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### Author

Altman, Allison Diamond

### Publication Date

2022

Peer reviewed|Thesis/dissertation

An idiographic approach to assess the negative effects of Instagram on mental health

By

Allison Diamond Altman

A dissertation submitted in partial satisfaction of the

requirements for degree of

Doctor of Philosophy

in

Psychology

in the

Graduate Division

of the

University of California, Berkeley

Committee in Charge:

Professor Aaron Fisher, Chair

Professor Stephen Hinshaw

Professor Adrian Aguilera

Summer 2022



## Abstract

An idiographic approach to assess the negative effects of Instagram on mental health

By

Allison Diamond Altman

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University of California, Berkeley

Professor Aaron J. Fisher, Chair

Social networking sites have grown extensively over the past decade, coinciding with the growing use of internet-enabled smartphones that allow access to these sites virtually in any place and at any moment. One social networking app, Instagram, allows for passive observation of other's photos, and extant research has connected this type of usage with myriad negative outcomes including lower self-esteem and depressed moods. Other findings, however, have produced equivocal results, indicating that use may not be harmful. The present studies investigated Instagram use on an idiographic basis to see if the true answer lies within the individual; that use is bad for specific people, but not necessarily everyone.

In Study 1 I employed contemporaneous analyses to examine how Instagram use and a variety of mood states were associated at any given point in time. Subjects ( $n=51$ ) were surveyed on Instagram use and mood eight times per day for twenty-one days. Nomothetic and idiographic network models were utilized, with strength centrality as a key measure to indicate the strength of using Instagram with other nodes in each individual network. Results indicated a significant variability in the relation between Instagram use and mood amongst the networks. The method's potential for analysis of individual symptom patterns is further demonstrated by three exemplar participants.

In Study 2 I examined how Instagram use and affect, jealousy, and social comparison were associated at any given point in time, as well as how they may have "driven" one another from moment to moment. Subjects ( $n=224$ ) were surveyed on their Instagram use and associated variables sixteen times per day for one week. Nomothetic and idiographic contemporaneous correlations and vector-autoregressive lagged models were used. Results demonstrate significant variability in the associations and the time-lagged predictive effects of using Instagram on affect, jealousy, and social comparison. At the group level, use was not predictive of changes in affect, jealousy, and social comparison. At the individual level, however, results varied greatly. In fact, participants who used Instagram more were lower in self-esteem; those meeting diagnostic criterion for substance use disorders, posttraumatic stress disorder, anorexia, social anxiety disorder, and binge eating disorder were more vulnerable to the effects of Instagram.

Together these findings highlight individual differences amongst social media use, identify key moderators for such relations, and most importantly underscore the importance of investigating the potential detrimental effects of social media use on an individual basis.

## Dedication

To my parents, Leslie and David, for their endless love and support throughout my life.

And to my husband Eli, for being my best friend and biggest cheerleader, and for the endless encouragement you have given me over the past seven years. I could not have done this without you.

## Acknowledgments

First I want to acknowledge Dr. Aaron Fisher, my graduate mentor. Dr. Fisher has encouraged me from the start to become the best scientist possible. I am thankful for his constant support of my career goals and for his drive, as it has pushed me to be creative in my work and step outside of my comfort zone. I also want to thank the other members of my dissertation committee, Dr. Stephen Hinshaw and Dr. Adrian Aguilera, for their mentorship and support, which began before this dissertation process commenced. I am extremely grateful for Dr. Hinshaw's mentorship over the years I have taught with him, and for his willingness to always sit with me and discuss research ideas, professional goals, and life outside of the lab.

I have also been fortunate to have the mentorship and guidance of many people outside of the University of California, Berkeley. I am deeply grateful for Dr. Esmé Shaller's mentorship in my clinical development; I would not be the clinician I am today without her, nor would this dissertation exist, as many of the ideas originally stemmed from my work with the UCSF Dialectical Behavior Therapy program and Dr. Shaller's mentorship. I also want to thank Dr. Ellen Herbst at the San Francisco VA, who has been an incredible role model for me over the past three years and has shown me how it is possible to embark on a career that blends clinical work and psychological research so beautifully.

The studies described in this dissertation would not have been made possible without the hard work and help of my many research assistants and members of Dr. Fisher's Idiographic Dynamics Lab, including Julia Levitan, Riley MacDanal, Oliver Krentzman, Philippa Le Cesne Byrne, and Hannah Adams.

Finally, I am grateful for the support of so many friends, colleagues, and family members both far and near who have supported me throughout graduate school and during the writing of this dissertation.

## An idiographic approach to assess the negative effects of Instagram on mental health

### The Problem

Social media is an integral part of many people's lives around the world. Facebook, one of the most widely-used social networking sites, has roughly 2.4 billion monthly active users as of 2019 (Facebook, 2020), and Instagram, a subsidiary of Facebook and a photo-sharing social networking app, has over 1 billion monthly active users (Instagram, 2020). Over the past decade the growing use of internet-enabled smartphones has allowed access to these sites in virtually any location and at any moment, and they are being used – by adolescents and adults – more than ever before (currently as many as 90% of U.S. young adults use social media and as many as 65% of U.S. adults do; Perrin, 2015). Along with this growth, researchers have become concerned about the potential negative effects of social media use, and concerns about the benefits and harms of social media have permeated the media in recent years. As early as 2007 (three years after the development of Facebook in 2004), social scientists examined the positive and negative effects of Facebook on relationships between groups and among individuals, yet the research questions primarily focused on how Facebook use affected relationships between companies and customers, students and faculty, and employees and employers – not about effects on the individual users (Lipka, 2007; Madge, Meek, Wellens, & Hooley, 2009; Mazer, Murphy, & Simonds, 2009; Karl, Peluchette, & Schlaegel, 2010a, 2010b). The earliest known research to pose the question of social media, specifically Facebook, being detrimental to an individual's health was published in 2009, and focused on whether increased Facebook use promoted jealousy (Muisse, Christofides, & Desmarais, 2009). The authors employed a cross-sectional survey-based approach to conclude that increased Facebook use did indeed promote more jealousy, while covarying individual, personality, and relationship factors.

Since that first article in 2009, there have been hundreds of empirical articles published about the negative effects of social media on a range of health-related phenomenon, including self-esteem, life satisfaction, mental health, and well-being (Kalpidou, Costin, & Morris, 2011; Valenzuela, Park, & Kee, 2009; Mehdizadeh, 2010; Kross, Verduyn, Demiralp, Park, & Lee, 2013). Popular-press articles discussing these studies in outlets such as Time Magazine, the New York Times, and the Atlantic have proliferated. Yet, outcomes have often produced equivocal results – that use is both prosocial and helpful (Jelenchick, Eikhoff, & Moreno, 2013; Przybylski & Weinstein, 2017; Ellison, Steinfield, & Lampe, 2007), and that use is detrimental (Kross, Verduyn, Demiralp, Park, & Lee, 2013; Steers, Wickham, & Acitelli, 2014; Shakya & Christakis, 2017). For a topic that pertains to billions of people around the world, this discrepancy has caused debate in interested parties that extend beyond social scientists and include millions of educators, parents, and individual social media users themselves.

Prior to answering the question of whether social media use is beneficial or detrimental, it seems essential to understand *why* social media might be helpful and *why* it might be harmful. Although mechanisms remain largely unknown, researchers typically point to social psychological theories of emotional contagion and social comparison. Emotional contagion is the tendency for one person's emotions or behaviors to promote or prompt similar emotions and behaviors in other people (Hatfield, Cacioppo & Rapson, 1993). Pertaining specifically to social media, it has been suggested that emotions can be passed through social networks, and data from a 20-year longitudinal study confirm that this can happen off-line with happiness (Fowler & Christakis, 2008). Since then, there have been multiple papers published about emotional



contagion on Facebook and Twitter (a 280-character delimited social media site and phone application), examining whether or not this can also happen via online social networks.

One study experimentally manipulated the Facebook news feeds of different groups, exposing them to either positive or negative information. Those exposed to positive emotions were more likely to make positively valenced posts afterwards, and the same with negative exposure (leading to negatively-valenced posts), providing experimental evidence that emotional contagion occurs without direct interaction between people and without nonverbal cues (Kramer, Guillory, & Hancock, 2014). A 2015 study corroborated these findings on Twitter, demonstrating that when participants were exposed to more positively-valenced Twitter posts, they were more likely to subsequently post positive Twitter messages themselves. As well, some individuals (termed ‘high susceptible’) were more likely to adopt others’ emotions in their posting yet others (‘low susceptible’) were not (Ferrara & Yang, 2015).

Do all social networking sites work via emotional contagion – and for everyone? Perhaps not, as one recent article found. A group in The Netherlands pitted emotional contagion against a second mechanism – social comparison – to see the effect of viewing strangers’ posts on Instagram. Contrary to an emotional contagion hypothesis, social comparison predicts that browsing positive posts from others would elicit thoughts that others are happier or better-off than the viewer, which in turn may have negative effects on viewers’ moods. These researchers found that the answer depended on pre-existing levels of social comparison orientation (whether or not people are more likely to compare themselves to others in general). For individuals high in social comparison orientation, viewing positive posts from strangers on Instagram led to lower positive affect, and for those low in social comparison orientation, viewing positive posts from strangers led to higher positive affect (de Vries et al., 2018). Thus, the mechanisms may be different across individuals. Further studies investigating these mediators have also found inconclusive mechanistic support (Feinstein et al., 2013; Vogel, Rose, Roberts, & Eckles, 2014).

### **Heterogeneity in Types of Social Media Use**

Aside from the inconclusive nature of extant findings and a lack of mechanistic understanding, three central issues exist with social media research to date. First is the sheer variety and heterogeneity of what constitutes social media and social media engagement. Initial instantiations operated more closely to mere structural networks—connecting users with minimal content but with little-to no-ability to engage with content and media outside of the platform. Current social media platforms such as Facebook are far more dynamic and multimedia, providing live chat, live video streaming, group, fan, and business pages, news posting, marketplaces, and access to political and news content—all of which may affect people in different ways. To address this problem, social media researchers have divided social media use into two categories: passive and active (Deters & Mehl, 2013; Krasnova, Wenninger, Widjaja, & Buxmann, 2013; Burke, Marlow, & Lento, 2010). Passive Facebook use (PFU) involves consuming content without producing it, such as viewing other’s photographs, scrolling through news feeds, and viewing other’s conversations, whereas active Facebook use refers to activities that involve direct exchanges with other individuals, such as commenting on other people’s posts, posting photos, and posting status updates. Several studies have investigated the effect of passive versus active Facebook use on well-being, with findings unequivocally supporting the notion that passive use is more harmful to health than active use (Tandoc, Ferrucci, & Duffy, 2015; Shaw, Timpano, Tran, & Joorman, 2015; Krasnova, Wenninger, Widjaja, & Buxmann, 2013; Verduyn et al., 2015). Work has also indicated that passive social media use is associated

with a 33% increase in depression symptoms (Escobar-Viera et al., 2018). Furthermore, a recent meta-analysis revealed that across all studies comparing passive versus active use, passive use emerged as having the most negative consequences on well-being (Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017).

Given the emerging evidence that passive Facebook use yields negative health effects, it is likely necessary for researchers to examine whether other social media platforms yield similar outcomes. Instagram, one such platform, is a prime target. With over 1 billion active users per month (Instagram, 2020), Instagram allows users to upload photos and videos that can be edited with filters, tags, and location information. The application allows for nonreciprocal following of other users, and users can browse content without active engagement, akin to passive use on Facebook. As Instagram has gotten more popular in recent years, scientists have been trying to understand the benefits and consequences of its use in order to inform what responsible use may be. Extant research has already shown that increased Instagram use may be associated with higher rates of depression, anxiety, and negative body image (Lup, Trub, & Rosenthal, 2015; Mills, Musto, Williams, & Tiggemann, 2018). Still, it should be stressed that most of this work is correlational in nature, and thus causal claims about the harms of Instagram cannot be made.

### **Idiographic Versus Nomothetic Methods**

As stated above, much existing work falls prey to the second central issue with existing social media research – that the majority of research to date has been comprised of data collected using cross-sectional and nomothetic methods. In other words, data are collected at a single time point and then aggregated across subjects. Inferences made from psychological and medical research (e.g. treatment development, personality research) are typically drawn from statistical tests conducted on aggregated, group-level data, with the implicit assumption that group-level inferences, or findings, will generalize to the individuals who comprise those groups. Often overlooked in this assumption is the problem of ergodicity. Broadly speaking, ergodicity refers to a process by which individual variation can be inferred from group-level data. Historically, the field of psychology has assumed that most processes are ergodic in nature. But this assumption is not always (or even often) upheld. Recently Fisher, Medaglia, & Jeronimus (2018) investigated this specific question – whether or not a variety of constructs typically assumed to be ergodic were so in nature – by comparing distributions of bivariate correlations for certain variables computed within-subjects to distributions of between-subjects correlations for the same variables. Across all six data sets (that spanned polysomnographic data to self-reported emotion data), they found that the processes were largely nonergodic—that is, that the statistical features of between-subject data were measurably different from within-subject features. In fact, they found that the variance at the individual level of analysis was up to four times larger than at the group level. Assuming ergodicity for nonergodic processes leads to misinterpretations of findings that can stall the pace of progress in many fields.

As it pertains to social media research, group-level work that assumes ergodicity often overlooks nuanced, quantifiable differences between psychological processes occurring within a single individual, as well as the difference in the effects between individuals. For example, researchers have already concluded that different types of use (active vs. passive) affect people in distinct ways – but what about that use affecting two individuals differently? Does a twenty-five-year-old single woman with a tendency to compare herself to others using Instagram have the same effect on her mental health as a thirty-eight-year-old married man with a history of depression? Some extant work that has looked at individual differences, and recent work from

our lab all point to the conclusion that Instagram use is highly unlikely to have the same effect for these two individuals.

