000) and men (r = .334, p < .000) was the relationship was between depressive symptoms and state sad mood, z = 2.75, p = .006.

Mediation and moderation

In contrast to the analysis including both women and men, bootstrap analysis did not reveal a significant indirect effect of Instagram use on depressive symptoms through social comparison for women or men when examined separately.

Consistent with the primary analyses, when women and men were evaluated separately, there was a significant indirect effect of Twitter use on depressive symptoms through world pessimism in women (β = .013, *95%CI* = .0053, .0217). However, the effect was not significant for the men in the sample.

Consistent with primary analyses, for women, negative SM experiences did not moderate the either relationship between Instagram (p = .55) or Twitter (p = .13) use and depressive symptoms. Similarly, for men, negative SM experiences did not moderate the relationship between Instagram use and depressive symptoms (p = .85). However, in men, in contrast to primary analyses, negative SM experiences *did* significantly moderate the relationship between Twitter use and depressive symptoms (M = -.0017, SE = .0008, t = -2.20, p = .03, *95%CI*[-.0032, -.0002]) such that, as individuals reported lower instances of negative experiences on SM, the relationship between Twitter use and depressive symptoms decreased.

Effects of acute Instagram and Twitter use

For women, there was a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Instagram* use on *social comparison*, $F(1, 218)$ = 10.37, p = .01, η^2 = .045. However, there was not a significant main effect for time, p = .114, nor for condition, p = .976. The interaction effect was driven by a significant decrease in social comparison scores in the 5-minutes condition from pre (M = 10.23) to post (M = 9.44). Follow-up paired samples t tests revealed that the difference between pre (M = 10.23) and post (M = 9.44) social comparison scores for the 5-minutes condition was significant $t(107)$ = 3.073, p = .003, Cohen's d = .17. There was a non-significant change in social comparison scores from pre (M = 9.72) to post (M = 9.99) Instagram exposure in the 30-minute condition, p = .196. Each of these results is consistent with the primary analyses. For men, in contrast to the primary analyses, there was not a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction, p = .70 or main effect for condition, p = .880. However, there was a significant main effect for time, $F(1, 67)$ =

26.80, $p < .001$, $\eta^2 = .285$, that was driven by a significant decrease in social comparison scores from pre ($M = 9.05$) to post ($M = 7.90$).

For women, there was not a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Twitter* use on *state sad mood*, $p = .31$ or main effect of condition, $p = .731$. There was a significant main effect for time $F(1, 226) = 16.34$, $p < .001$, $\eta^2 = .067$, that was driven by a significant decrease in state sad mood scores from pre ($M = .989$) to post ($M = .620$). These results are consistent with our primary results that revealed the interaction and main effect for condition were not significant, but the main effect for time was significant. For men, there was not a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction, $p = .70$, main effect for time, $p = .49$, nor main effect for condition, $p = .44$. These results are somewhat consistent with the primary results with the exception of the main effect for time.

For women, there was a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Twitter* use on *state angry mood*, $F(1, 226) = 4.429$, $p = .04$, $\eta^2 = .020$. There was not a significant main effect for time $p = .316$, nor for condition, $p = .572$. The interaction effect was driven by an increase in state angry mood scores in the 30-minutes condition from pre ($M = .72$) to post ($M = 1.05$). Follow-up paired samples t tests revealed that the difference between pre ($M = .85$) and post ($M = .74$) state angry mood scores for the 5-minutes condition was not significant, $p = .381$; however, there was a trend-level change from pre ($M = .72$) to post ($M = 1.05$) Twitter exposure in the 30-minute condition, $t(97) = -1.946$, $p = .055$, Cohen's $d = -.23$. These results are in contrast to our primary results which revealed a non-significant interaction effect, main effect for time and condition. For men, consistent with our primary results, there was not a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of Twitter use on state angry mood, p = .33, main effect for time, p = .33, nor main effect for condition, p = .89.

For women, there was not significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of *Twitter* use on *state pessimism*, p = .38,, main effect for condition, p = .651, nor main effect for time, p = .144. For men, there was also not a significant interaction for the effects of Twitter use on state pessimism, p = .33, main effect for time, p = .33, nor main effect for condition, p = .89. Both of these results are consistent with our primary analyses. See Table 2 for gender differences of the primary results.

Table 2. Gender differences in the primary analyses.

	Female	Male
1. Instagram depression correlation	**Non**	**Non**
2. Twitter depression correlation	**Non**	**Non**
3. Indirect effect of Instagram on depression through social comparison	Non	Non
4. Indirect effect of Twitter on depression through pessimism	**Significant**	Non
5. Interaction effect of Instagram use and negative SM experiences on depression	Non	Non

6. Interaction effect of Twitter use and negative SM experiences on depression	**Non**	Significant
7. Condition x time (Instagram & social comparison)	**Significant**	Non
8. Condition x time (Twitter & state sad mood)	**Non**	**Non**
9. Condition x time (Twitter & state angry mood)	Significant	**Non**
10. Condition x time (Twitter & state pessimism)	**Non**	**Non**

Note: bolded items indicate results that are consistent with primary results.

Effects of Anxiety

Including anxiety as a covariate allows for the examination of the relationships between Instagram or Twitter usage and depressive symptoms, pessimism, social comparison, and other variables while controlling for the unique variance of anxiety. Depression and anxiety are highly comorbid (Aina & Susman, 2006) and there is the possibility of anxiety contributing additional variance to the various models examining depressive symptoms. Additionally, examining anxiety as an outcome variable in place of depression will allow us to determine if our non-significant analyses with depressive symptoms are relevant to anxiety. Previous research has established a relationship between SM use and dispositional anxiety and higher probability for anxiety disorders (Vannucci et al., 2017).

Anxiety as a covariate

Anxiety symptoms (as measured by the GAD-7) or state anxious mood, were entered as a covariate in all analyses that had significant results with depression symptoms or state sad mood, respectively, in the primary analyses.

When GAD-7 was entered a covariate in the indirect effects model of *Instagram* use on depressive symptoms through *social comparison*, the indirect effect was no longer statistically significant as indicated by the presence of zero in the confidence interval (β = -.0005, *95%CI*[-.0021, .0011]).

When GAD-7 was entered a covariate in the indirect effects model of *Twitter* use on depressive symptoms through *world pessimism*, the indirect effect remained significant as indicated by the absence of zero in the confidence interval (β = .0019, *95%CI*[.0002, .0045]).

Anxiety as an outcome variable

Anxiety symptoms (as measured by the GAD-7) or state anxious mood, were entered as an outcome variable in all analyses that had non-significant results with depression symptoms or state sad mood, respectively, in the primary analyses.

Zero-order correlations indicated that Instagram use (r = -.61, p = .15) and Twitter use (r = -.03, p = .52) were not significantly associated with anxiety. This is consistent with the primary analyses that revealed non-significant associations between depressive symptoms and Instagram and Twitter use.

Consistent with primary analyses, there was a significant indirect effect of Instagram use on anxiety through social comparison as indicated by the absence of zero in the confidence interval (β = .0069, *95%CI*[.0003, .0141]). There was also a significant indirect effect of Twitter use on anxiety through world pessimism as indicated by the absence of zero in the confidence interval (β = .0081, *95%CI*[.00019, .0149]). Both indirect effects are consistent with our primary analyses regarding depressive symptoms.