Although many studies have investigated the effect social media has on well-being, they have typically focused on between-subjects designs, asking if those who use social media more or less than their peers experience lower or higher levels of well-being. This work assumes ergodicity and overlooks the quantifiable differences that may occur for a single individual. Several scientists (Whitlock & Masur, 2019; Orben, Dienlin, & Przybylski, 2019) have stressed the importance of utilizing within-subjects designs in order to understand whether a single individual's social media use is associated with that specific individual's well-being, rather than designs that illustrate group-level associations. The clear suggestion is that experience sampling methods are the most likely designs to yield useful insights into use and well-being (Whitlock et al., 2019).

To date, six studies have followed these proposals and investigated within-person associations of social media use, primarily focusing on adolescents. Orben et al. (2019) assessed time spent using social media and life satisfaction using random-intercept cross-lagged panel models, and found a small negative reciprocal within-person association between the two variables. Similarly, Boers et al. (2019) utilized random-intercept multilevel models to determine the connection between screen time and depression, and found significant within-person associations between increased social media use time and increased depressive symptoms in the same year. Beyens et al. (2020) utilized an ecological momentary assessment approach and found that the association between social media use and affective well-being differed strongly across adolescents; for 46% of individuals, social media use was associated with feeling better, for 10% it was associated with feeling worse, and for 44% it was not associated with any changes in affective well-being. Rodriguez et al. (2021) similarly analyzed experience sampling data collected over two weeks and found that associations between social media use and depression symptoms differed substantially from individual to individual in both strength and kind, with some individuals feeling more depressed after using social media, and others feeling less depressed after using social media. Finally, both Coyne et al. (2020) and Jensen et al. (2019), both utilizing longitudinal designs, failed to find evidence for within-person associations between social media use and depression.

Together, these studies highlight the importance of factoring in individual differences when researching the impact of social media use on mood and well-being. Approaching social media research in a purely nomothetic manner fails to capture this variability, and again may be the reason extant work has produced ambiguous results.

### **Issues with Cross-Sectional Nature of Current Findings**

The within-person studies outlined above are important for illustrating the inter-individual variability of their social media findings – yet they still have produced equivocal findings. I argue that the majority of the work is limited due to its contemporaneous nature, meaning that the analyses often reflect *concurrent* relationships only, failing to provide information about temporally-structured, predictive relationships. Thus, temporal precedence remains an important and still unexplored area of social media research. As stated previously, the overwhelming majority of the work to date has been cross-sectional in nature. Contemporaneous time series models, although superior in their ability to reflect within-person associations over many observations, nevertheless remain unable to explore directional relationships from moment

to moment. Importantly, the disputes over Facebook research are largely due to the inability to draw directional (potentially *causal*) conclusions from correlational data.

For example, a large body of work from 2011 through 2018 concluded that increased Facebook use was associated with depression (O’keeffe & Clarke-Pearson, 2011; Nesi & Prinstein, 2015; Twenge, Joiner, Rogers & Martin., 2018; Booker, Kelly & Sacker, 2018), which led to the development of terms such as *Facebook depression* in the media to warn parents of the dangers of social media use (O’keeffe & Clarke-Pearson, 2011). Yet, this work was performed cross-sectionally, meaning that the research teams recruited subjects and surveyed them at a single point in time on their symptoms of depression, other mood factors and mental health variables, and Facebook usage. There was no way of uncovering whether increases in Facebook use at one time point led to increases in depressive symptoms at the next time point, or whether the reverse was true – that increased depressive symptoms at one time point led to increased Facebook use at the next – or whether a third, unmeasured variable was really the source of this association. Thus, the authors could not infer causality from their cross-sectional design, yet both in scientific articles and popular press articles, authors such as Twenge (2018) claimed that Facebook use caused depression, warning against the dangers of using it.

Recently Heffer, Good, Daly, MacDonell, & Willoughby (2019) wrote a rebuttal to these types of studies, arguing that the lack of directionality and temporal assessments are critical limitations to this body of work. They used a longitudinal cross-lagged analysis of the relation between frequency of daily social media use and a well-validated measure of depressive symptoms in a sample of young adults and adolescents between 2010 and 2018. In short, social media use did not predict future depressive symptoms in adolescent females, undermining Twenge, Joiner, Rogers & Martin’s (2018) key claims. Their results did, however, reveal a marginally significant relation between greater social media use at one time point and depressive symptoms at the next time point among adolescent males. Although these longitudinal designs are advantageous over the cross-sectional ones, they still involved asking participants about their social media use only one time per year. Social media habits of adolescents may change frequently over the course of the year (or even a month), however, so limiting measurement to one time per year may fail to capture the true nature of a participant’s use. They remain between-subject designs, which fail to capture the variability at the individual level.

This third critical issue – the lack of temporal order to the majority of social media research – can be overcome by employing intensive repeated measurement, or ecological momentary assessment designs, as Kross, Verduyn, Demiralp, Park, & Lee (2013) did to investigate Facebook use on two components of well-being, current emotion and life satisfaction. Kross et al. surveyed participants five times a day over a two-week period on their affect and Facebook use and conducted time-lagged analyses to investigate the effect of Time 1 Facebook use on Time 2 affect. The more people used Facebook, the worse they subsequently felt. The authors also investigated the opposite – whether Time 1 affect had any effect on Time 2 Facebook use – which it did not. By using ecological momentary assessment (EMA) techniques, the researchers could determine the direction of effects, providing temporal ordering to their conclusions. Although lagged analyses remain correlational in nature, these findings may point to potential causal hypotheses which experimental designs can address.

In the meantime, additional work remains to be done at time scales closer to the temporal scaling of social media use and affective variations. Quite simply, individuals do not use social media or experience affect over weeks or months, but over minutes and hours. Thus, extant longitudinal work on social media use, even at the level of the individual, may fail to provide

meaningful insights when methods rely on data collected at time points months or years apart. There is a clear need for research designs that use data collected over shorter periods of time—time periods that better reflect the constructs and dynamics at play in social media use and affect.

### **Social Media as Avoidance?**

In addition to methodological concerns, a particularly important potential mechanism that has been overlooked in extant work is the question of social media use as an avoidance strategy. Avoidance is a key symptom of distress disorders such as major depressive disorder (MDD) and generalized anxiety disorder (GAD). A large body of literature has documented how this maladaptive coping mechanism can paradoxically perpetuate symptoms by suppressing negative emotionality (Mennin, Heimberg, Turk, & Fresco, 2005), providing distraction from emotional topics (Borkovec & Roemer, 1995), and precluding the emotional processing of fearful stimuli (Borkovec, Alcaine, & Behar, 2004). By avoiding seemingly emotionally evocative experiences, avoidance is negatively reinforced as a coping mechanism and symptoms of MDD and GAD perpetuate and even increase in nature (e.g., Hayes, Wilson, Gifford, Follette, & Strosahl, 1996). A common critique of social media use in the media is that it perpetuates procrastination by providing a distraction from real-life, yet this topic has only been empirically tested in one study, which investigated whether users' motivations for cell phone and Internet use was related to negative mental health outcomes. Panova & Lleras (2016) examined how students used their phone to cope or escape from an anxiety-inducing situation, and found that phone usage offered a small “security blanket” effect, lowering initial negative reactions to stress but not lowering it over the long-term. It thus served as an avoidance strategy. Furthermore, using such devices for emotional coping was associated with higher rates of distress disorders. Although this study was done on overall phone usage, it nevertheless suggests that use itself can be a form of avoidance. Because of the inherently passive nature of Instagram and the ease at which individuals can access it, I predict that Instagram use may be a form of avoidance for certain individuals, namely those higher in symptoms of depression and anxiety.

Presently, there is a great deal to be understood about the effect of social media use, specifically Instagram, on mental health, and what motivations for use may be. Thus, I seek to clarify this relation by assessing the factors that may moderate it – that is, for whom is use more detrimental, and for whom is it may be more benign. Understanding the link between Instagram use and mental health is essential for proposing interventions in a clinical framework and for informing what responsible phone usage should be for adolescents and adults alike.

### **COVID-19 and its impact on Social Media Use**

At the time of this writing, the COVID-19 pandemic is an ongoing global pandemic of coronavirus disease 2019, caused by SARS-CoV-2, first identified in Wuhan, China in December 2019. The disease quickly spread and was recognized as a worldwide pandemic by the World Health Organization on March 11<sup>th</sup>, 2020. Shortly after, the United States, along with other countries, responded by declaring a national emergency, and individual states enacted versions of stay at home orders. In California, executive and public health orders were passed on March 19, 2020 that directed all Californians to stay home except to go to essential jobs or to shop for essential needs (e.g. for groceries or medications). These widespread orders and lockdowns across the world encouraged people to spend the majority of their time at home, and in the following months many researchers suggested strong effects on people's mental health. Recent work has started to investigate the impact of the COVID-19 pandemic on health. Many

studies have found that immediate effects of the pandemic, including social distancing from others, social isolation, and social and economic discord in the United States, were among the major contributors towards increased sadness, fear, frustration, helplessness, loneliness, and nervousness (Ahorsu et al., 2020; Sakib et al., 2020). Studies across the world on the impact of the pandemic have found support for increased suicide attempts (Bhuiyan et al., 2020; Dsouza et al., 2020; Griffiths and Mamun, 2020), increased psychological strain (Ahorsu et al., 2020), increased depression, confusion, stress, and anxiety in previously healthy individuals (Shigemura et al., 2020; Ho et al., 2020), increased depression and anxiety in healthcare workers (Pappa et al., 2020), and increased anxiety in college students (Cao et al., 2020). As time goes on, it is expected that many more studies will be conducted investigating the impact the pandemic has had on people's well-being and psychological health.

The COVID-19 pandemic is likely to have affected social media habits as well. A survey of over 4,500 participants found that the majority of people noted an increase in their social media consumption (72%) and posting (43%) during the pandemic, noting the biggest increases in Instagram use (69%) during quarantine (Hootsuite, 2021). Other work found that 43% of people said in early March 2020, at the start of stay at home orders, that they would increase their use of Instagram if confined to their homes during the coronavirus (Tankovska, 2021). Moreover, a recent study investigating social media use of both parents and children alike found that 82.3% of children increased their use of social media during the COVID-19 pandemic. This study also found significant positive associations between child anxiety and child social media use, and discovered that children with greater anxiety were more likely to have increased their technology uses and to use social media (Drouin et al., 2020). Between July and September 2020, Instagram added more than 76 million users, reaching a total of 1.16 billion total users by October 2020 (Hootsuite, 2021). This increased time spent on social media platforms such as Instagram further underscores the importance of understanding how it may impact people's mood, well-being, and mental health – as any deleterious impacts have the potential to be further amplified during the pandemic, adding increased burden to an already stressful time.

## **Aims and Hypotheses**

### **Study 1:**

Study 1 utilized EMA to explore the idiographic nature of Instagram use and how such use is associated with mood, via contemporaneous network models. Collecting intensive, repeated time-series data from each participant allowed us to estimate models of Instagram use and key mood variables on a person-by-person basis. Using strength centrality networks to compare the strength of specific nodes associated with Instagram uses in networks across participants, data were combined into an aggregate dataset for nomothetic analyses. This procedure afforded determination of how Instagram use connects to symptoms of positive or negative moods--and whether patterns are similar or different across individuals.

### **Study 2:**

Study 2 expanded on Study 1 and utilized EMA to examine the moment-to-moment (i.e. lagged) relationships among Instagram use and mental health. Both contemporaneous and time-lagged data structures were used in order to examine how these items were associated at any given point in time and how they may have driven each other from moment to moment. Participants completed demographic and baseline measures of well-being, affect, mental health, and internet usage, including the Satisfaction with Life Questionnaire, the Beck Depression

Inventory, the Rosenberg Self-Esteem Scale, the Scale for Social Comparison Orientation, the Social Provision Scale, and the Instagram Addiction Scale. Key variables of social media usage including number of followers and number of individuals they follow and the breakdown of whether or not these followers are strangers or known to the individual were also collected. Phone surveys were administered 16 times a day for one week, assessing questions about their Instagram use (reporting of any use and, if so, number of minutes used) over the preceding time since the past survey, other social media use, direct contact with others, avoidance, and questions about current affect, jealousy, and social comparison. Aside from our interest in overall affect, jealousy and social comparison were chosen specifically because of past research suggesting that they are highly implicated in social media use (Elphinston & Noller, 2011; Krasnova et al., 2013; Muise et al., 2009; Lup, Trub, & Rosenthal, 2015). This approach will allow for investigation of the timing of participants' Instagram use and psychological states.

Phone addiction and specifically social media addiction have been hot topics in popular culture in the recent years, and large technology companies (e.g., Samsung and Apple) have recently proposed methods to decrease addiction and help users utilize "responsible" phone usage. Yet, research to date has not adequately identified how social media companies such as Instagram affect mental health. This work has the significance to clarify a link between Instagram use and negative affect on a person-specific basis, and to reveal certain moderators of this interaction, which are crucial for proposing interventions and informing what responsible phone usage might be for teens and adults alike.

### **Study 1:**

The goal of the present study is to understand the links between Instagram use and mood at the individual level of analysis, over time, by collecting data idiographically and creating person-specific networks of Instagram use and mood variables. This is a particularly important endeavor given the strong evidence that nomothetic models, which rely on variation from person-to-person, may not generalize to specific predictions about a single individual (Molenaar, 2004). Consequently this research may help researchers understand the importance of idiographic work within the social media sphere.

### **Methods**

#### **Participants**

The sample was composed of 51 undergraduate participants from the University of California, Berkeley's research participant pool. In the following reporting, three participants will be used as exemplars to demonstrate person-level conclusions. Participants from the University of California, Berkeley's research participant pool (RPP) were eligible to sign up for the study in exchange for course credits. Sixty-two participants initially signed up and completed baseline measures. Nine participants enrolled but dropped out before completing all study components; their data were not included. The final sample included 42 women (82%) and 9 men (18%), with an average age of 20.04 ( $SD=2.18$ ). Of all 51 participants, 35% were Asian ( $n=19$ ), 31% were Hispanic/Latino ( $n=16$ ), 25% were Caucasian ( $n=13$ ), 6% designated their cultural background as 'Other' ( $n=3$ ), and 2% were African American ( $n=1$ ). Exclusion criteria were as follows: being under the age of 18; not having English proficiency (both written and spoken); not having regular access to a mobile phone that receives text messages, has internet

access, and has a touchscreen; and not being an Instagram user for at least the past 30 days. All participants consented to the study and were compensated via class credits. IRB approval was obtained by the University of California, Berkeley Institutional Review Board.

### **Procedure**

During the summer of 2018, participants signed up to participate in the study from an online portal in exchange for course credit. After participants passed initial eligibility criteria, they presented to the lab, were presented with and completed informed consent, and completed a demographic questionnaire. Participants were then introduced to the smartphone-based EMA data collection system used to administer surveys eight times a day for the following two weeks (with an average of 16 days). Beginning at least 30 minutes after each participant's self-reported wake-up time, surveys arrived approximately every two hours via SMS text message. Individuals clicked a link in the text message and were taken to a 15-item survey, with each item asking them to rate their experience and Instagram use over the preceding two hours using a 0-100 visual analog slider (continuous) and on a yes/no basis. Items were presented in randomized order, and participants were instructed to complete these surveys for a minimum of 14 days.

### **Daily Survey Items**

The daily surveys included a total of 15 items, including those from extant Diagnostic and statistical manual for mental disorders, 5<sup>th</sup> ed. (American Psychiatric Association, 2013) major depressive disorder (MDD) and generalized anxiety disorder symptom criterion, plus items pertaining to jealousy, thwarted belongingness, and social comparison. Participants also answered the question "In the time that has passed since the last survey, have you used Instagram?" Participants rated their experience of each symptom domain over the preceding two hours (the surveys were randomized to roughly a two-hour interval schedule) on a 0–100 visual analog slider, with anchors of not at all and as much as possible anchored at the 0 and 100 positions, respectively. The Instagram question was answered via yes/no. All participants in the study completed an average of 103 observations over 16 days; the three exemplars completed an average of 97 observations over 17 days.

### **Approach to Statistical Analysis**

For each participant, contemporaneous correlation matrices were computed. After computing the standard contemporaneous matrix, we estimated a sparse partial correlation network using a LASSO regularization method implemented in R (version 3.3.1; R Core Team, 2015) with package qgraph (Epskamp et al, 2012). The contemporaneous correlations between variables at time  $t$  were exogenous and thus not conditioned on any predictors. These correlations allow the construction of concentration networks similar to recent work in PTSD (McNally et al., 2015), MDD (van Borkulo et al., 2015), and other disorders (Wigman et al., 2015)—albeit at an idiographic, rather than nomothetic level. Strength centrality was then calculated by taking the sum of the edge weights associated with a given node. Individual strength centrality was computed for every participant and then the data was combined into a larger dataset for nomothetic analyses.

## **Results**

### **Between-Subject Results**



As noted above, concentration models derived from the correlations at time  $t$  were used to calculate the contemporaneous strength across the 15 variables, thus reflecting the centrality of each node as a function of its connectivity to the overall network. All present analyses focus on the *Used Instagram* node in the networks. For each result, values were normalized within participants (divided by the maximum value) in order to make them comparable across participants.

### Contemporaneous Networks

Figure 1 presents the results for the average normalized contemporaneous strength for *Used Instagram* across all 51 individual contemporaneous concentration networks. Values were normalized such that the maximum strength was 1 and the minimum was 0. The minimum value was exhibited by 9 participants (18%), indicating that for these individuals there was little to no relation between the *Used Instagram* node in their networks and any other mood variables. The maximum value was 0.53, indicating that, at most, *Used Instagram* exhibited only a middling influence over other nodes. The mean was 0.19, indicating that for the average participant there was a small relation between the *Used Instagram* node and the other nodes in the networks.

### Exemplar Participants

Whereas nomothetic analyses help to assess generalizable features of Instagram use across all participants, the strength of the idiographic approach lies in generating more granular results that provide rich detail at the individual level. Three exemplar participants are described here to highlight key features of the present analytic approach. Figures 2, 3, and 4 display the network models for P007, P057, and P024, respectively.

**Example 1 – Participant 7 (P007).** Figure 2 presents the network model for P007, a 20-year-old White female. P007 had one of the highest normalized strength values in the sample (*normalized strength*=0.50), indicating that this participant had one of the strongest relations between the *Used Instagram* node and all other variables assessed in her individual network, as compared across participants. In P007's network, the *Used Instagram* node exhibited its strongest positive relations with the nodes *Jealous* and *Worried*. As the networks were contemporaneous, this pattern shows that for her, using Instagram was highly connected with feelings of jealousy and worry. There were also weaker positive associations between the *Used Instagram* node and the nodes *Content*, *Enthusiastic*, *Anxious*, *Energetic*, and *Depressed*.

**Example 2 – Participant 57 (P057).** Figure 3 presents the network model for P057, a 20-year-old Hispanic/Latino female. P057 had relatively weaker connections from the *Used Instagram* node to other nodes in this individual's network when compared to other participants (*normalized strength*=0.02). *Used Instagram* was most strongly and positively associated with the *Depressed* node, yet this connection was fairly weak. Thus, for this individual, using Instagram was significantly but weakly connected to feelings of depression.

**Example 3 – Participant 24 (P024).** Figure 4 presents the network model for P024, a 23-year-old White female. For the *Used Instagram* node, P024 had a higher strength centrality than 80% of the networks (*normalized strength*=0.41). The strongest positive relation was between *Used Instagram* and *Jealous*. This participant also exhibited two weaker associations from the *Used Instagram* node: a positive association with *Energetic*, and a negative association with *Accepted*. This pattern indicates that, during sampling windows in which this individual reported using Instagram, she likewise reported higher levels of feeling jealous, relatively higher levels of feeling energetic, and relatively lower levels of feeling accepted.

## Discussion

The present study aimed to explore the idiographic nature of using Instagram and how its use connects to mood using contemporaneous networks (i.e., concurrent associations between depressive symptoms and Instagram use). Collecting intensive time-series data from each participant allowed me to estimate models of Instagram use and key mood variables on a person-by-person basis, using established network analysis procedures (Epskamp and Fried, 2016). Normalized strength was used as a centrality measure, which was calculated by taking the sum of the edge weights associated with a given node. After the individual strength centrality was computed for every participant, data were combined into a larger dataset for nomothetic analyses.

The histogram of the normalized strength values across individuals (Figure 1) highlights the importance of the idiographic approach. Although many participants (18%) exhibited no relation between Instagram use and mood contemporaneously, the remaining 42 did have some degree of association with various mood variables. Approaching social media research in a nomothetic manner fails to capture this variability and may be one reason extant work has produced equivocal results. Furthermore, the exemplar participants illustrate such variability. Participants 7 and 24 exhibited strong relations between Using Instagram and key negative mental health variables, including feeling jealous, depressed, and worried. Yet, Participant 57 did not exhibit such patterns. It may be the case that for Participants 7 and 24, using Instagram is more harmful than it is for participant 57, and thus different recommendations of use should be used for these different individuals.

### Limitations

Limitations of the current study include the contemporaneous nature of the networks, the way Instagram use was assessed, and the use of an undergraduate sample. First, the networks were contemporaneous in nature, meaning there was no temporal precedence among the variables, and no ability to examine predictive effects from one moment to the next. Although an important first step for visualizing the relationships among the variables of interest—and how they differ between individuals—these effects should be interpreted with caution. Within the current study’s data collection paradigm, Instagram use was assessed with a yes/no question over the preceding two hours. Therefore, the relationship between Instagram use and other variables at a single timepoint (as is used in contemporaneous networks) may be based on Instagram use anytime in the preceding two hours since the last survey, and as a consequence, symptoms that affected other symptoms relatively rapidly (i.e., Instagram use affecting feelings of sadness within 5 minutes and then dissipating) may not have been detected, despite an ostensibly *true* relation between the variables. Finally, the sample comprised undergraduates, so future work using a community sample is needed to explore how Instagram use and mood relationships may differ depending on age.

### Conclusions

The strengths of the current study are likely to outweigh the limitations and highlight the idiographic nature of social media use among college students. We see this as an important contribution to social media research, as recent work on social media, including that on Instagram, has produced equivocal results. Our results lead us to argue that nomothetic

investigations of social media use are limited and will fail to capture the independent nature of the effects. Future work should aim to validate these findings in community samples. More importantly, it should investigate them on a temporally, predictive nature using lagged association networks (Fisher et al., 2017) and assess the moderators for these relations (i.e., do pre-existing levels of depression, or age, or social comparison levels moderate the relationship between Instagram use and negative mood?), truly answering the question of “for whom is social media detrimental?” Once the field understands these answers, we can move forward with important interventions aimed at reducing the deleterious effects for specified individuals.

### **Study 2:**

Study 2 extends Study 1 in three ways. First, the sampling frequency in Study 2 for the EMA measurements was increased to 16 times per day, allowing us to more closely assess the immediate impacts using a structural equation modeling (SEM) approach. Second, Study 2 includes a broader participant population and increased sample size, with the potential for making results more generalizable to a wider population. Third, Study 2 includes a full clinical diagnostic interview, allowing us to assesses clinical diagnoses as potential moderators of the relations between Instagram use and affect, social comparison, and jealousy.

Four key aims will be addressed: (1) investigate the overall relation between Instagram use and mental health symptoms at the nomothetic and idiographic levels using a lagged model (see Figure 5 with affect as an example); (2) assess whether group-level or trait characteristics of the sample (i.e. age, sex, pre-existing social comparison orientation) moderate the observed lagged models, explaining for which individuals the observed relations between Instagram use and increase in negative affect are stronger and for which they are weaker (see Figure 6 with jealousy as an example); (3) examine to what extent Instagram is used for avoidance by assessing the contemporaneous relations between Instagram use and avoidance at the nomothetic and idiographic levels; and (4) assess whether group-level psychopathological characteristics of the sample (i.e., psychopathological diagnosis, depression symptoms, and anxiety symptoms) strengthen or moderate the contemporaneous relation between Instagram use and avoidance.

I hypothesize the following. (1) In the nomothetic analyses, increased Instagram use will not be significantly associated with increases in three mental health items: affect, jealousy, and social comparison, but in the idiographic analyses, certain individuals will show increased Instagram use to be significantly associated with increases in three mental health items: affect, jealousy, and social comparison. (2) Trait social comparison orientation, pre-existing internalizing disorder symptoms, and female sex will each positively moderate the relations between Instagram use and increase in mental health symptoms. (3) At the nomothetic level there will be no significant contemporaneous correlation between Instagram use and avoidance but for some individuals there will be strong contemporaneous correlations. (4) Diagnoses of anxiety disorders (including generalized anxiety disorder, social anxiety disorder, and panic disorder), and pre-existing symptoms of anxiety will positively moderate the contemporaneous relation between Instagram use and avoidance.

## **Method**

### **Participants**

A sample of 224 participants were recruited: 119 undergraduate students from the University of California, Berkeley's research participant pool (RPP), and 105 community participants online via Reddit. For the RPP participants, students were eligible to sign up for the study in exchange for course credits. For the community subjects, participants were eligible if they met all study requirements (detailed below). The final sample included 154 people who identified as Female (68.8%), 68 identified as Male (30.4%), and 2 identified as Nonbinary (0.8%), with an average age of 22.4 ( $SD=4.0$ ). Of all 224 participants, 45.5% identified as Asian ( $n=102$ ), 31.3% as White ( $n=70$ ), 8.5% as Hispanic/Latino ( $n=19$ ), 7.6% as African American ( $n=17$ ), 5.8% as Mixed Race ( $n=13$ ), and 1.3% designated their cultural background as 'Other' ( $n=3$ ). Inclusion criteria were that participants 1) were between 18-35 years old (as reports indicate that 65% of users in 2019 were between the ages of 18-35; Clement, 2019), 2) had access to a web-enabled smart phone and were willing to use it to complete assessments multiple times per day, 3) had been using Instagram for at least one month, and 4) were monolingual or sequential-multilingual speakers of, and literate in, English (this criterion was selected based on evidence that emotion may be experienced or expressed differently when a person uses their second language; Caldwell-Harris, 2014). Full participant characteristics are depicted in Table 1.

## Measures

**The Mini-International Neuropsychiatric Interview (Sheehan et al., 1998)** The Mini International Neuropsychiatric Interview (M.I.N.I.) is a semi-structured clinician-administered psychiatric diagnostic interview to assess the presence of DSM-IV Axis I diagnoses. With a short administration time of 15-30 minutes, the M.I.N.I. is a short but accurate structured interview for research and clinical settings. Previous work has shown the M.I.N.I. to be reliable and valid (with high sensitivity and concordance with other interviews for diagnoses; Sheehan et al., 1998).

**Satisfaction with Life Scale (Diener, Emmons, Larsen, & Griffen, 1985).** The Satisfaction with Life Scale (SLS) is a 5-item scale designed to measure global cognitive judgments of one's life satisfaction, rather than positive or negative affect. Participants rate how much they agree or disagree with each statement on a 7-point likert scale. The coefficient alpha for the scale has ranged from .79 to .89, indicating that the scale has high internal consistency (Pavot & Diener, 2008). The scale was also found to have good test-retest correlations (.84, .80 over a month interval; Pavot & Diener, 2008).

**Penn State Worry Questionnaire (Meyer, Miller, Metzger, & Borkovec, 1990).** The Penn State Worry Questionnaire (PSWQ) is a 16 item self-report measure of pathological worry. Previous factor analysis indicated that the PSWQ assesses a unidimensional construct with internal consistency of .91 (Meyer et al., 1990). High retest reliability (ranging from .74-.93) was also demonstrated across periods ranging from 2 to 10 weeks (Molina & Borkovec, 1994).