Consistent with primary analyses, results revealed a non-significant interaction of *Instagram* use and negative SM experiences on anxiety as indicated by the presence of zero in the confidence interval (M = .0005, SE = .0005, t = .85, p = .75, *95%CI*[-.0006, .0015]). Also consistent with primary analyses, there was a non-significant interaction of *Twitter* use and negative SM experiences on anxiety as indicated by the presence of zero in the confidence interval (M = .0000, SE = .0005, t = -.036, p = .97, *95%CI*[-.0011, .0010]).

In contrast to results regarding Instagram and social comparison, results revealed a non-significant Condition x time interaction of *Instagram* use and state anxiety, $F(1, 289) = .68$, $p = .41$, $\eta^2 = .002$. Additionally, results revealed that the main effect for condition was not significant, $F(1, 289) = .61$, $p = .44$, $\eta^2 = .002$. The main effect for time was significant, $F(1, 289) = 121.40$, $p < .001$, $\eta^2 = .296$. State anxiety scores before the SM manipulation were significantly higher (M = 3.10) than after the SM manipulation (M = 1.68).

Consistent with the results for Twitter and state mood, results revealed a non-significant Condition x time interaction of *Twitter* use and state anxiety, $F(1, 295) = .15$, $p = .70$, $\eta^2 = .000$. Additionally, results revealed that the main effect for condition was not significant, $F(1, 295) = .39$, $p = .53$, $\eta^2 = .001$. The main effect for time was significant, $F(1, 295) = 99.30$, $p < .001$, $\eta^2 = .252$. State anxiety scores before the SM manipulation were significantly higher ($M = 2.90$) than after the SM manipulation ($M = 1.59$). Follow-up paired samples t-tests revealed that the difference between pre ($M = 3.00$) and post ($M = 1.65$) state anxiety scores for the 5-minutes condition was significant ($M = 1.35$, $SD = 2.21$, $p < .001$, Cohen's $d = .51$) and that the difference between the pre ($M = 2.78$) and post ($M = 1.53$) state anxiety scores for the 30-minutes condition was also significant ($M = 1.25$, $SD = 2.26$, $p < .001$, Cohen's $d = .51$).

Social Comparison Severity

In line with previous research (e.g. Yoon et al., 2019), the primary hypothesized analyses above used social comparison *frequency*. However, we also wanted to explore the analyses further using the social comparison *severity* subscale. In contrast to the primary results, there was no significant indirect effect of Instagram use on depressive symptoms through social comparison *severity* as indicated by the presence of zero in the confidence interval ($\beta = -.035$, *95%CI*[-.0111, .0042]).

In contrast to our primary results, the condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of Instagram use on social comparison *severity* scores was not statistically significant, $F(1, 289) = 2.487$, $p = .12$, $\eta^2 = .009$. There were non-significant main effects for condition, $F(1, 289) = .161$, $p = .69$, $\eta^2 = .001$ and time, $F(1, 295) = .323$, $p = .57$, $\eta^2 = .001$.

Other Pessimism Subscales

Similar to the Social Comparative Evaluation Scale, the Pessimism Scale (PS) splits into subscales. The Pessimism Scale splits into a subscale that measures pessimism about the *world* and pessimism regarding other *people.* Previous research (e.g. Lerman & Ghosh, 2010; Pew Research Center, 2015; Johnston & Davey, 2011; Pfua et al., 2006; Park, 2016) guided the decision for world pessimism to be included in the primary analyses however, it is important to examine other types of pessimism in relation to Twitter use and depressive symptoms. In contrast to the primary results, there was no significant indirect effect of Twitter use on depressive symptoms through pessimism about *people* as indicated by the presence of zero in the confidence interval ($\beta = -.0031$, *95%CI*[-.0091, .0021]).

In contrast to our primary results, there was a significant condition (30 minutes, 5 minutes) x time (pre, post) interaction for the effects of Twitter use on pessimism about *people* scores $F(1, 295) = 4.110$, $p = .04$, $\eta^2 = .014$. The main effects for condition, $F(1, 289) = .221$, $p = .64$, $\eta^2 = .001$ and for time, $F(1, 295) = 3.184$, $p = .08$, $\eta^2 = .011$, were not statistically significant. The interaction effect was driven by a significant increase in pessimism about people scores in the 5-minutes condition from pre ($M = 12.91$) to post ($M = 13.93$) and in the 30-minutes condition from pre ($M = 12.95$) to post ($M = 13.98$). Follow-up paired samples t tests revealed that the difference between pre ($M = 12.91$) and post ($M = 13.93$) pessimism about people scores for the 5-minutes condition was significant $t(163) = -4.470$, $p < .001$, Cohen's $d = --.33$. There was a significant increase in pessimism about people scores from pre ($M = 12.95$) to post ($M = 13.98$) Twitter exposure in the 30-minutes condition, $t(132) = -3.990$, $p < .001$, Cohen's $d = -.31$.

Other Metrics of SM Use

As mentioned previously, (see "Social Media Usage Data", pg. 10 and 11), in total, we collected four measures of SM usage per social media application (Twitter and Instagram): time spent on the application in the last 24 hours, percentage of battery life spent on the application in the last 24 hours, and percentage of battery life spent on the application over the past 7 or 10 days. Because of discrepancies in the number of days that data was collected per different software updates, time spent from the past 7 or 10 days were averaged by the number of days in order to create a measure of "average daily usage" for each application. For the primary analyses, "average daily usage" was used. However, the other metrics of SM use give different information about participants' usage and are important to examine. In order to examine the other metrics of SM use, hypotheses 1, 2, 3, 4, 5a, and 5b were tested with the other three metrics of SM use.

In contrast to the primary results, percentage of battery life spent on Instagram in the last 24 hours ($p = .003$) and percentage of battery life spent on Instagram over the past 7 or 10 days ($p = .004$) were significantly associated with depressive symptoms. All other correlations with the other metrics of Instagram and Twitter use were not significantly different from the primary results. For all correlations, see Table 3 (see Appendix, page: 81).

Consistent with primary analyses, bootstrap analysis revealed a significant indirect effect of time spent on Instagram in the past 24 hours on depressive symptoms through social comparison as indicated by the absence of zero in the confidence interval (β = .002, *95%CI* = .0001, .0060). In contrast to primary analyses, there was not a significant indirect effect of percentage of battery life spent on Instagram in the past 24 hours on depressive symptoms through social comparison as indicated by the presence of zero in the confidence interval (β = .002, *95%CI* = -.0090, .0130) nor for the percentage of battery life spent on Instagram in the past 7 or 10 days on depressive symptoms through social comparison (β = -.002, *95%CI* = -.0136, .0112).

Consistent with primary analyses, bootstrap analysis revealed a significant indirect effect of each metric of Twitter use (time spent on Twitter in the past 24 hours, percentage of battery life spent on Twitter in the past 24 hours, and percentage of battery life spent on Twitter in the past 7 or 10 days) on depressive symptoms through world pessimism as indicated by the absence of zero in the confidence interval (β = .060, *95%CI* = .0015, .0112; β = .027, *95%CI* = .0066, .0482; β = .025, *95%CI* = .0080, .0463, respectively).