**Beck Depression Inventory (Beck, Rush, Shaw, & Emery, 1979).** The Beck Depression Inventory (BDI) is a 21-item self-report measurement of symptoms of depression (including cognitive, affective, somatic, and motivational symptoms). Each item represents a symptom of depression, and respondent rate their responses on a 0-3 likert scale of intensity. Previous analyses have illustrated that the BDI has excellent internal consistency, convergent validity, and divergent validity (Beck, Steer, & Garbin, 1988).

**Emotion Regulation Questionnaire (Gross & John, 2003).** The Emotion Regulation Questionnaire (ERQ-10) measures participants' tendency to regulate their emotions in two ways:

(1) cognitive reappraisal; and (2) expressive suppression. Participants respond to each item on a 7 point likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Previous analyses have indicated alpha reliabilities of 0.79 for reappraisal and 0.73 for suppression, and test-retest reliability across 3 months was 0.69 for both scales (Gross & John, 2003).

**Rosenberg Self-Esteem Scale (Rosenberg, 1965).** The Rosenberg Self-Esteem Scale is a 10-item scale that measures global self-worth by measuring both positive and negative feelings about one's self. Items are presented on a 4-point likert scale with answers ranging from strongly agree to strongly disagree. Previous work has shown the Rosenberg Self-Esteem Scale to be a reliable and valid quantitative tool for self-esteem assessment with high internal consistency (0.77) and good test-retest reliability (0.85; Rosenberg, 1965; Silber & Tippett, 1965).

**Iowa-Netherlands Comparison Orientation Measure (Gibbons & Buunk, 1999).** The Iowa-Netherlands Comparison Orientation Measure (INCOM) measures the tendency to engage in social comparison, and consists of 11 items presented on a five-point scale ranging from strongly disagree to strongly agree. This measure has been widely used since its inception and work to date has shown that the INCOM has high validity (Schneider & Schupp, 2011).

**Bergen Facebook Addiction Scale (Andreassen, Torsheim, Brunborg, & Pallesen, 2012).** The Bergen Facebook Addiction Scale (BFAS) was developed to assess Facebook addiction, and consists of 18 items that comprise six core features of addiction: salience, mood modification, tolerance, withdrawal, conflict, and relapse. Each item is scored on a 5-point likert scale ranging from very rarely to very often, with higher scores indicating greater Facebook addiction. Previous analyses have indicated that this scale has high internal consistency (0.83) and test-retest reliability (0.82; Andreassen et al., 2012).

**Instagram Addiction Scale (Kircaburun & Griffiths, 2018).** The Instagram Addiction Scale (IAS) was developed using a modified version of Internet Addiction Test (IAT; Young, 1998) and is comprised of 15 questions presented on a 0-6 likert scale from "never" to "always." The IAS was modified by changing the word "Internet" with "Instagram" on the IAT. Previous work using EFA and CFA have shown that the scale is valid and reliable in assessing Instagram addiction levels of university students (Kircaburun & Griffiths, 2018). The scale places individuals into four levels of addiction: non-addiction (15–37), mild addiction (38–58), moderate addiction (59–73), and severe addiction (over 73).

**EMA surveys.** The daily surveys included a total of seven items designed to measure affect, jealousy, social comparison, Instagram use, other media use, direct human interaction, and avoidance. All surveys were sent and responded through via the LifeData application, with which participants were assisted downloading while in the lab (for the in-person portion), or via a video linked at the end of the online M.I.N.I. administration (for the online/remote portion). On each survey, participants were instructed to rate their current experience of each domain of affect, jealousy, and social comparison at the current time on a 0–100 visual analog slider, with anchors of not at all and as much as possible anchored at the 0 and 100 positions, respectively. The Instagram questions were assessed over the preceding time period since the last survey via a yes or no dichotomous presentation, and if answered yes, a follow-up question of how much time spent on Instagram was asked. Other media, direct human interaction, and avoidance were assessed over the preceding time period since the last survey via the same yes/no dichotomous scale. Surveys were completed sixteen times a day, and were estimated to take 0.5-1 minutes each. Surveys were sent at a randomized time in 30-minute long blocks over an 8-hour period from 11:00am – 7:00pm. This sampling window was chosen based on evidence indicating that Instagram global engagement peaks at the 11am hour and continues until 4pm (West, 2019); thus

this peak engagement window was chosen for sampling. The participants had from the time a survey was sent until the time the next survey was sent to respond. The answers were time-stamped. Participants were sent an average of 107 surveys, with a minimum of 67 and maximum of 215. Participants completed an average of 98 surveys, with a minimum of 58 and a maximum of 192. Average survey compliance was 91%, with a minimum of 80% and maximum of 100% across the entire sample.

### **Procedure**

Data collection began in January 2020 through the RPP program. With the start of the COVID-19 pandemic in March 2020, the entire procedure changed to a remote, online format. For the in-person portion from January-March 2020, undergraduate participants were recruited through the RPP program, and after completing a brief online survey to determine initial eligibility, they presented to the Idiographic Dynamics Lab at UC Berkeley. A trained research assistant conducted the M.I.N.I, and then participants were instructed to complete demographic and baseline measures of well-being, affect, psychopathology, and Instagram and Facebook addiction. Key variables of social media usage including number of followers and number of individuals they follow and the breakdown of whether or not these followers are strangers or known to the individual were also collected.

Participants were then introduced to the EMA system. In order to systematically ensure that participants were responding to prompts consistently, they were given a list of synonyms and vignettes corresponding to each of the seven constructs that were assessed during the EMA period. A trained experimenter reviewed each of the items in detail, asking participants to generate examples of times they had experienced category in their own lives. To ensure correct understanding, participants were presented with a new set of seven vignettes corresponding to each EMA question category and were asked to appropriately categorize them. Their response data was recorded, and they were given corrective feedback as to the accuracy as necessary. In the event that participants were able to correctly respond to the vignettes after multiple attempts, they were compensated for the lab portion of the study and were not asked to continue participation in the next steps of the study.

After this, participants were given instructions on how to use the EMA system on their smartphones, including instructions and a step-by-step walkthrough of how to correctly download the LifeData application, which was used to send the EMA prompts. Participants were asked to complete the assessments when prompted for the following week. Participants were told that their compensation for participating in the study was contingent upon their completing at least 80% of the assessments. A sampling frequency of 16 times per day was used, This is at the faster end of published EMA studies in the emotion literature, and was hypothesized to be frequent enough to detect a signal of the immediate effect of social media while still minimizing participant burden and hopefully maximizing our ability to retain participation over the entirety of the sampling period.

### **Procedural adaptations for COVID-19**

Again, because of the COVID-19 pandemic and government-mandated shelter-in-place orders starting in March 2020, all data collection shifted to a remote, online-based format. Undergraduate participants continued to be recruited through the RPP program. After completing a brief screener to determine eligibility, participants were presented with an overview of the study and directed to an online consent form. If they agreed to participate and signed the consent

form, they were prompted to enter their information. After confirming eligibility, the study team contacted eligible participants and sent them a link to a Qualtrics survey which included all of the demographic and baseline measures from the initial in-person study visit (including measures of well-being, affect, psychopathology, and Instagram and Facebook addiction, as well as key variables of social media usage including number of followers and number of individuals they follow and the breakdown of whether or not these followers are strangers or known to the individual). At the end of the survey they were provided with a new link, which opened an online-version of the M.I.N.I. Once they reached the end of the M.I.N.I., they were directed to a YouTube video that introduced subjects to the EMA system, including instructions and a step-by-step walkthrough of how to correctly download the LifeData application, as well as a detailed overview of each of the items to be assessed, with examples given for each item. As was done in the February-March 2020 data collection phase, participants were asked to complete the assessments when prompted for the following week, and were told that their compensation for participating in the study was contingent upon their completing at least 80% of the assessments. A sampling frequency of 16 times per day continued to be used.

## **Data Analytic Plan**

### **Preliminary Analyses**

For each individual's time series, each of the key EMA variables were duplicated and lagged by one observation, in order to provide values for time point ( $t$ ) and the preceding time point ( $t-1$ ). Before conducting all analyses, variables were plotted to assess for normality. Prior to the main analyses, the contemporaneous correlations among the variables were estimated.

### **Primary Analyses**

#### **Hypothesis 1.**

**Nomothetic models.** To assess the lagged hypothesis that increased Instagram use at one time point predicts increased negative affect at the nomothetic level, a lagged vector-autoregressive model was tested for its fit to the group aggregated covariance matrix, using the structural equation modeling 'lavaan' package in R (Roseel, 2012; R Core Team, 2016). To construct this model, all autoregressive paths were specified (e.g. Instagram use at  $t-1$  predicting Instagram use at  $t$ , affect at  $t-1$  predicting affect at  $t$ ). To test hypothesized relations, cross-lagged paths were specified for Instagram use at  $t-1$  predicting affect at  $t$ , as was the path to test the competing directional hypothesis, affect at  $t-1$  predicting Instagram use at  $t$  (See Figure 5). Three indices were used to examine fit: the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Non-normed Fit Index (NNFI). Models were deemed acceptable when these indices were  $< 0.080$ ,  $> 0.95$ , and  $> 0.95$ , respectively.

**Idiographic models.** After testing the hypothesized relations at the group level, we then tested the theoretical model at the individual level. To do so, the raw survey data from each individual dataset was inputted into R. and the lagged vector-autoregressive model described above tested for its fit to each individual dataset using separate, person-specific models. As each person was fit to three models (for affect, jealousy, and social comparison), a total of 672 models were conducted (224 participants x three models). As previously noted, final models for each individual were determined by fit statistics; a well-fitting model for a single individual for one variable tested indicates that the structural relations in that individual's time series data is structurally consistent with the proposed lagged regression model. Each beta path between the

hypothesized relation paths was then combined into an aggregate dataset for moderation analyses.

### **Hypothesis 2.**

**Moderation analyses.** To assess whether theoretically-relevant group-level characteristics of the sample (measured at baseline) moderated the relationships between Instagram use and affect, jealousy, and social comparison, we examined whether all theoretically important variables (including demographic variables, social comparison orientation, female gender, internalizing disorder diagnoses, self-reported symptoms of depression and anxiety, and level of Instagram and Facebook addiction) predicted changes in the three outcome variables assessed in the idiographic models described above (affect, jealousy, social comparison). All models were conducted in R (Version 1.3.1103).

### **Hypothesis 3.**

**Nomothetic models.** To examine the contemporaneous correlations between Instagram use and avoidance at the nomothetic level, data from each individual's time series were combined into a larger nomothetic dataset. Pearson correlations between the contemporaneous (Time  $t$ ) avoidance and contemporaneous (Time  $t$ ) Instagram use were estimated using the R package 'Hmics' (Harrell, 2019).

**Idiographic models.** After testing the hypothesized correlational relations at the group level, we then tested the model at the individual level. Each individual's time series data were inputted into R, and, as described above, Pearson correlations were calculated between the contemporaneous (Time  $t$ ) avoidance and contemporaneous (Time  $t$ ) Instagram use, using the R package 'psych' (Revelle, 2021). Individual correlation coefficients were then combined into a dataset for moderation analyses.

### **Hypothesis 4.**

**Moderation analyses.** To assess whether theoretically-relevant group-level characteristics of the sample (measured at baseline) moderated the strength of the correlation between avoidance and Instagram use, we examined whether psychopathological variables (including anxiety disorder diagnosis as measured by the M.I.N.I., and symptoms of anxiety as measured by the PSWQ) predicted the strength of the correlation coefficient between avoidance and Instagram use. All models were run in R using ordinary least squares regression.

### **Exploratory Analyses**

Finally, I took a data-driven approach for both moderation analyses in Aims 2 and 4. Specifically, exploratory moderation analyses investigated whether demographic variables such as socioeconomic status, age, education, self-report measurements of emotion regulation, self-esteem, optimism, life satisfaction, social support, and clinical diagnoses such as substance use disorders and eating disorders moderated the relations described above.

## **Results**

### **Survey Response and Contemporaneous Correlations**

Participants completed an average of 98 observations over the week-long EMA period, ranging from 58 to 192. In total, participants completed 21,988 assessments (91.78% average



compliance). In 36% of all assessments, participants had used Instagram ( $n = 7,935$ ). Bivariate contemporaneous correlations between Instagram use, affect, jealousy, and social comparison (estimated for the group level and for each person) showed pronounced variability across the sample. Between-person correlations between Instagram use and affect, Instagram use and jealousy, and Instagram use and social comparison were  $r = -0.01$ ,  $r = 0.17$ , and  $r = 0.20$ , respectively. Within-person correlations between Instagram use and affect ranged from  $r = -0.78$  to  $r = 0.54$  ( $M_r = -0.04$ ), within-person correlations between Instagram use and jealousy ranged from  $r = -0.37$  to  $r = 0.77$  ( $M_r = 0.12$ ), and within-person correlations between Instagram use and social comparison ranged from  $r = -0.41$  to  $r = 1.00$  ( $M_r = 0.14$ ). Summary statistics of between- and within-person correlations and histograms of within-person correlations are presented in Table 2 and Figure 7, respectively.

### **Nomothetic SEM Models**

Three lagged vector autoregressive models were fit to the data for the three constructs of affect, jealousy, and social comparison. Although the lagged vector autoregressive models each showed excellent fit to the group-aggregated data (RMSEA < 0.001, SRMR < 0.001, CFI = 1.00, TLI = 1.00 for each), coefficients for the hypothesized cross-lagged paths were quite small, approaching zero in all three models (see Table 3). Thus, at the group level, our models showed an exclusively autoregressive structure. Across the sample, Instagram use, affect, jealousy, and social comparison significantly predicted themselves over time, but these variables did not exhibit significant cross-lagged relationships.

### **Idiographic SEM Models**

The hypothesized lagged vector-autoregressive model was then fit to each idiographic time series, one person at a time (224 total). This model was well-fit to 100% of the participants' datasets according to the criteria specified above. Of these 224 models, 153 (68.3%) revealed an exclusively autoregressive structure (similar to the nomothetic exploratory model). The remaining 71 individuals (31.7%) exhibited at least one significant cross-lagged path between Instagram use, affect, jealousy, and social comparison, with pronounced variability across participants. Frequencies of lagged paths are reported in Table 4.

### **Moderation analyses**

Moderation analyses were computed via OLS regression analyses, with predictor variables as potential moderators, and outcome variables as the idiographic vector-autoregressive beta paths between Instagram use and affect, jealousy, and social comparison, respectively. Four theoretically motivated OLS regression models were conducted for each of the three variables, totaling twelve models. For all OLS regression analyses, rows of data with missing surveys were excluded as a function of listwise deletion.

The first model assessed whether Instagram usage demographics, collected at baseline, predicted individual differences in the beta paths between Instagram use and affect, jealousy, and social comparison, respectively. Results indicated that number of followers (taken at baseline) moderated the relation between Instagram use predicting affect and jealousy, such that the fewer followers someone had, the more likely it was that Instagram use was linked with feeling better ( $\beta = -0.21$ ,  $F(219) = 2.711$ ,  $p < 0.04$ ,  $R^2 = 0.05$ ) and the more likely it was that Instagram use would make them feel jealous ( $\beta = -0.31$ ,  $F(192) = 1.701$ ,  $p < 0.00$ ,  $R^2 = 0.08$ ). Time spent on Instagram positively moderated the relation between Instagram use and social comparison, such

that the more time spent on Instagram, the more likely Instagram use was associated with social comparisons to others ( $\beta = 0.18$ ,  $F(194) = 1.12$ ,  $p < 0.04$ ,  $R^2 = 0.05$ ).

The second model assessed whether more general demographic variables predicted individual differences in the beta path between Instagram use and affect, jealousy, and social comparison, respectively. Results indicated no significant predictor variables.

The third model assessed whether symptoms from self-report variables collected at baseline (including the Satisfaction with Life Scale, Penn State Worry Questionnaire, Beck Depression Inventory, Emotion Regulation Questionnaire, Rosenberg Self-Esteem Scale, Iowa-Netherlands Comparison Orientation Measure, Bergen Facebook Addiction Scale, and the Instagram Addiction Scale) predicted individual differences in the beta paths between Instagram use and affect, jealousy, and social comparison, respectively. Results indicated no significant predictor variables.

The fourth and final model assessed whether clinical diagnoses, as determined by the M.I.N.I., predicted individual differences in the beta paths between Instagram use and affect, jealousy, and social comparison, respectively. Results are presented in Table 5. A diagnosis of current substance use disorder significantly predicted the beta path between Instagram use and affect ( $\beta = 0.82$ ,  $p = 0.003$ ). Diagnoses of current posttraumatic stress disorder ( $\beta = 0.17$ ,  $p = 0.032$ ), current substance use disorder ( $\beta = 1.32$ ,  $p = <0.001$ ), and current anorexia ( $\beta = 0.46$ ,  $p = 0.032$ ) significantly predicted the beta path between Instagram use and jealousy. Lastly, diagnoses of current substance use disorder significantly predicted the beta path between Instagram use and social comparison ( $\beta = 0.73$ ,  $p = 0.030$ ). No other clinical diagnoses were found to be significant.

Competing directional hypotheses were also tested, in order to assess whether certain variables moderated the relation between lagged affect, jealousy, and social comparison as predictors of Instagram use. As described above, four theoretically-motivated OLS regression models were conducted for each of the three variables, totaling twelve models. For all OLS regression analyses, rows of data with missing surveys were excluded as a function of listwise deletion.

The first model assessed whether Instagram usage demographics, collected at baseline, predicted individual differences in the beta paths from affect to Instagram use, jealousy to Instagram use, and social comparison to Instagram use, respectively. Results indicated no significant predictor variables.

The second model assessed whether demographic variables predicted individual differences in the beta paths from affect to Instagram use, jealousy to Instagram use, and social comparison to Instagram use, respectively. Job status significantly predicted the beta paths from social comparison to Instagram use ( $\beta = -0.17$ ,  $F(207) = 1.345$ ,  $p < 0.04$ ,  $R^2 = 0.06$ ); no other demographic variables were found to be significant.

The third model assessed whether symptoms from self-report variables collected at baseline (including the Satisfaction with Life Scale, Penn State Worry Questionnaire, Beck Depression Inventory, Emotion Regulation Questionnaire, Rosenberg Self-Esteem Scale, Iowa-Netherlands Comparison Orientation Measure, Bergen Facebook Addiction Scale, and the Instagram Addiction Scale) predicted individual differences in the beta paths from affect to Instagram use, jealousy to Instagram use, and social comparison to Instagram use, respectively. Results are presented in Table 6. Both ratings of one's life satisfaction and social comparison orientation were significant predictors of the beta path from affect to Instagram use at the  $p <$

0.05 level, indicating that these variables moderated the relation between affect and Instagram use.

The fourth and final model assessed whether clinical diagnoses, as determined by the M.I.N.I., predicted individual differences in the beta paths from affect to Instagram use, jealousy to Instagram use, and social comparison to Instagram use, respectively. A diagnosis of current social anxiety disorder significantly predicted the beta path from affect to Instagram use ( $\beta = -0.19$ ,  $F(202) = 0.818$ ,  $p < 0.03$ ,  $R^2 = 0.08$ ), such that having a social anxiety disorder negatively moderated the relationship between increased affect predicting Instagram use. No other clinical diagnoses were found to be significant.

### **Nomothetic Contemporaneous Correlation Models**

Data from each individual time series were combined into a larger nomothetic dataset to assess contemporaneous correlations between Instagram use and avoidance at the nomothetic level. A Pearson correlation was conducted between the contemporaneous (Time  $t$ ) avoidance and contemporaneous (Time  $t$ ) Instagram use. Results indicate a significant positive correlation between avoidance and Instagram use,  $r(22,069) = 0.19$ ,  $p = < .001$ .

### **Idiographic Contemporaneous Correlation Models**

The correlation between Instagram use and avoidance was then conducted on each idiographic time series data, one person at a time (224 total). Results indicated significant variability. Of these 224 models, 23% ( $N = 51$ ) revealed a significant contemporaneous correlation between Instagram use and avoidance. Forty-six of these significant correlations were positive, and five were negative. The remaining 77% of individuals ( $N = 173$ ) exhibited no significant contemporaneous correlation between Instagram use and avoidance. Frequencies of these within-person contemporaneous correlations between are presented in Figure 8.

### **Moderation analyses**

Moderation analyses were computed via OLS regression analyses, with predictor variables as potential moderators, and the outcome variables as the idiographic contemporaneous correlation coefficient between Instagram use and avoidance. Three OLS regression models were conducted. For all OLS regression analyses, rows of data with missing surveys were excluded as a function of listwise deletion.

The first model assessed whether demographic variables predicted individual differences in the idiographic contemporaneous correlation coefficient between Instagram use and avoidance. Increased age significantly predicted the correlation coefficient between Instagram use and avoidance ( $\beta = 0.23$ ,  $F(181) = 0.873$ ,  $p = 0.04$ ,  $R^2 = 0.05$ ); no other demographic variables were found to be significant.

The second model assessed whether symptoms from self-report variables collected at baseline (including the Satisfaction with Life Scale, Penn State Worry Questionnaire, Beck Depression Inventory, Emotion Regulation Questionnaire, Rosenberg Self-Esteem Scale, Iowa-Netherlands Comparison Orientation Measure, Bergen Facebook Addiction Scale, and the Instagram Addiction Scale) predicted individual differences in the idiographic contemporaneous correlation coefficient between Instagram use and avoidance. Decreased self-esteem, as measured by the Rosenberg Self-Esteem Scale, significantly predicted the correlation coefficient between Instagram use and avoidance ( $\beta = -0.25$ ,  $F(182) = 1.727$ ,  $p = 0.02$ ,  $R^2 = 0.08$ ); no other self-report variables were found to be significant.

The third model assessed whether clinical diagnoses, as determined by the M.I.N.I., predicted changes in the idiographic contemporaneous correlation coefficient between Instagram use and avoidance. Results are presented in Table 7. Diagnoses of current substance use disorders (specifically hallucinogenic use disorder and inhalant use disorder) and current binge eating disorder were significant predictors of the contemporaneous correlations at the  $p < 0.05$  level. This indicates that these variables moderated the correlations between Instagram use and avoidance in that diagnoses predicted a stronger correlation between Instagram use and avoidance at the individual level.

## Discussion

The aims of the present study were to first expand upon the findings from Study 1 by exploring the idiographic effects that Instagram use has on affect, jealousy, and social comparison at the level of the individual, and second to understand potential moderators, or factors, influencing these individualized relations. The potentially beneficial and deleterious consequences of social media use on mood and psychopathology have been contested in the literature to date, with numerous contradictory findings. Several researchers have documented negative outcomes associated with social media use (Kalpidou, Costin, & Morris, 2011; Valenzuela, Park, & Kee, 2009; Mehdizadeh, 2010; Kross, Verduyn, Demiralp, Park, & Lee, 2013), whereas others have found benign, or even beneficial outcomes (Jelenchick, Eikhoff, & Moreno, 2013; Przybylski & Weinstein, 2017; Ellison, Steinfield, & Lampe, 2007). Possible reasons for such inconsistent findings include (1) the heterogeneity in the types of social media use that have been studied and the (2) nomothetic and (3) cross-sectional nature of the majority of study designs

Pertaining to heterogeneity, the present study sought to overcome this by focusing specifically on Instagram, a platform that allows nonreciprocal following of other users, largely mimicking “passive use,” a type associated with the most negative outcomes for health across all social media platforms (Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017). I also addressed the issue of ergodicity by collecting intensive repeated measures at the level of the individual, with explicit contrast to group-level findings. The critical issue – the lack of temporal order in the majority of social media research – was addressed in the present study by the use of intensive repeated measurement, or ecological momentary assessment, to assess directional hypotheses from temporally structured predictive relations. Results revealed marked individual heterogeneity in responses to Instagram use, demonstrating the importance of including both between-subjects and within-subjects levels of analysis.

In support of our first hypothesis, increased Instagram use did not significantly predict increases in the three mental health items of interest (affect, jealousy, and social comparison) at the group level. Although the three lagged vector autoregressive models each showed excellent fit to the group-aggregated data (RMSEA  $< 0.001$ , SRMR  $< 0.001$ , CFI = 1.00, TLI = 0.00 for each), coefficients for the hypothesized cross-lagged paths approached zero in all three models (see Table 3). The models all exhibited an exclusively autoregressive structure, an important factor in demonstrating how existing nomothetic designs may overlook nuanced, quantifiable differences between psychological processes occurring within a single individual, as well as the difference in the effects between individuals.

Furthermore, the hypothesis idiographic analyses would reveal, for certain individuals, that increased Instagram use was significantly associated with increases in three mental health

items—*affect*, *jealousy*, and *social comparison*—was supported. Of the 224 total participants, 71 (31.7%) exhibited at least one significant cross-lagged path between Instagram use, *affect*, *jealousy*, and *social comparison*, with pronounced variability across participants (Table 4 reviews the frequencies of lagged paths in the idiographic SEM models).

There are two important takeaways from these findings. First, there is substantial disagreement between the group-level and individual-level analyses. Second, group-level findings cannot generalize to individuals that comprise those groups, in the context of social media research. Note that this is common in many other domains of human subjects research (Fisher et al., 2018).

The second hypothesis, that trait social comparison orientation, pre-existing internalizing disorder symptoms, and female sex would each positively moderate the relationships between Instagram use and increase in mental health symptoms, was partially supported. Posttraumatic stress disorder significantly moderated Instagram use with respect to increased jealousy, yet no other hypothesized moderators were found to be significant. Yet the number of followers someone had, the time spent on Instagram (baseline reported values), and current diagnoses of substance use disorder, posttraumatic stress disorder, and anorexia were all significant moderators of one or more of the relations between Instagram use and either *affect*, *jealousy*, or *social comparison*. Specifically, the more followers someone had on Instagram, the more likely it was that Instagram use would make them feel worse ( $\beta = -0.21$ ,  $F(219) = 2.711$ ,  $p < 0.04$ ,  $R^2 = 0.05$ ), and the fewer followers someone had, the more likely it was that use would make them feel jealous ( $\beta = -0.31$ ,  $F(192) = 1.701$ ,  $p < 0.00$ ,  $R^2 = 0.08$ ). Perhaps a higher number of followers puts an added layer of pressure on users, making them feel that they have to portray a certain image that may not be what they are truly experiencing in the moment when posting a photo or interacting on the app. Recent reports have suggested that “influencers” – people who have built a sizeable social network of people following them and are in turn paid to promote certain brands or products—are more likely to develop anxiety and depression from using the app (Gritters, 2019). The added pressure may be the reason why someone with more followers is more vulnerable to the negative effects of Instagram use. Conversely, having fewer followers may lead someone to compare themselves with other users with more followers, in turn making them more jealous after using Instagram.

Additionally, the more time people spent on Instagram (reported at baseline through phone battery percentages, an objective measure of phone use), the more likely they were to socially compare themselves to others after using it ( $\beta = 0.18$ ,  $F(194) = 1.12$ ,  $p < 0.04$ ,  $R^2 = 0.05$ ). Recent work has shown that certain characteristics may contribute to why people spend more time on Instagram, including being more addicted to social media and having lower life satisfaction (Yesilyurt & Solpuk Turhan, 2020). The more time spent on Instagram may provide more opportunities to succumb to the negative effects of use, including, as our data show, *jealousy* as one of those outcomes. It is quite possible that social media use may become more detrimental the more time one uses it, at least for some users.