Consistent with primary analyses, bootstrap analysis revealed no significant interactions between each metric of Instagram use (time spent on Instagram in the past 24 hours, percentage of battery life spent on Instagram in the past 24 hours, and percentage of battery life spent on Instagram in the past 7 or 10 days) and negative SM experiences on depressive symptoms as indicated by the presence of zero in the confidence interval (*M* = -.0001, *SE* = .0003, *t* = -.26, *p* = .79, *95%CI*[-.0007, .0005]; *M* = -.0001, *SE* = .0012,

t = -.12, p = .90, *95%CI*[-.0026, .0023]; M = -.0005, SE = .0014, t = -.36, p = .72, *95%CI*[-.0033, .0023], respectively).

Consistent with primary analyses, bootstrap analysis revealed a no significant interactions between each metric of Twitter use (time spent on Instagram in the past 24 hours, percentage of battery life spent on Instagram in the past 24 hours, and percentage of battery life spent on Instagram in the past 7 or 10 days) and negative SM experiences on depressive symptoms as indicated by the presence of zero in the confidence interval (M = .0001, SE = .0004, t = .24, p = .81, *95%CI*[-.0007, .0009]; M = .0000, SE = .0016, t = .01, p = .99, *95%CI*[-.0031, .0031]; M = .0020, SE = .0016, t = 1.30, p = .19, *95%CI*[-.0010, .0051], respectively).

CHAPTER IV

CONCLUSION

The current study evaluated the relationship between two social media platforms, Instagram and Twitter, and depressive symptoms. In contrast to prior work that has found a relationship between social media use and depression (e.g., Yoon et al., 2019; Vahedi & Zannella, 2019, Sherlock & Wagstaff, 2018), most hypotheses of the current study were not supported. See Table 4. Notably, we did not find a significant direct relationship between Instagram use and depression symptoms or Twitter use and depression symptoms. However, we did find evidence of indirect effects of Instagram and Twitter use on depressive symptoms. Specifically, there was an indirect effect of Instagram use on depressive symptoms through social comparison and Twitter use on depressive symptoms through pessimism. In addition, there was a significant condition by time interaction for the effects of Instagram use on social comparison; however, in opposition to our hypothesis, the interaction effect was driven by a significant *decrease* in social comparison scores in the 5-minutes condition from pre-exposure to post-exposure.

Exploratory analyses revealed potential avenues for additional work. Study results are discussed in more detail below.

Table 4. Primary hypotheses.

Hypothesis	Supported? (Yes/No)
H1: Association between increased Instagram use and increased depressive symptoms.	No
H2: Association between increased Twitter use and increased depressive symptoms.	No
H3: Indirect effect of Instagram use on depressive symptoms through social comparison.	Yes
H4: Indirect effect of Twitter use on depressive symptoms through social comparison.	Yes
H5a: Negative SM experiences would moderate the relationship between Instagram use and symptoms of depression with a stronger relationship between Instagram and depression with more negative SM experiences.	No
H5b: Negative SM experiences would moderate the relationship between Twitter use and symptoms of depression with a stronger relationship between Twitter and depression with more negative SM experiences.	No
H6: Compared to 5 minutes of Instagram use, 30 minutes of Instagram use would lead to increased social comparison.	No
H7a: Compared to 5 minutes of Twitter use, 30 minutes of Twitter use would lead to increased social state sad mood.	No
H7b: Compared to 5 minutes of Twitter use, 30 minutes of Twitter use would lead to increased social state angry mood.	No
H7c: Compared to 5 minutes of Twitter use, 30 minutes of Twitter use would lead to increased social state pessimism.	No

Hypothesized Results

Generally, some of our results are consistent with prior literature and some are inconsistent. Regarding our hypothesized correlations, our results are inconsistent with the broader literature that has found associations between the variables. Cross-sectional and longitudinal studies have found associations between self-reported time spent on Instagram and depressive symptoms (Lup et al., 2015; Sherlock & Wagstaff, 2018; Frison & Eggermont, 2017) and to a lesser degree, Twitter use and depressive symptoms (Jeri-Yabar et al., 2019). There are many potential explanations for our contrasting results regarding the correlations.

In the current study, SM usage data was collected directly from the participants' cell phones rather than having participants self-report their SM usage. Although using self-report methods is a common method of data collection, is it possible that collecting objective measures of SM use influenced these previously identified relationships. Thus far, there have only been a handful of studies that include an experimental component and only one study that employs the same method of SM data collection as the current study (see, Hunt et al., 2018). The majority of studies that collect information about SM usage do so via self-report which can create error related to social-desirability bias (Fisher & Katz, 1999) and memory biases (Shiffman, Stone, & Hufford, 2007). The differences between our method of data collection versus previous studies that use self-report methods may account for some of our contradictory results.

It is also possible that the relationship between SM use and mental health may differ by age cohorts. The mean age of our sample was 19.08 (*SD* = 1.23) and recent research has indicated that this age group represents a large portion of SM users with 90% of individuals aged 18-29 having at least one SM profile (Escobar-Viera et al., 2019). With Facebook, Twitter, and Instagram being created in 2004, 2006, and 2010, respectively, it is very likely that our sample had exposure to these SM sites throughout their youth and subsequent development into young adults. Due to early exposure of SM, it may be the case that these individuals react differently to SM usage than individuals who did not grow up with exposure to SM sites. Some research suggests that SM use allows for identity experimentation and opportunities for social support and self-disclosures (Ko & Kuo, 2009; Davis, 2012). It is possible that the age group of our sample may actually benefit from some types of SM usage in some circumstances.

Regarding hypothesis 3, our result is consistent with prior literature that has found associations between Instagram use, social comparison, and depression (Yoon et al., 2019). Further, this result is also consistent with research that demonstrates a partial mediating effect of Instagram use on depressive symptoms through social comparison (Sherlock & Wagstaff, 2018). Our results demonstrated an indirect effect of Instagram use on depressive symptoms through social comparison, which potentially suggest that there are certain features within Instagram that are contributing to detrimental social comparisons which are leading increased depressive symptoms. It is possible that users are being exposed to more idealized images through Instagram creating an unrealistic expectation. This notion has been supported in prior research studies that found that Instagram has higher rates of trends such as “fitspiration”, or posting “motivating” photos of one’s body that encourage others to follow trendy dietary and exercise plans (Tiggemann & Zaccardo, 2015). These photos potentially result in users comparing themselves to an image or individual that has been edited, further creating an unrealistic expectation. Further, it has been indicated that even celebrities, “influencers”, and even individuals without a significant following on Instagram edit their photos to an unrealistic degree, and research has demonstrated that viewing these images can result in higher social comparison and body dissatisfaction (Tiggemann & Anderberg, 2019). However, the relationship between Instagram, social comparison, and mood may be complicated as indicated by our experimental results.

In regards to hypothesis 4, although this relationship has not been studied directly, our results are similar to the existing literature. Although our Twitter use manipulation did not produce expected findings, in the cross-sectional data there was an indirect effect of average daily Twitter usage on depressive symptoms through world pessimism. Though we did not assess the content that participants were exposed to on Twitter, the results may be due to the features within Twitter such as the “trending page”, various news pages, and the “retweet” function allow for the widespread coverage of news and information, often negatively-worded (Lerman & Ghosh, 2010; Pew Research Center, 2015). This creates the potential for the rapid and widespread dissemination of negative news stories. There has also been research that has examined pessimism as a moderator of the relationship between negative news and depressive symptoms however, in the current study, it was hypothesized that exposure to negative news via Twitter is the source of pessimism, which is the mechanism by which depressive symptoms emerge (McNaughton-Cassill, 2001). Considering these results, it is possible that while using Twitter, users are exposed to negative news stories either through their feed or through the various news pages and are experiencing higher levels of pessimism, resulting in increased depressive symptoms.