Regarding clinical diagnoses, analyses revealed that current diagnoses of substance use disorder, anorexia, and, as hypothesized, posttraumatic stress disorder, were all significant moderators. Substance use disorder positively moderated the relationship between Instagram use and *affect*, *jealousy*, and *social comparison*, such that those with diagnoses of substance use disorders were more likely to have increased *affect* after using Instagram, but also more likely to have increased *jealousy* and *social comparison* (results depicted in Table 5). Understanding these findings is of critical importance, as reports show that by 12<sup>th</sup> grade, about two-thirds of students

have tried alcohol, about 20% have reported using a prescription medicine outside of a prescription (Johnson et al., 2014), and about half of all high-school students have reported using marijuana (Kann et al., 2013). Physicians, public health experts, and psychologists have emphasized the severity of these problems, as 19.7 million American adults aged 12 and older have battled substance use disorders in the recent years, and more than 90% of those who have addictions started to drink alcohol or use drugs before the age of 18 (SAMHSA, 2018). The positive moderating effect of substance use disorder on increased affect after using Instagram may be due motivational factors – people who are struggling with substance use themselves may see people who have gone through recovery and succeeded, which increases their mood and motivates them to do the same. “Sober influencers,” deemed by media outlets as profiles promoting sobriety, are growing in popularity. If those with substance use disorders see these accounts, they may compare themselves to them in an aspirational way. Yet doing so could also increase jealousy, as our data showed, because of this upwards social comparison. It will be important in future research to understand the content of what populations diagnosed with substance use disorders are viewing on Instagram to understand underlying mechanisms of this interaction.

Finally, diagnoses of posttraumatic stress disorder and anorexia each positively moderated the relationship between Instagram use and jealousy; those with either diagnosis were more likely to have increased jealousy after using the app (results depicted in Table 5). These findings are in line with our original hypothesis that internalizing disorders such as posttraumatic stress disorder would moderate the effects that Instagram use has on mental health. Symptoms of posttraumatic stress disorder include alterations to cognition that can lead to negative interpretations of ambiguous stimuli, as well as diminished expectations to lead a fulfilling life. These cognitive changes may explain why this diagnostic group feels more jealous after using Instagram than other clinical populations. As existing work has already shown that posttraumatic stress disorder symptoms are significantly correlated with the overuse of smartphones despite negative consequences (Contractor, Weiss & Elhai, 2018), it is of utmost importance to incorporate the current findings into interventions aimed at reducing posttraumatic stress disorder symptoms, perhaps by involving psychoeducation about social media and exposures to reduce time spent on social media apps such as Instagram.

Perhaps even more important is the discovery of the anorexia diagnosis as a moderator of increased jealousy after Instagram use. It is now established that social media use is associated with increases in negative body image and other disordered eating behaviors (Homan et al., 2012; Tiggemann et al., 2009; Lee et al., 2014), and as well as increased eating disorder diagnoses (Nagata et al., 2021). An important underlying mechanism here might be comparisons with unrealistic perceptions of body image. Many Instagram accounts– including celebrities, athletes, models, and “influencers” – oftentimes portray images of very thin, white, abled bodies that are typically photoshopped and edited to appear that way. Common symptoms of anorexia include distorted perceptions of one’s own weight, and thus by viewing these unrealistic portrayals of other people’s bodies online, one is more likely to become jealous. This jealousy, in turn, might exacerbate other symptoms of the disorder, such as going to extreme efforts to control their weight, or engaging in dangerous behaviors such restricting or purging as an outcome of such jealousy. Understanding that jealousy increases after Instagram use in this specific population is important from a clinical standpoint for several reasons, both from an assessment perspective, and more importantly from an interventional one. If the field can develop interventions aimed at both reducing the time spent on social media and at reframing the

images one is seeing online as part of treatment for anorexia, perhaps we can improve treatment outcomes for this highly lethal psychiatric disorder.

Although I was most interested in assessing the impact of using Instagram on mental health, I also thought it was important to test the competing directional hypotheses, to assess whether or not certain variables moderated the effect to which affect, jealousy, and social comparison predict Instagram use. Results revealed numerous significant predictor variables. First, job status significantly moderated the relation between social comparison and Instagram use ( $\beta = -0.17$ ,  $F(207) = 1.345$ ,  $p < 0.04$ ,  $R^2 = 0.06$ ): those who had lower job status were more likely to use Instagram after socially comparing themselves to others. This tendency might be due to demands of jobs and time available for Instagram use – lowered job status includes people who are unemployed, employed part-time, and students, all of whom may have additional time to devote to social media use, rather than spending time in a more demanding or time-consuming job. This may make it more likely that when they feel they are comparing themselves to others, they reach to Instagram to confirm or deny this fact, based on the profiles they are viewing. A few studies to date have investigated motives for Instagram use, yet they have widely focused on undergraduate samples (Huang & Su, 2018). Our findings emphasize the need for a more diverse participant pool in order to understand different effects amongst individuals and groups, as student status in and of itself greatly affects motivations for use.

Second, life satisfaction and trait social comparison moderated the relationship between affect and Instagram use. Results (depicted in Table 6) indicate that the lower life satisfaction a participant had, the more likely they were to use Instagram as a result of feeling more negative. Also, the higher someone was in trait social comparison orientation, the more likely they were to use Instagram as a result of feeling more negative. Lowered life satisfaction is associated with increased risk for both Internet addiction and social media addiction (Longstreet & Brooks, 2017), and perhaps using Instagram when feeling negative – as shown by our data – may contribute to and perpetuate this “addictive” cycle. Similarly, research has shown that individuals higher in trait social comparison orientation are more likely to use social media sites more heavily, to be more negatively affected by an acquaintance’s social media profile, and to experience loneliness as an outcome of Instagram use (Yang, 2016; Bergagna & Tartaglia, 2018). That these individuals are also more likely to turn to Instagram when experiencing low affect may mediate some of these established findings, and also points to a specific vulnerability this population shares. Understanding the mechanisms underlying why these personality traits make one more likely to use Instagram when feeling bad is an important next step for future research.

Moreover, current social anxiety disorder moderated the relationship between affect and Instagram use, such that the diagnosis made it more likely that someone would use Instagram as a result of decreased affect. Instagram use likely serves as a safety behavior here – a form of avoidance, distraction, or checking – which decreases anxiety in the short term, but may increase it in the long term and perpetuate symptoms. Other work has corroborated the idea that people high in social anxiety are more likely to use safety-seeking behaviors, but also more likely to negatively interpret ambiguous scenarios on social media (Carruthers, Warnock-Parkes, & Clark, 2019). People experiencing social anxiety might benefit from understanding how their use functions in the context of their anxiety, and it will be important for clinicians to assess for and target the use of social media sites like Instagram as a safety behavior in cognitive behavioral therapy for social anxiety disorder.

Contrary to the third hypothesis, at the nomothetic level there was a significant contemporaneous correlation between Instagram use and avoidance ( $r(22069) = 0.19, p < 2.2e-16^{***}$ ). These correlations varied greatly between individuals, with 51 (23%) exhibiting a significant contemporaneous correlation between Instagram use and avoidance (46 of these were positive, and 5 were negative; frequencies of these within-person contemporaneous correlations between are presented in Figure 8). Research based on the group-level analysis would point to the conclusion that people, overall, do use Instagram as a method of avoidance. Yet, as indicated above, these findings again do not generalize to the individuals comprising this group, as the remaining 173 individuals (77%) exhibited no significant contemporaneous correlation between Instagram use and avoidance.

Finally, our fourth hypothesis, that diagnoses of anxiety disorders (including generalized anxiety disorder, social anxiety disorder, and panic disorder) and pre-existing symptoms of anxiety would positively moderate the contemporaneous relationship between Instagram use and avoidance, was not supported. Diagnoses of anxiety disorders and pre-existing levels of anxiety did not moderate the contemporaneous correlation coefficient between Instagram use and avoidance, yet other factors did, including increased age, lower self-esteem, current substance use disorder, and current binge eating disorder. Although not the diagnoses nor symptoms we originally had predicted, these findings indicate that those who exhibit certain traits are more likely to use Instagram as a form of avoidance. Self-esteem has been implicated in current literature as a negative outcome of increased social media use for adolescents (Woods & Scott, 2016; Jan, Soomro, & Ahmad, 2017), and our findings are among the first so suggest that not only is decreased self-esteem important to investigate as an outcome of use but that lowered self-esteem at baseline may make someone more susceptible to using Instagram, and perhaps other social media outlets, as a form of behavioral avoidance. As avoidance behaviors serve as temporary respites that paradoxically increase anxiety and other stressors in the long term (Hofmann & Hay, 2019; Heimberg et al., 2014), it is important to assess for and develop interventions to mitigate these behaviors for these specified individuals.

Furthermore, for young adults diagnosed or meet symptom criterion for both substance use disorders and binge eating disorder, the same is more likely to occur. Substance use disorders are an increasingly salient concern for young adults in the United States, and research has shown that in emerging adults (aged 18-22), greater social media use is related to more alcohol consumption, more problematic alcohol use, and more frequent drug use (Ohannessian et al., 2017). Similarly for binge eating, recent work has shown that for adolescents, each additional hour spent on social media was associated with a 62% higher risk of binge eating disorder one year later (Nagata et al., 2021), increasingly important in light of older work indicating that social media use is associated with increases in negative body image and other disordered eating behaviors (Homan et al., 2012; Tiggemann et al., 2009; Lee et al., 2014). Though not causal in nature, these associations point to a potential relationship between social media use and clinical diagnoses of substance use and binge eating. Although we did not assess the temporal nature of Instagram use predicting these behaviors here, our results do indicate that those with existing substance use and binge eating disorder symptoms – whether or not these were exacerbated by Instagram use itself – are more likely to use Instagram as a means of avoidance, perhaps perpetuating a damaging cycle.

As predicted, our results confirm that nomothetic investigations of social media use have limited generalizability and fail to capture the independent nature of the effects of use on young adults. By investigating these constructs in temporally, using lagged vector-autoregressive



models, and assessing potential moderators, we were able to answer the question of “for whom is social media detrimental?” – indicating that for those with more social media followers, those who spend more time on social media, those with lower self-esteem, and those meeting clinical criterion for diagnoses of substance use disorders, posttraumatic stress disorder, anorexia, or binge eating disorder, the potential for damage appears greatest. . With such understanding, we can move forward with important interventions aimed at reducing the harmful effects for such specified individuals.

### General Discussion

Overall, this two-study investigation into the links between Instagram use and mental health adds to the growing body of literature examining social media use and its potential antecedents and consequences on adolescents and young adults. Specifically, the pattern of findings underscores the importance of investigating social media at the individual level, in addition to the group level. Our individual and group level outcomes are also in line with previous research showing that a large body of work across diverse realms of psychological science has overestimated the accuracy of aggregated statistical estimates, or the extent to which processes are ergodic in nature (Fisher et al., 2018). In Study 1 we observed that across subjects, idiographic network analyses and calculations of normalized strength values illustrated that 18% of participants exhibited no relation between Instagram use and mood contemporaneously, while the remaining 82% did exhibit some degree of association between Instagram use and various mood variables. These results are consistent with Rodriguez et al. (2021) and Beyens et al (2020), two of the only studies to date that have investigated social media use in a similar manner by analyzing experience sampling data. Both found that associations between social media use and depression symptoms differed strongly across adolescents. Together, these findings confirm that approaching social media research in a nomothetic manner would fail to capture this variability and may be one reason previous work has produced equivocal results.

Study 2 extended these results by increasing the sampling frequency in order to assess time-lagged directional effects of use on three theoretically important variables of affect, jealousy, and social comparison. Results again revealed marked individual heterogeneity in responses to Instagram use, demonstrating the importance of exploring these relations at both the between-subjects and within-subjects levels. Specifically, group-level analyses of the three lagged vector autoregressive models each showed excellent fit to the aggregated data (RMSEA < 0.001, SRMR < 0.001, CFI = 1.00, TLI = 1.00 for each), yet coefficients for the hypothesized cross-lagged paths approached zero in all three models (see Table 3), revealing non-significant findings. At the individual level, however, 31.7% exhibited at least one significant cross-lagged path between Instagram use, affect, jealousy, and social comparison, with pronounced variability across participants (see Table 4 as a summary).

Importantly, we also discovered that the number of followers one had ( $\beta = -0.21$ ,  $F(219) = 2.711$ ,  $p < 0.04$ ,  $R^2 = 0.05$ ;  $\beta = -0.31$ ,  $F(192) = 1.701$ ,  $p < 0.00$ ,  $R^2 = 0.08$ ), the reported time spent on Instagram ( $\beta = 0.18$ ,  $F(194) = 1.12$ ,  $p < 0.04$ ,  $R^2 = 0.05$ ), and diagnoses of substance use disorder, posttraumatic stress disorder, and anorexia (Table 5) all moderated the relationships between Instagram use and affect, jealousy, and/or social comparison. Although our original hypotheses regarding moderators were not all supported, it is essential to know which subgroups may be more at risk for social media’s negative effects. These individual moderator findings may reflect vulnerability factors, explaining for whom Instagram use may be more detrimental, and

may help clinicians understand the role social media is more likely to play in these specific clinical populations. Specifically, the discovery that those meeting criterion for anorexia are more likely to feel jealous after Instagram use is critical. Anorexia is one of the most lethal psychiatric disorders, and if the field can develop interventions to reduce these negative effects, we can potentially improve treatment outcomes in a significant way.

Furthermore, our investigation into social media use as an avoidance strategy revealed significance at the group level, but not necessarily within all individuals. Although social media use has been critiqued for serving as an easy procrastination and distraction tool (thus serving as a short-term avoidance strategy), few researchers have actually studied this topic specifically, and those that have discovered phone usage overall to offer a “security blanket” effect by lowering initial negative reactions to stress but increasing the rates of distress disorders overall (Panova & Lleras, 2016). We initially predicted that Instagram use may serve as an avoidance strategy for certain individuals—and found that at the group level, use did in fact coincide with avoidance of people, places, and things ( $r(22,069) = 0.19, p < .001$ ). Yet, as predicted, results at the individual level indicated significant variability: of the 224 models,  $N = 51$  (23%) revealed a significant contemporaneous correlation between Instagram use and avoidance, and the remaining  $N = 173$  individuals (77%) exhibited no significant contemporaneous correlation between Instagram use and avoidance. Whereas our initial hypothesis that those diagnosed with anxiety disorders or exhibiting symptoms consistent with anxiety disorders would be more likely to use Instagram as an avoidance strategy were not supported by the data, we did discover that participants lower in self-esteem, and those diagnosed with substance use and binge eating disorders were in fact more likely to use Instagram to avoid. As noted above, previous work has indicated all three of these as outcomes of social media use (Woods & Scott, 2016; Jan, Soomro, & Ahmad, 2017; Ohannessian et al., 2017; Nagata et al., 2021). The current findings highlight the possibility that they might also perpetuate use via positive feedback loops occurring within specific individuals that would be useful to target in future clinical interventions.