The results of hypotheses 5a and 5b are inconsistent with previous research that has examined the moderating effect of negative experiences while using SM. Previous literature has demonstrated that the nature of the experiences that occur on SM sites is more predictive of depressive symptoms than the time spent using the SM site. More specifically, a greater amount of self-reported negative experiences strengthens the relationship between SM usage and depressive symptoms (Vahedi & Zannella, 2019; Davila et al., 2012). Our results did not reveal this relationship; however, there was a direct effect between depressive symptoms and negative SM experiences suggesting that negative SM experiences may not qualify the relationship between Instagram or Twitter use and depressive symptoms rather, negative SM experiences directly relates to depressive symptoms.

There are many possible explanations for the lack of an indirect relationship between Twitter and depressive symptoms through negative SM experiences. In a recent meta-analysis (Vahedi & Zanella, 2019), “negative social media experiences” was defined to include more problematic SM use such as addictive use whereas, the current study only defined “negative SM experiences” as interactions or exposure to content that the user would deem negative in quality. We did not define “negative SM experiences” to include Internet or SM addiction. It could be the case that because this meta-analysis included more severely problematic use, there was a stronger effect. Additionally, other studies have examined negative experiences regarding SM sites such as MySpace, Facebook, and other Instant Messaging platforms (Davila et al., 2012). However, the current study was examining Instagram and Twitter. It is possible that there are differences in the types or frequency of interactions, or exposures to negative content, that users experience between different SM applications or sites. It may be the case that while using MySpace, Facebook, or IM sites, that users are exposed to a higher amount of interactions than while using Instagram or Twitter thus, creating the potential for a higher amount of negative interactions. Additionally, the current study assessed "negative SM experiences" with a single item. It could be the case our method failed to detect an effect due to the broad nature of the question.

To our knowledge, the current study was the first to examine the relationship between Instagram use and social comparison with an SM use manipulation; however, our results are in opposition to literature that uses cross-sectional data. It is possible that when using Instagram for a brief period time (e.g. 5 minutes), the user does not meet the threshold at which they would begin engaging in detrimental social comparisons. It could be the case that a brief session of Instagram use is actually beneficial to the user in that, the shortened time frame exposes the user to stimuli that boosts confidence or self-esteem, resulting in lower social comparisons. In fact, a small body of research suggests that benign envy creates a sense of inspiration in response to Instagram usage, further resulting in positive affect (Meier & Schäfer, 2017). There is also a growing body of literature to suggest that the "body positivity" movement is becoming more popular on Instagram. This movement allows individuals to view content that is inclusive of diverse individuals. Research that has been conducted about body positive Instagram content has revealed lifted mood, higher body appreciation, and lower body dissatisfaction in participants (Cohen et al., 2019). Another possible reason for our null results regarding the 30-minutes group could be that our manipulation was not robust enough to detect changes. It could the case that significant detrimental social comparisons develop as a result of chronic and long-term Instagram use that occurs over an extended period of time. This notion would explain our significant indirect effect of Instagram use on depressive symptoms through social comparison while also explaining the failure to detect an effect in the 30-minutes of usage group.

Results regarding the Twitter use manipulation were in opposition to our hypotheses and to similar literature that has shown that a large majority of individuals (86%) who use Twitter are seeking information about news stories (Rosenstiel et al., 2015) and that state sad mood is related to negative news stories (Johnston & Davey, 2011; Pfua et al., 2006). State angry mood has also been implicated in users' exposure to negative news on Twitter. However, in the aforementioned study, the effect was strongest among older adults in comparison to young adults (Park, 2015). Our results did not replicate these effects for many possible reasons. Our sample was almost entirely composed of young adults which could explain the differences in our results compared to previous studies that have found stronger effects in older adults. Additionally, previous research paradigms have involved exposure to constructed negative news stories rather than participants' actual Twitter news feeds which can have significant variability in the types and frequency of news and information displayed. It is very likely that heavily controlled research paradigms display different content than an actual Twitter news feed. Because of the variability in a typical Twitter news feed, it is possible that our sample was not exposed to the amount of negative news stories necessary to result in increased angry or sad mood. We did not ask or measure the types of content that our sample was exposed to, or interacted with, while completing the Twitter use manipulation. It is possible that our sample sought out different types of content than samples in other research studies.

Regarding state pessimism, although there are no existing studies that have examined pessimism as an outcome or effect of Twitter use, our results did not support out hypothesis or replicate similar literature. Previous literature has revealed that pessimism might moderate the relationship between negative news exposure and depressive symptoms however, for our Twitter manipulation, we hypothesized pessimism to be an outcome variable (McNaughton-Cassill, 2001). Similar to our results with social comparison and Instagram use, it is possible that our manipulation was not robust enough to detect changes. It could the case that significant levels of world pessimism develop as a result of chronic and long-term Twitter use that takes place over an extended period of time.

Exploratory Results

Although some of our hypotheses were not supported, exploratory analyses revealed interesting results. There was a significant indirect effect of Twitter use on depressive symptoms through world pessimism for women but not for men. Prior literature suggests that motivations for information-seeking through social media is equal between men and women and a result, it is possible that the content and information sought from Twitter has differing effects on men and women (Krasnova et al., 2017). Further, research has also revealed that women may be more prone to ruminating about negative news resulting in more negative outcomes whereas men are more likely to demonstrate hostility in response to negative news (Lachlan et al., 2010). These studies may explain why the indirect effect of Twitter use on depressive symptoms through pessimism was significant for women but not for men. It may be the case that women were experiencing higher pessimism and depressive symptoms as a mechanism of rumination while men's emotionality in response to Twitter use was expressed differently.

Regarding the SM manipulation, our results showed that women's social comparison scores significantly decreased from pre- to post-Instagram use in the 5-minutes condition suggesting that using Instagram for a short amount of time (5 minutes) results in lower social comparison scores. Our results also revealed a non-significant increase in women's social comparison scores for the 30-minutes of Instagram use group. Together, these results potentially suggest that spending a longer amount of time results in more potential for the women in our sample to compare themselves to other users while using Instagram for a very brief period of time creates the opposite effect. Our results also suggest the possibility that if users spent longer than 30 minutes on Instagram, social comparison scores may have significantly increased from pre- to post-usage.

When examining anxiety as an outcome variable, there was a significant indirect effect of Instagram use on anxiety through social comparison. This result is similar to recent research that demonstrated increased anxiety in response to image-conscious (photos of fitness, influencers, or models) photos on Instagram (Kohler et al., 2020). Additionally, when controlling for anxiety, the indirect effect of Twitter use on depressive symptoms through world pessimism remained significant, and when examining anxiety as an outcome variable, there was a significant indirect effect of Twitter use on depressive symptoms through world pessimism. Although these relationships have not been established previously, there are some studies to suggest that anxiety increases in response to emergency events reported on Twitter (Oh et al., 2010; Jones & Silver, 2019). Our results potentially suggest that Twitter activity can lead to both anxiety and depressive symptoms because of increased pessimism in response to the stimuli that the user is interacting with.

Regarding our other metrics of SM use, unlike the primary analysis results, percentage of battery life spent on Instagram in the last 24 hours was significantly associated with depressive symptoms, and percentage of battery life spent on Instagram over the past 7 or 10 days was significantly associated with depressive symptoms. In line with our primary results, there was a significant indirect effect of time spent on Instagram in the past 24 hours on depressive symptoms through social comparison. There was a significant indirect effect of time spent on Twitter in the past 24 hours on depressive symptoms through pessimism. There was also a significant indirect effect of percentage of battery life spent on Twitter in the past 24 hours on depressive symptoms through pessimism. Finally, there was a significant indirect effect of percentage of battery life spent on Twitter in the past 7 or 10 days on depressive symptoms through pessimism.

These results regarding different metrics of Instagram and Twitter use are interesting because when examining the percentage of battery spent of a certain application, those metrics are indicative of the priority given to that application. It may be the case that users who are devoting higher percentages of their battery life to Instagram and Twitter are not allocating their battery life to other applications or other sources of entertainment or interaction in order to balance the effects of their Instagram or Twitter use. Our results regarding Twitter specifically give good support to the notion that while individuals are using Twitter, they are exposed to a type of content or interaction that results in pessimism, which then results in higher depressive symptoms. Our results illustrate that both time spent on Twitter and percentage of battery life spent on Twitter both result in higher depressive symptoms through world pessimism.

Limitations and Strengths

The results of the current study should be evaluated in light of its limitations. First, the current study is cross sectional in design and therefore we cannot infer a causal relationship between the variables. It may be that individuals with higher depressive symptoms use Instagram and Twitter more than individuals with no depressive symptoms. Additional longitudinal and experimental work will be needed to clarify these relationships. Second, the current study examined an undergraduate student sample which may not generalize to other populations. The individuals who participated in the study may have had different levels of exposure to social media over the course of their lives compared to other populations (e.g., middle aged and older adults). Future work should investigate these relationships in other populations. Additionally, participants with Androids were excluded due to our method of data collection of Instagram and Twitter use. This resulted in our sample only possessing iPhones however, this is representative of the broader young adult population and only 2.2% of our sample was excluded based on phone type. Data suggests that iPhones are in the majority (Statista, 2019).

This study also has notable strengths. The current study had a large sample size which allowed us to detect small effects and provides greater confidence in the robustness of the results. Additionally, the current study gathered Instagram and Twitter use data directly from the participants' phones rather than relying on self-report estimations, allowing for a more accurate and precise measurement of Instagram and Twitter use.

Conclusion

The current study simultaneously replicated prior literature while contributing novel information to the field. The current study supports the notion of social comparison as a mediating variable in the relationship of Instagram use and depressive symptoms. The results of this study also support the mediating role of pessimism in the relationship between Twitter use and depressive symptoms. However, in contrast to prior literature, our results did not support negative experiences while using SM as a moderating variable between Instagram use nor Twitter use and depressive symptoms although this could be related to previous research using a broader definition for "negative SM experiences" than the current study. Our results from the SM usage manipulation were more complicated. There was a significant decrease in social comparison from pre- to post-Instagram use in the 5-minutes group. For the Twitter use group, our results did not reveal any significant effects. Our results potentially suggest that Instagram and Twitter use have detrimental outcomes when users are engaging in higher amounts of usage on a weekly or daily basis but that the effects of Instagram and Twitter use are less severe when measured in during smaller time frames (e.g. 5 minutes and 30 minutes). Future research should focus on examining the types of content that users are interacting with in order to gain a more nuanced understanding of the effects of their SM use. Additionally, in order to further develop our understanding of SM use and depression, it would be beneficial to conduct more experimental studies where participants are assigned to use certain SM applications for sites for specific amounts of time while limiting usage of other SM sites in order to examine changes in depressive symptoms, other mental health outcomes, and potentially identify the optimal level of SM usage.

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APPENDICES

APPENDIX A

Review of the Literature

Depression is a common, recurrent disorder with 17.3 million U.S. adults experiencing at least one major depressive episode and 11 million U.S. adults experiencing severe impairment due to a major depressive episode at some point in their lifetime (NIMH, 2017). Furthermore, according to the most recent data, rates of depressive episodes are highest among young adults (aged 18-25) with 13.1% reporting a depressive episode (NIMH, 2017). Depression in young adulthood is associated with a number of detrimental outcomes including increased risk for future psychopathology, substance use, lower education attainment, unemployment, and risk for suicide ideation and suicidal behaviors (Duffy et al., 2019; Boden et al., 2007; Fergusson & Woodward, 2002; Fletcher, 2010; Kessler et al., 1995; Mojtabai et al., 2015; Patten, 2017; Woodward & Fergusson, 2017). Additionally, the incidence of a major depressive episode has increased by 46%, 122%, 59%, and 39% for individuals aged 18-19, 20-21, 22-23, and 24-25, respectively, from 2009 to 2017 (Twenge, 2019). Given the prevalence and seriousness of depression in young adults, it is important to identify potential causes and maintaining factors for these problems.

Social media has become a popular medium for sharing information with family and friends, connecting with others through posting photos and personal updates, sharing and receiving news information, and other online social networking activities (Pittman & Reich, 2016; Pew Research Center, 2018; Alhabash & Ma, 2017). Young adults are the most avid users of social media with 88% of young adults using some type of social media (Pew Research Center, 2018). Although there are many possibilities for the increases in depression among young adults, because rates of depression have increased over the same period as increases in the use of social media (especially among young adults), social media has been implicated as a potential contributor (e.g., Twenge et al, 2019).

Though emerging research has found an association between social media use and depression (e.g., Lin et al., 2016; Vanucci et al., 2017; Yoon et al, 2019; Vahedi & Zanella, 2019), a number of questions remain about this potential relationship. For example, it is not yet clear *why* there is such a relationship. Thus, there is a need to examine the potential moderators and mediators of social media use and depression. In addition, the majority of the past research has combined all social media applications and websites into a single overarching construct. Doing so assumes that all social media have similar effects on users and obscures potential differences between platforms. It would be more valuable to examine the effects of specific social media platforms to better understand their unique contributions to mental health. An additional limitation in this area of research involves the way in which information about social media use is being collected, mainly via self-report. Self-report bias is a major methodological issue, including during the measurement of social media use. Research has suggested that respondents will often display biases in their self-reported behaviors due to social-desirability bias (Fisher & Katz, 1999) and a variety of memory biases (Shiffman, Stone, & Hufford, 2007).

The current study proposes to examine two specific, widely used social media platforms, Instagram and Twitter, while using objective measures of usage, to better understand the unique associations between each platform and depression symptoms in young adults. The current study also proposes to examine potential mediators and moderators of social media use and depression.

Social Media

Social media (SM), also referred to as social networking sites, are a series of social networks located within online websites and phone applications in which users are able to create and share content with friends and family members (Pittman & Reich, 2016). Since their inception, the use of SM sites has increased rapidly with approximately 70% of Americans using SM sites in 2018, compared to 38% in 2009 (Pew Research Center, 2018).

Instagram, with over 500 million active daily users (Clement, 2019), is a photo-sharing SM platform that allows users to apply filters to their photos, "tag" other users in photos, and write descriptions of any length for their photos, which are then uploaded to a timeline where other users have the ability to view, like, share, and comment on the photo (Alhabash & Ma, 2017; Pittman & Reich, 2016). Twitter, with 80 million active daily users in 2019, allows users to interact with followers using 280-character "tweets" that can contain words, links, photos, and videos that are posted to a chronological timeline. Users can interact with others using mentions, replies, and hashtags as well as follow accounts in order to read others' tweets (Clement, 2019; Alhabash & Ma, 2017; Pittman & Reich, 2016).