### **Limitations**

Although the three main limitations of Study 1 (including the contemporaneous nature of the analyses, the longer two-hour time scale of the ecological momentary assessment sampling design, and the fact that it was limited to an undergraduate population) were addressed in the methodology of Study 2, Study 2 is not without limitations. First, data were collected both prior to and during the COVID-19 pandemic, and thus the study design required manipulation after data collection had begun, including switching the M.I.N.I. from an in-person to a remote format. Although we worked to minimize any potential confounds to the data this might have added, it nevertheless may have affected the data in ways we did not account for. Second, while our study assesses the specific type of social media use (Instagram), it does not dissociate between active and passive forms of use. Instagram was chosen for the fact that it largely mimics passive use by design (with users able to browse content without posting it themselves), but we did not assess whether use over the previous 30 minutes involved browsing other’s content or posting their own. Future work should aim to distill the passive versus active dichotomization of Instagram use, as previous studies have implicated passive use as being connected to more negative outcomes in terms of mental health and well-being (Tandoc, Ferrucci, & Duffy, 2015; Shaw, Timpano, Tran, & Joorman, 2015; Krasnova, Wenninger, Widjaja, & Buxmann, 2013; Verduyn et al., 2015). Third, though our sample was ethnically diverse, it was limited to ages of 18-35, in order to capture these processes in young adults, and thus may not generalize to those younger

than 18 or older than 35. Although much of social media research focuses on adolescents and young adults (for many reasons, some being that they are the demographics most likely to utilize social media platforms, and that they are perhaps most vulnerable to any negative effects), future work should aim to replicate this work in different age groups. Finally, although data were collected using ecologically momentary assessment methods that pinged participants in real time, we still relied on self-reports of Instagram use. Self-reports may be subject to recall bias, and using real-time data collection methods like we did here can help to minimize this effect (Shiffman, Stone, & Hufford, 2008). Still, participants may have engaged in social media use without their awareness (Rodriguez et al., 2020) and thus may not have responded accurately to the EMA prompt. Although not technically possible now, future work in conjunction with social media use apps such as Instagram would allow for exact documentation of use rather than relying on self-reports. Until this is the case, however, real-time data collection methods are the most robust and able to minimize recall biases.

### **Conclusions**

Nonetheless, the benefits of this two-study investigation outweigh the limitations, and findings support the growing notion that nomothetic investigations into social media are insufficient at truly understanding the potential harm use may have on individuals. Following calls from various researchers (Fisher et al., 2018; Kross et al., 2020; Rodriguez et al., 2021;), we examined the differential effects Instagram use has on affect, jealousy, and social comparison, as well as how these may differ depending on demographic characteristics, mental health status, personality traits, and more. Our findings indicate, like those that have investigated social media in an idiographic manner before us (Rodriguez et al., 2021; Beyens et al., 2020), that relations at the group level do not generalize to every individual that comprises those groups. Specifically, we found that across all analyses there were individuals for whom Instagram use was unrelated at the same time point (Study 1) or had little effect at a later time (Study 2) on various mental health and mood variables. Yet there were others for whom Instagram use was quite closely related at the same time point (Study 1) or had a significant effect at a later time (Study 2) on those same mental health and mood variables, highlighting the importance of research into individual differences. The moderation analyses performed in Study 2 indicate that certain mental health diagnoses and personality characteristics make one more susceptible to potential negative effects of Instagram – a finding that has myriad clinical implications. Now that we are one step closer to understanding who is at the most risk of elevated mood symptoms after using Instagram, we can educate those groups as well as move forward with developing interventions aimed at reducing the deleterious effects for these specified individuals – an essential step in the process to understand and help inform what responsible phone usage is in a time where social media has become a ubiquitous part of the majority of people's lives across the world.

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Table 1: Participant Demographics &amp; Survey Statistics.

|                   | <b>Undergraduate Subjects</b><br><i>n</i> = 119 (53.1%)   | <b>Community Subjects</b><br><i>n</i> = 105 (46.9%)                                 |
|-------------------|---|---|
| Age               | Mean: 20.65<br><i>SD</i> : 2.81   | Mean: 24.4<br><i>SD</i> : 4.3   |
| Sex               | Male: <i>n</i> = 18 (15.1%)<br>Female: <i>n</i> = 101 (84.9%)                                   | Male: <i>n</i> = 50 (47.6%)<br>Female: <i>n</i> = 55 (52.4%)                        |
| Gender            | Male: <i>n</i> = 17 (14.3%)<br>Female: <i>n</i> = 100 (84.0%)<br>Nonbinary: <i>n</i> = 2 (1.7%) | Male: <i>n</i> = 51 (48.6%)<br>Female: <i>n</i> = 54 (51.5%)<br>Nonbinary: 0 (0.0%) |
| Education         | Median = 3<br>Mean = 2.9<br><i>SD</i> = 0.6   | Median = 4<br>Mean = 3.8<br><i>SD</i> = 1.1   |
| SES               | Median = 7<br>Mean = 6.41<br><i>SD</i> = 1.6  | Median = 6<br>Mean = 6.1<br><i>SD</i> = 1.7   |
| Surveys Sent      | Median = 107<br>Mean = 109.3<br><i>SD</i> = 15.7  | Median = 101<br>Mean = 104.7<br><i>SD</i> = 16.1                                    |
| Surveys Completed | Median = 96<br>Mean = 99.4<br><i>SD</i> = 14.3  | Median = 95<br>Mean = 96.8<br><i>SD</i> = 13.7                                      |

*Note.* SES = Socioeconomic Status (MacArthur scale of 0-10); Education coded as: 1 = “some high school”, 2 = “graduated high school”, 3 = “some college”, 4 = “college degree”, 5 = “master’s degree”, 6 = “advanced degree (i.e. PhD, MD, JD)”.

Table 2: Summary Statistics for between- and within-person contemporaneous correlations of study variables.

| <b>Variables</b>         | <b>Instagram Use &amp; Affect</b> | <b>Instagram Use &amp; Jealousy</b> | <b>Instagram Use &amp; Social Comparison</b> |
|--------------------------|-----------------------------------|-------------------------------------|--|
| <i>Idiographic Model</i> |                                   |                                     |  |
| Range                    | -0.78 to 0.74                     | -0.37 to 0.77                       | -0.41 to 1.00                                |
| Mean                     | -0.04                             | 0.11                                | 0.14   |
| Median                   | -0.03                             | 0.08                                | 0.10   |
| SD                       | 0.17                              | 0.18                                | 0.19   |
| <i>Nomothetic Model</i>  |                                   |                                     |  |
| Value                    | -0.01                             | 0.17***                             | 0.20***                                      |

*Note.* First, within-person correlations between each of the study variables were computed. Here, the mean represents the nomothetic average of the within-person correlations for each pair of variables. \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

Table 3: Completely standardized solution values for nomothetic lagged vector-autoregressive model.

| <b>Constructs</b>  | <b>Beta value</b> | <b><i>p</i>-value</b> |
|--|-------------------|-----------------------|
| Instagram use ( <i>t</i> -1) predicting Affect ( <i>t</i> )                | 0.045             | < 0.001***            |
| Instagram use ( <i>t</i> -1) predicting Jealousy ( <i>t</i> )              | -0.010            | 0.330                 |
| Instagram use ( <i>t</i> -1) predicting Social Comparison ( <i>t</i> )     | -0.019            | 0.063                 |
| Affect ( <i>t</i> -1) predicting Instagram use ( <i>t</i> )                | 0.010             | < 0.001***            |
| Jealousy ( <i>t</i> -1) predicting Instagram use ( <i>t</i> )              | 0.038             | < 0.001***            |
| Social Comparison ( <i>t</i> -1) predicting Instagram use ( <i>t</i> )     | 0.041             | < 0.001***            |
| Instagram use ( <i>t</i> -1) predicting Instagram Use ( <i>t</i> )         | 0.256             | < 0.001***            |
| Affect ( <i>t</i> -1) predicting Affect ( <i>t</i> )                       | 0.639             | < 0.001***            |
| Jealousy ( <i>t</i> -1) predicting Jealousy ( <i>t</i> )                   | 0.699             | < 0.001***            |
| Social Comparison ( <i>t</i> -1) predicting Social Comparison ( <i>t</i> ) | 0.713             | < 0.001***            |

*Note.* \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

Table 4: Frequencies and directions of significant cross-lagged paths across vector-autoregressive idiographic models ( $n = 224$ ).

|                      | <b>Instagram<br/>Use →<br/>Affect</b> | <b>Instagram<br/>Use →<br/>Jealousy</b> | <b>Instagram<br/>Use →<br/>Social<br/>Comparison</b> | <b>Affect →<br/>Instagram<br/>Use</b> | <b>Jealousy →<br/>Instagram<br/>Use</b> | <b>Social<br/>Comparison →<br/>Instagram Use</b> |
|----------------------|---------------------------------------|---|--|---------------------------------------|---|--|
| Frequency<br>of Path | 11                                    | 14                                      | 14   | 23                                    | 20                                      | 19   |
| Positive             | 6                                     | 6                                       | 8  | 12                                    | 15                                      | 14   |
| Negative             | 5                                     | 8                                       | 6  | 11                                    | 5                                       | 5  |

Figure 1: Histogram of Normalized Values for intraindividual strength of Used Instagram at time  $t$ .