Although the SM user base has broadened to include a wide range of ages, young adults (ages 18-29) are the most avid users of SM platforms as well as the most avid users of both Instagram and Twitter, with 88% of young adults using some type of SM, 75% of young adults using Instagram, and 44% of young adults using Twitter (Pew Research Center, 2018). As noted above, there has been an increase in the prevalence of depression among young adults over the time period during which SM has become widespread (Twenge et al, 2019). As such, a number of recent studies have examined the relationship between SM use and depression.

Effects of Social Media Use on Depression

Thus far, several studies have demonstrated a general association between increased SM use and increased symptoms of depression. A recent meta-analysis of such studies revealed a small, but positive relationship (r = .165) between SM use and self-reported depressive symptoms (Vahedi & Zannella, 2019). This meta-analysis included 55 studies with a total sample size of 80,533 participants. These studies included a range of participant demographic characteristics with 54% of the total sample being female, 28% Caucasian, and a mean age of 47. Notably, this meta-analysis included studies investigating any SM platform and the effects of different platforms on depression was not assessed.

Another meta-analysis examined studies that investigated time spent on SM and/or frequency of checking SM and severity of depression symptoms specifically in young adults (Yoon et al., 2019). Results revealed a small, positive correlation between time spent on SM and depression (r = .11, 95% CI [.08-.14]) and between frequency of checking SM and depression (r = .10, 95% CI [.03-.16]). The time spent analyses involved a total of 33 studies with a sample size of 15,881 which was 59% female with a mean age of 22. For the frequency analyses, a total of 12 studies were included with a sample size of 8,041, which was 66% female with a mean age of 18.

These meta analyses provide evidence that SM use is associated with depression symptoms, but they did not investigate potential differences in SM platforms in their relationship with depression symptoms. Different SM platforms may have differing effects on users' mental health and each platform may involve unique mediators or moderators of these effects. Instagram and Twitter have emerged as two of the most popular SM sites with 75% of young adults using Instagram and 44% of young adults using Twitter (Pew Research Center, 2018). As such, investigating the relationship between the use of these specific SM platforms and depression symptoms will likely be helpful in advancing this field of research.

Effect of Instagram on Depression

Research examining the psychological effects of Instagram are in the preliminary stages mostly due to the novelty of the application. Instagram was created in 2010, and although extremely popular, it is relatively new in comparison to Facebook, which was created in 2004. A large part of the research examining Instagram has focused on categorizing various types of photos that are posted to Instagram (Hu et al., 2014; Miles, 2014; Mackson et al., 2019) and problematic and addictive use of the application (Jackson & Luchner, 2017; Kircaburun & Griffiths, 2018; Mackson et al., 2019). Further, machine-learning can identify and predict depression from the characteristics of Instagram photos (Reece & Danforth, 2017). However, only a small number of studies have specifically examined the relationship between Instagram use and symptoms of depression.

Recent studies have found varying degrees of associations between Instagram use and depression. In a sample consisting of 129 young women (*M* age = 24.60), results demonstrated that self-reported time spent on Instagram during the span of one week was positively associated with depression ($r = .49$; Sherlock & Wagstaff, 2018). This study demonstrates an association between Instagram use and depression, but was cross-sectional and could not determine whether there was a causal relationship.

In a longitudinal study of 440 adolescents (*M* age = 15), Instagram use at Time 1 predicted depressive symptoms seven months later ($r = .11$, $p < .001$; Frison & Eggermont, 2017). More specifically, this effect on depression was found for engaging in browsing ($r = .15$, $p < .001$) as well as posting ($r = .15$, $p < .001$) and liking ($r = .14$, $p < .001$) while using Instagram. This study indicates a longitudinal, and potentially causal, relationship between Instagram and depressive symptoms. However, it provides little information about *why* there may be such a relationship.

In a cross-sectional study of 117 young adults (*M* age = 23), self-reported daily time spent on Instagram was associated with higher depressive symptoms ($r = .18$; Lup et al., 2015). This effect was mediated by social comparison suggesting that greater Instagram use leads to more negative social comparison, which leads to increased symptoms of depression. Other studies (that did not specifically evaluate depression) have also found an association between Instagram use and negative social comparison in the context of body image and self-esteem (Vogel et al., 2014; Lewallen & Behm-Morawitz, 2016).

Social comparison is considered in more detail below (see "Potential Mediators and Moderators")

Effect of Twitter on Depression

Much of the research involving Twitter, like that of other SM sites and applications, is focused on using information from SM posts to identify and predict mental health problems (Coppersmith et al., 2014; McClellan et al., 2017). However, we are aware of only one study that has specifically examined the relationship between Twitter use and depression. This study included 212 university students between the ages of 18 and 35 (45.3% female) and examined differences in the rates of Twitter, Instagram, and Facebook use among individuals experiencing depression (Jeri-Yabar et al., 2019). They found that individuals experiencing depression were almost twice as likely to use Twitter over other SM sites such as Instagram and Facebook. Results of this study suggest that the relationship between Twitter use and depression should be investigated further.

Potential Mediators and Moderators

As stated previously, although the existing research demonstrates a relationship between SM use and symptoms of depression, few studies attempt to answer the question as to *why* there is such a relationship. Examining specific psychological constructs that potentially operate between SM and depression will provide a deeper understanding of SM's effect on users. Potential mediators and moderators that will be considered in this study are: social comparison, pessimism, negative SM experiences, and state negative mood as a consequence of using SM.

Social Comparison

Upward social comparison involves the natural inclination to compare the self to other individuals who are higher in status. SM provides a never-ending, rich stream of information about different individuals that the user is "following" and against whom the user could compare themselves. Although this can be adaptive by allowing the individual to self-motivate, this process can also become maladaptive by creating an attentional bias to more successful individuals which encourages more negative self-talk (Blease, 2015).

Research has demonstrated a link between SM use, social comparison, and depression. A recent meta-analysis revealed a relationship between general social comparison on SM, upward social comparison on SM, and depression (Yoon et al., 2019). Specifically, this study revealed that general social comparison on SM has a small association with depression (r = .23, 95% CI [.12-.34], p < .001), and upward social comparison on SM has a medium association with depression (r = .33, 95% CI [.20-.47], p < .001). Further, a study that examined 619 adolescents found that technology-based social comparisons on SM sites have a strong association with depression (r = .34, p < .001; Nesi & Prinstein, 2015).

Social comparison as a mediator between SM use and depression has mainly been examined in research regarding Instagram due to the highly visual nature of the application. A constant "highlight reel" of other individuals potentially may lead users to believe that others on the application are leading happier and better lives overall (Lup & Trub, 2015; Vanucci et al., 2017; Mehdizadeh, 2010). While also detrimental in the "real-world", social comparison is especially pernicious in online settings due to the meticulous nature of user self-presentation. SM sites allow the user to create a precise online persona usually emphasizing the user's best attributes (Vogel et al., 2014).

A recent study found that social comparison demonstrated a partial mediating effect between Instagram use and depressive symptoms in a sample of young adult women (Sherlock & Wagstaff, 2018). Although limited, research suggests that social comparison potentially plays a role in the relationship between Instagram use and depression.

Pessimism

Though it has not been studied directly, a potential mediator of Twitter use and depression symptoms could be pessimism about the state of the world due to exposure to negative news media through Twitter. Research has shown that news consumption through SM has increased by 50% since 2009 (Weeks & Holbert, 2013). A widely used feature of Twitter is the "trending page", which is equipped with various genres of trending topics including the "news page" or "world events page". In addition to users having the capabilities to message and tweet with one another about world events, Twitter users also have access to an almost never-ending stream of news reporting. Research has demonstrated that news information is spread throughout Twitter and is generally able to permeate deeply through Twitter networks, thus allowing for widespread coverage of news events (Lerman & Ghosh, 2010). It has been noted that Twitter displays the most negatively-worded news in comparison to other SM sites (Pew Research Center, 2015). Considering these factors, it raises the question as to whether the ubiquity of negative news reporting on Twitter could influence user's mental health by creating increased levels of pessimism which then leads to increased levels of depression.

Additionally, research regarding the effects of news coverage suggest that negative news is more often reported than news that is positive or uplifting in nature (Garz, 2014; Rozin & Royzman, 2001). Further, research regarding exposure to negative news suggests that exposure to graphic and disturbing news can have detrimental effects on the viewer. For example, a study examining differences between viewing positive, neutral, or negative news clips in a sample of young adults (n = 30, $M = 23$) found that the "negative news" group displayed higher depressive symptoms after viewing the negative news clip. Importantly, in this study, pessimism moderated this effect with higher pessimism leading to a stronger relationship between negative news viewing and depressive symptoms (McNaughton-Cassill, 2001). Given the relationships between Twitter, negative news, pessimism, and depression symptoms, it may be the case that Twitter use is associated with depression through increased pessimism.

Negative SM Experiences

Recent research suggests that the quality or nature of experiences on SM also has consequences for depression. A recent meta-analysis revealed a moderating effect on the relationship between SM and severity of depression such that, more frequent negative experiences on SM were associated with higher self-reported depressive symptoms (Vahedi & Zannella, 2019). This meta-analysis compared general SM use to SM use that included negative quality interactions and results revealed that negative quality use produced a stronger effects size on depression than general SM use ($r = .27$ and $r = .11$, respectively). These results suggest that the quality of interactions and experiences on SM sites may moderate the relationship between the amount of time spent using an SM site and depression symptoms (Vahedi & Zannella, 2019; Davila et al., 2012).

Twitter and State Mood

Although research regarding Twitter and depression is limited, there are some studies that have examined mood, particularly sad and angry mood, in response to Twitter use due to the popularity of the application for seeking information about news. Research has shown that a large majority of individuals who use Twitter, use the application to learn about the news (86%), and that the majority of trending topics are related to news stories (Rosenstiel et al., 2015; Kwak et al., 2010). In general, sad mood has been implicated in exposure to negative news stories (Johnston & Davey, 2011; Pfua et al., 2006). Exposure to negative news stories on Twitter, specifically, results in increased anger (Park, 2016). Reactivity of sad and angry mood has been implicated in depression and depression vulnerability (e.g., Ellis et al., 2013; van Rijsbergen et al., 2013). Given the existing research on mood, depression, and Twitter, sad and/or angry mood may mediate the relationship between Twitter use and depression.

Methodological Issues in Studies of SM and Depression

The majority of research examining SM use and mental health uses self-report methods to collect information about individuals' usage rates. Even the most recent research studies have used self-report items created by researchers (Sherlock & Wagstaff, 2018) or self-report questionnaires (Coyne et al., 2020). There are no studies to our knowledge that have gathered objective measures of SM use.

As noted above, self-report data are often affected by social-desirability bias (Fisher & Katz, 1999) and memory biases (Shiffman, Stone, & Hufford, 2007). Social-desirability bias (SDB) is the most commonly studied response bias within the social sciences. SDB posits that respondents provide answers on measures that are motivated by their social system in an attempt to avoid negative social implications, either imagined or real (Fisher & Katz, 1999). Self-report methods may also be affected by memory biases. Extant literature has demonstrated that recall is not only affected by random error, but is often systematically biased by current mood state, saliency effects, and recency effects (Shiffman, Stone, & Hufford, 2007). Given the risk of bias inherent in self-report, more accurate and objective measures of SM use would be beneficial in moving the research forward.

The overwhelming majority of young adults with access to the internet use their SM accounts through mobile smartphones (Villanti et al., 2017). Smartphones often record a significant substantial amount of information about the owner of the phone including the amount of time and percentage of battery the user is spending on certain applications. In particular, iPhone operating system iOS 12 and later allowed iPhones to record time spent on any given application from the past 24 hours and from the past two, four, seven, or ten days depending on the specific iOS version. Other smartphones such as Androids collect similar information such as units of data used for a specific application or central processing unit (CPU) time used. This feature on smartphones offers an objective way to measure SM use rather than relying on self-report.

The Current Study

Considered altogether, research has demonstrated an association between SM use and depression (Vahedi & Zannella, 2019; Yoon et al., 2019). Although more limited, research has demonstrated a relationship between depression and Instagram use (Frison & Eggermont, 2017; Lup et al., 2015; Sherlock & Wagstaff, 2018) and between depression and Twitter use (Jeri-Yabar et al., 2019). In addition, factors such as social comparison, pessimism, negative SM experiences, and state mood may mediate or moderate these relationships. Mobile phones offer native tools to more accurately and objectively measure SM use.

As part of a larger, ongoing lab study, the proposed study will gather SM use data from participants' phones along with self-report measures of depression symptoms, social comparison, pessimism, and negative SM experiences. They will also complete an in-lab SM manipulation to evaluate the effects of SM on state mood, social comparison, and pessimism.

Hypotheses

SM Use and Depression Symptoms

H1: Increased Instagram use will be associated with increased symptoms of depression.

H2: Increased Twitter use will be associated with increased symptoms of depression.

Mediators and Moderators of SM Use and Depression Symptoms

H3: Social comparison will mediate the relationship between Instagram use and depression symptoms with more Instagram use associated with increased upward social comparison, which would be associated with increased symptoms of depression. Social comparison has not been evaluated in the context of Twitter, so no specific hypothesis will be made for social comparison and Twitter.

H4: Given the past research linking negative news and pessimism (McNaughton-Cassill, 2001) and Twitter and negative news (Park, 2016), it is hypothesized that pessimism will mediate the relationship between Twitter use and symptoms of depression with more Twitter use associated with increased pessimism, which will be associated with increased symptoms of depression. There is less evidence for a potential relationship between Instagram and pessimism, so no specific hypothesis will be made regarding their relationship.

H5: Negative SM experiences will moderate the relationship between Instagram use and symptoms of depression with a stronger relationship between Instagram and depression with more negative SM experiences (H5a). We expect the same moderating relationship between negative SM experiences, Twitter, and symptoms of depression (H5b).

Acute Effects of Instagram or Twitter Use

To evaluate the effects of acute use of Instagram or Twitter, participants will be randomly assigned to one of four in-lab SM exposures: Instagram use for 30 minutes, Instagram use for 5 minutes, Twitter use for 30 minutes, Twitter use for 5 minutes (see the "SM Manipulation" below for more details).

H6: Compared to 5 minutes of Instagram use, it is expected that 30 minutes of Instagram use will lead to increased social comparison (H6).

H7: Compared to 5 minutes of Twitter use, it is expected that 30 minutes of Twitter use will lead to increased state sad mood (H7a), increased state angry mood (H7b), and increased state pessimism (H7c).

APPENDIX B

Measures

PHQ-9

Over the last 2 weeks, how often have you been bothered by the following problems?

	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself-or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed? Or the opposite—being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3
9. Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3

If you checked off any problems, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people? Circle one:

Not difficult at all   Somewhat difficult   Very difficult   Extremely difficult

Social Comparative Evaluation Scale (SCES)

	Never	Once per week or less	Several times per week	Nearly everyday	Multiple times per day
I compare my social life with other's social lives	0	1	2	3	4
I find myself comparing my life to others' lives while using social media.	0	1	2	3	4
I check my social media to see what others are doing in their everyday lives.	0	1	2	3	4
I compare my accomplishments with others' accomplishments to find out how well I've done.	0	1	2	3	4
I try to figure out if others experience the same problems as me.	0	1	2	3	4
	Disagree strongly	Disagree	Neutral	Agree	Agree strongly
Others have better lives than me.	0	1	2	3	4
I don't have as many fun experiences as others do.	0	1	2	3	4
I am not as happy as other people are.	0	1	2	3	4
Other people have more accomplishments than me.	0	1	2	3	4

Other people have less problems than I do.	0	1	2	3	4

The Pessimism Scale

Please indicate your level of agreement with each statement below.

	Strongly Disagree	Disagree	Neither agree or disagree	Agree	Strongly Agree
I have great faith in the future.	1	2	3	4	5
I am satisfied with my life.	1	2	3	4	5
Others are generally here for me when I need them.	1	2	3	4	5
I look forward to the future with hope and enthusiasm.	1	2	3	4	5
On the whole, I am satisfied with myself	1	2	3	4	5
At times, the future seems unclear to me.	1	2	3	4	5
I feel I have many things to be proud of.	1	2	3	4	5
I generally feel confident in myself.	1	2	3	4	5

There is a lot of good in the world.	1	2	3	4	5
People are mostly selfish and unkind.	1	2	3	4	5
Our society is heading in the right direction.	1	2	3	4	5
The world is a terrible place right now.	1	2	3	4	5
People are usually helpful to each other.	1	2	3	4	5
Our country is falling apart.	1	2	3	4	5
Most people are good people.	1	2	3	4	5
Things in the world are getting worse.	1	2	3	4	5
People will exploit your emotions to hurt you.	1	2	3	4	5
Most people cannot be trusted.	1	2	3	4	5

Negative Social Media Experiences

Thinking about your social media usage generally, what percentage of your social media experiences are NEGATIVE?

% 0 100

POMS/PANAS

Below is a list of words that describe feelings people have. Please read each one carefully. Then circle one answer to the right which best describes much you are feeling that way RIGHT NOW.

		Not at all	**A little**	**Moderately**	**Quite a bit**	**Extremely**
1.	Irritated	0	1	2	3	4
2.	Angry	0	1	2	3	4
3.	Sad	0	1	2	3	4
4.	Annoyed	0	1	2	3	4
5.	Down	0	1	2	3	4
6.	Blue	0	1	2	3	4

Table 3. Means, standard deviations, and correlations between variables.

Measure	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Time on Instagram – 24 hrs.	-											
2. % of Instagram – 24 hrs.	.489***	-										
3. % of Instagram – 7/10 days	.381***	.789***	-									
4. Time on Twitter – 24 hrs.	.267***	.002	-.030	-								
5. % of Twitter – 24 hrs.	.036	.034	.002	.707***	-							
6. % of Twitter – 7/10 days	-.057	-.021	-.023	.544***	.721***	-						
7. Neg. SM Exp.	-.038	.003	-.108*	-.005	-.042	.009	-					
8. PHQ-9	-.002	-.073	-.124**	.043	-.006	.031	.257***	-				
9. SCES Freq.	.064	.011	-.011	-.045	-.063	-.060	.206***	.229***	-			
10. World PS	-.062	-.095**	-.085	.103*	.132**	.130**	.236***	.308***	.091*	-		
11. State Sad Mood	-.017	-.017	-.030	.024	.044	.071	.142**	.506***	.106**	.165***	-	
12. State Angry Mood	.018	-.003	.027	-.022	.010	.032	.112**	.080	.080	.113**	.556***	-
Mean	38.00	12.00	12.05	21.51	7.30	6.95	26.37	5.80	9.37	14.05	.98	.92
SD	38.10	9.44	8.20	26.93	7.91	8.00	17.35	5.00	4.46	3.16	1.88	1.75

Note. *** = p < .001; ** = p < .01; * = p < .05; Avg. Instagram Use = Average Instagram Usage; Avg. Twitter Use = Average Twitter Usage; Neg. SM Exp. = Negative Social Media Experiences; PHQ-9 = Patient Health Questionnaire – 9 item; SCES Freq. = Social Comparison Frequency subscale; World PS = Pessimism Scale World Pessimism subscale; State sad mood = POMS State sad mood items; State angry mood= POMS State angry mood item

Oklahoma State University Institutional Review Board

Date:	08/03/2018
Application Number:	AS-18-81
Proposal Title:	Social Media Use and Mental Health
Principal Investigator:	Emma Unruh Dawes
Co-Investigator(s):	
Faculty Adviser:	Tony Wells
Project Coordinator:	
Research Assistant(s):	
Processed as:	Expedited

Status Recommended by Reviewer(s): Approved

Approval Date: 08/03/2018

Expiration Date: 08/02/2019

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

The final versions of any recruitment, consent and assent documents bearing the IRB approval stamp are available for download from IRBManager. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be approved by the IRB. Protocol modifications requiring approval may include changes to the title, PI, adviser, other research personnel, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms.
2. Submit a request for continuation if the study extends beyond the approval period. This continuation must receive IRB review and approval before the research can continue.
3. Report any unanticipated and/or adverse events to the IRB Office promptly.
4. Notify the IRB office when your research project is complete or when you are no longer affiliated with Oklahoma State University.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact the IRB Office at 223 Scott Hall (phone: 405-744-3377, irb@okstate.edu).

Sincerely,

Hugh Crethar, Chair Institutional Review Board

VITA

Emma Unruh-Dawes

Candidate for the Degree of

Master of Science

Thesis: AN EXAMINATION OF POTENTIAL MEDIATORS AND MODERATORS OF THE RELATIONSHIP BETWEEN SOCIAL MEDIA USE AND DEPRESSION SYMPTOMS

Major Field: Psychology

Biographical:

Education:

Completed the requirements for the Master of Science in Psychology at Oklahoma State University, Stillwater, Oklahoma in December 2020.

Completed the requirements for the Bachelor of Science in your Psychology at Oklahoma State University at Stillwater, OK in 2018.

Research experience:
Clinical Psychology Doctoral Student – Behavior, Affect, and Thinking Lab, Director: Dr. Tony T. Wells, Ph.D.
Projects: Social Media and Mental Health (Designed Study), Analysis of Instagram Content (Designed Study), and Accuracy in Screening for Suicide Attempts and Suicide Deaths: A Pooled Analysis

Professional Memberships: American Association of Suicidology, American Foundation for Suicide Prevention, Graduate Psychology Student Government Association, Oklahoma Psychological Association, Oklahoma State University Psi Chi Psychology Honors Club, The National Society for Leadership and Success, Oklahoma State University Psychology Club