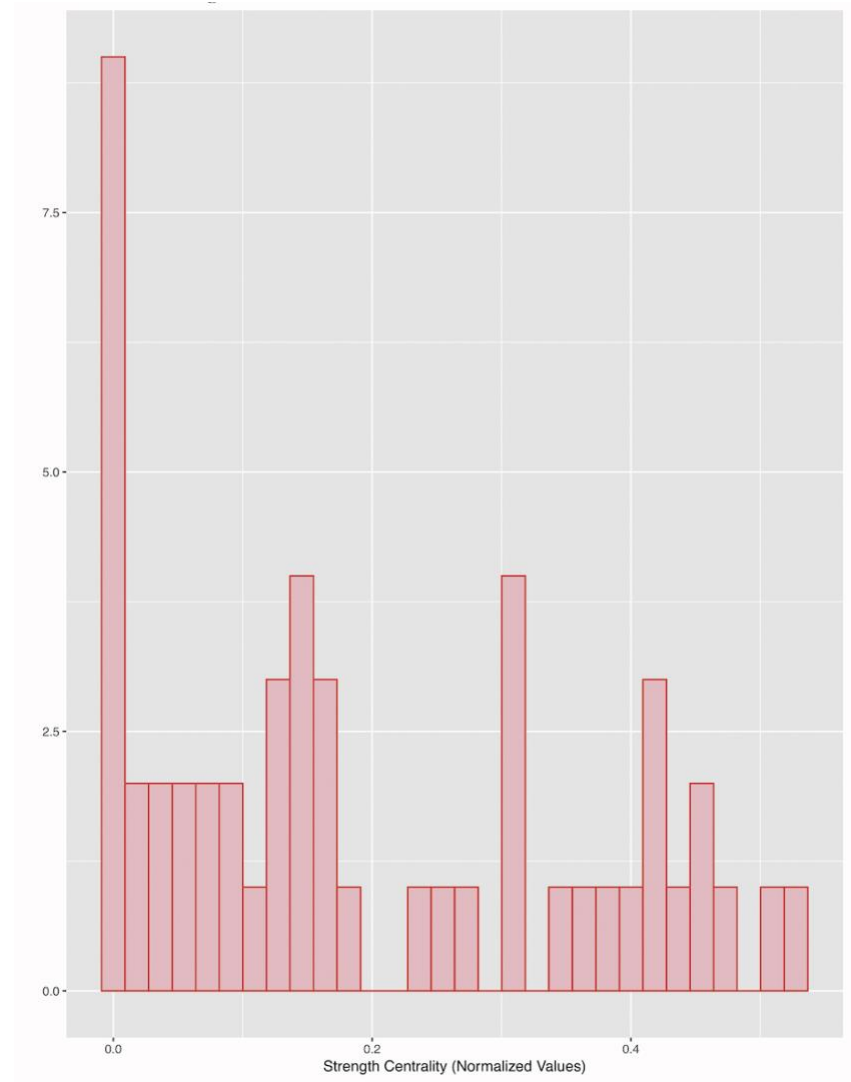




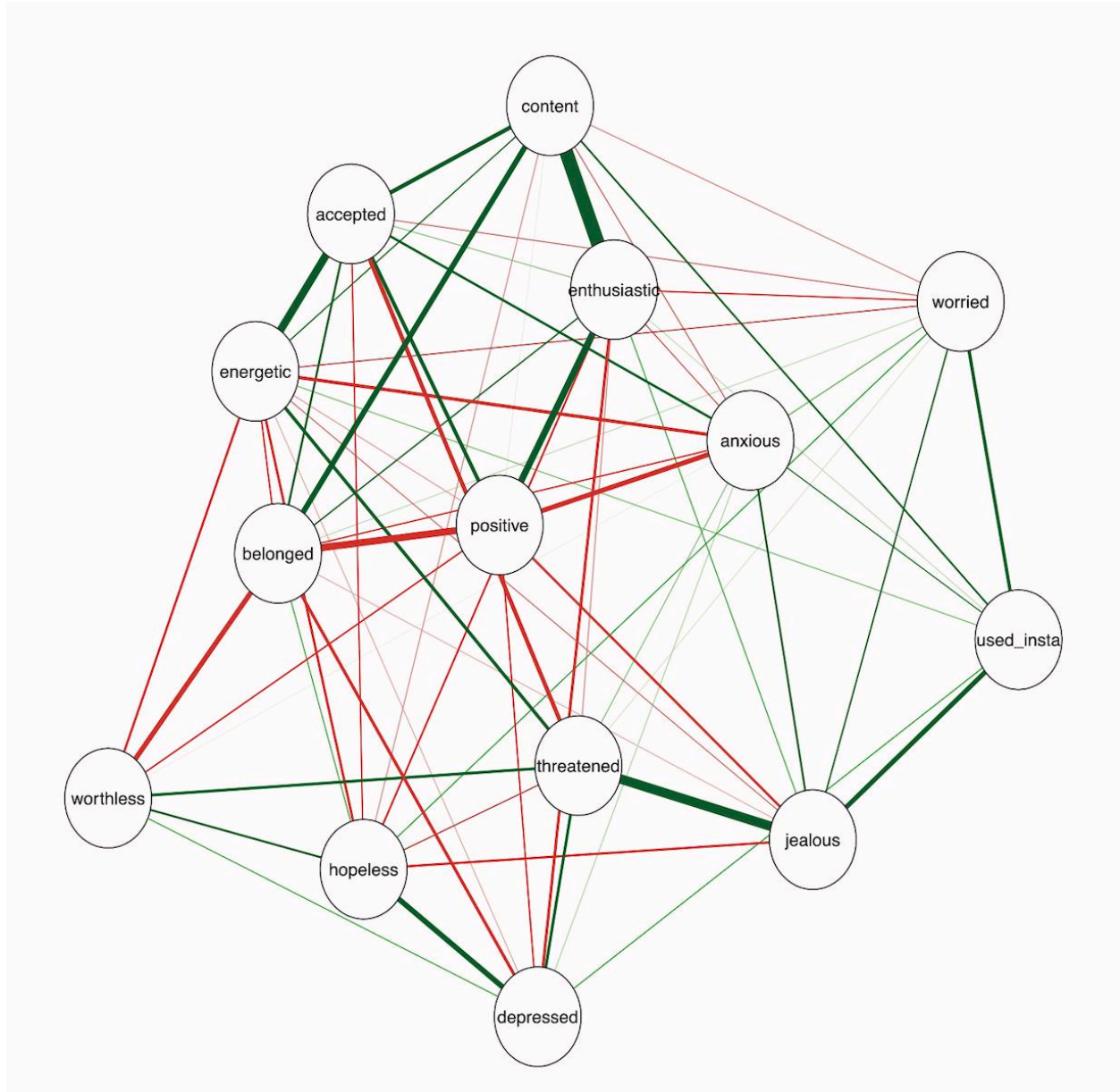
Figure 2: Contemporaneous concentration network at time  $t$  for P007.



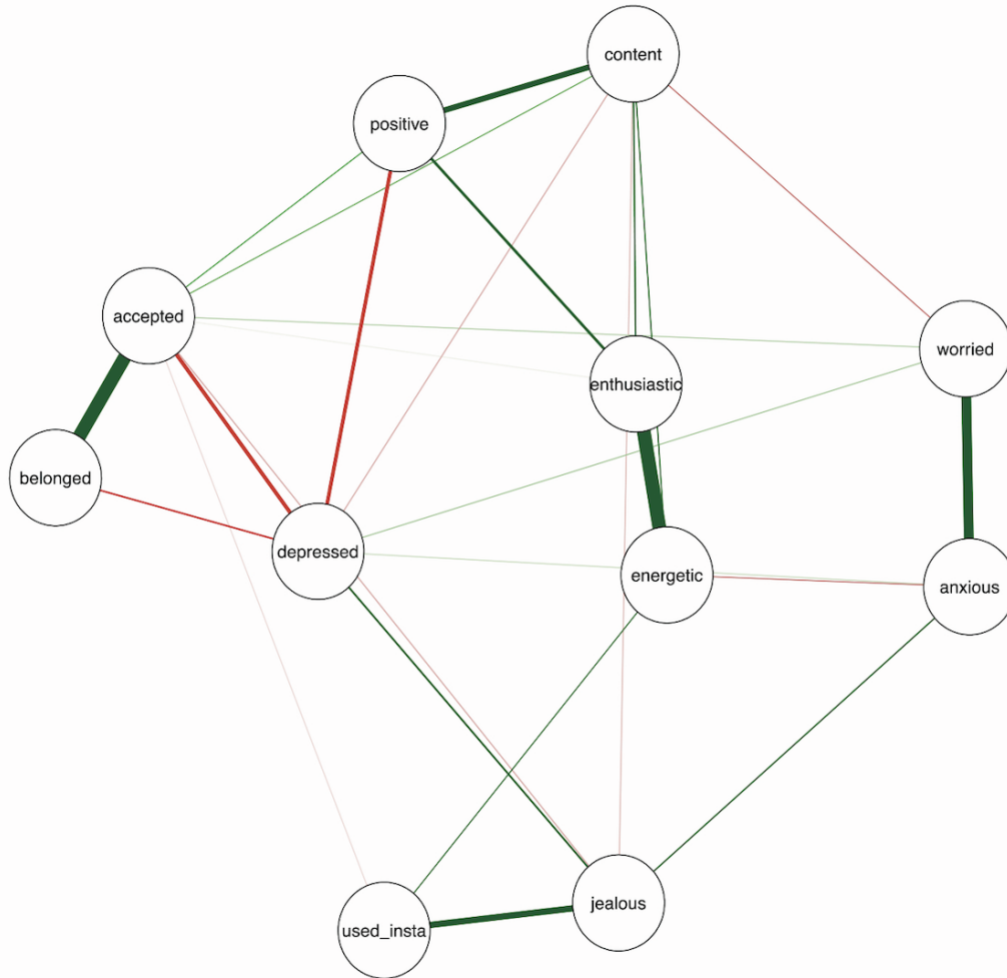
Figure 4: Contemporaneous concentration network at time  $t$  for P024.

Figure 5: Lagged model to assess impact of Instagram use on mental health.

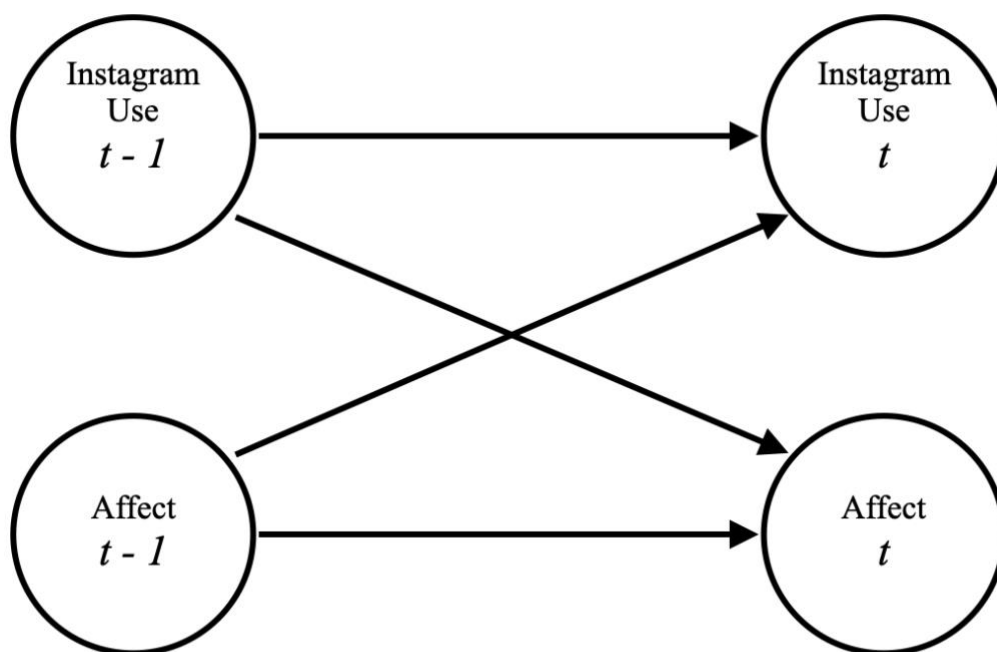


Figure 6: Moderation model to assess moderators of the relationship between mental health and Instagram use.

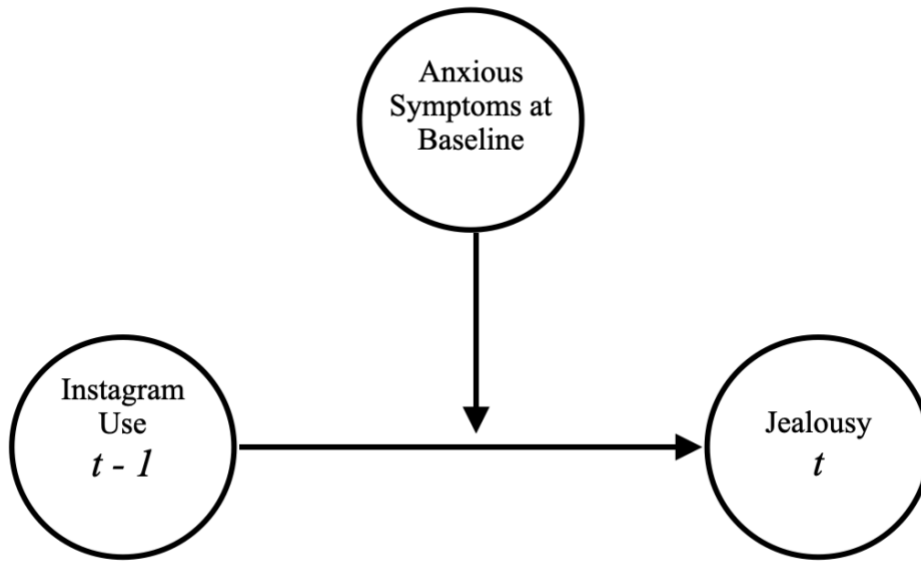


Figure 7: Distributions of within-person contemporaneous correlations of study variables.

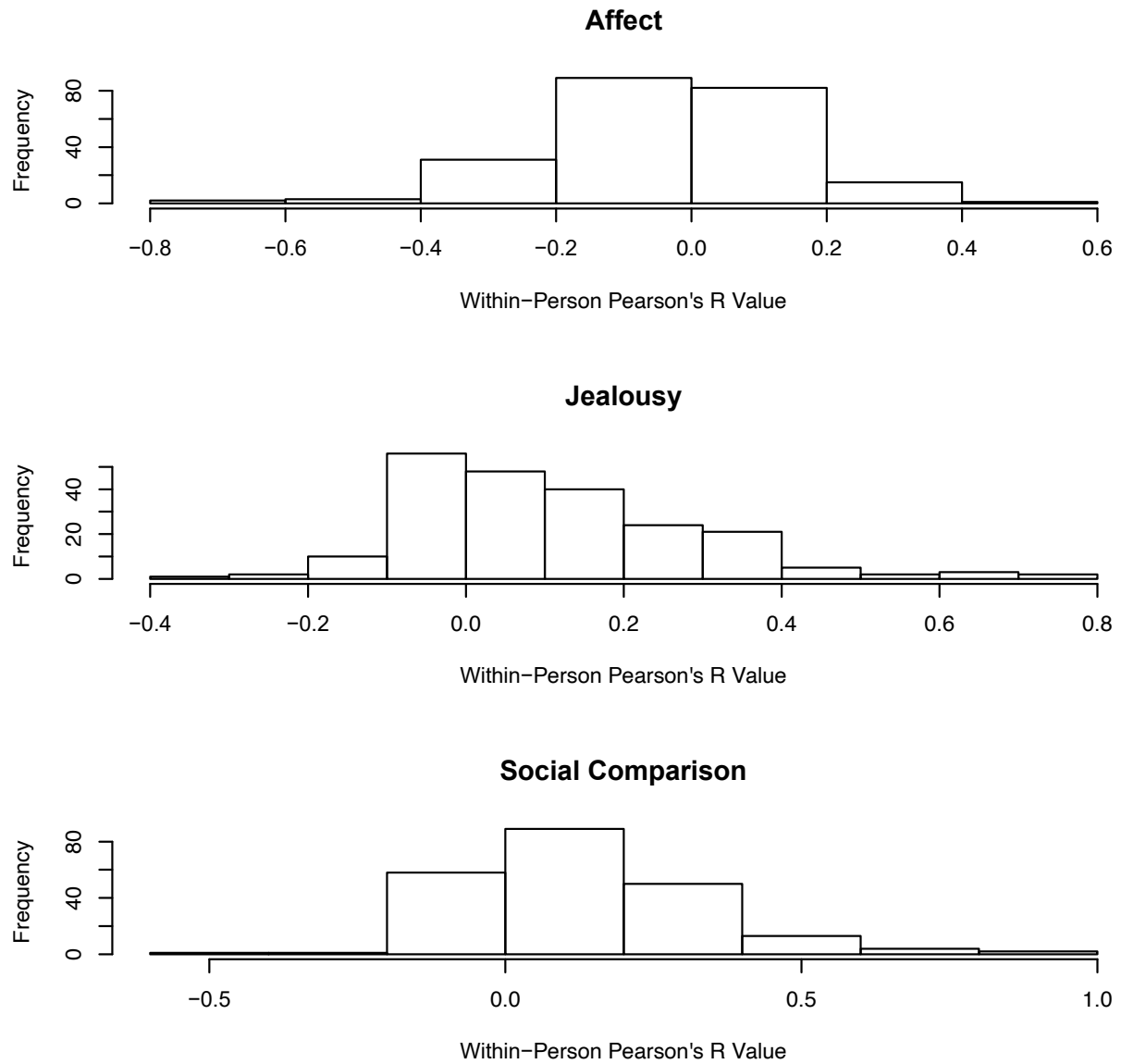


Figure 8. Distributions of within-person contemporaneous correlations of Instagram use & avoidance.

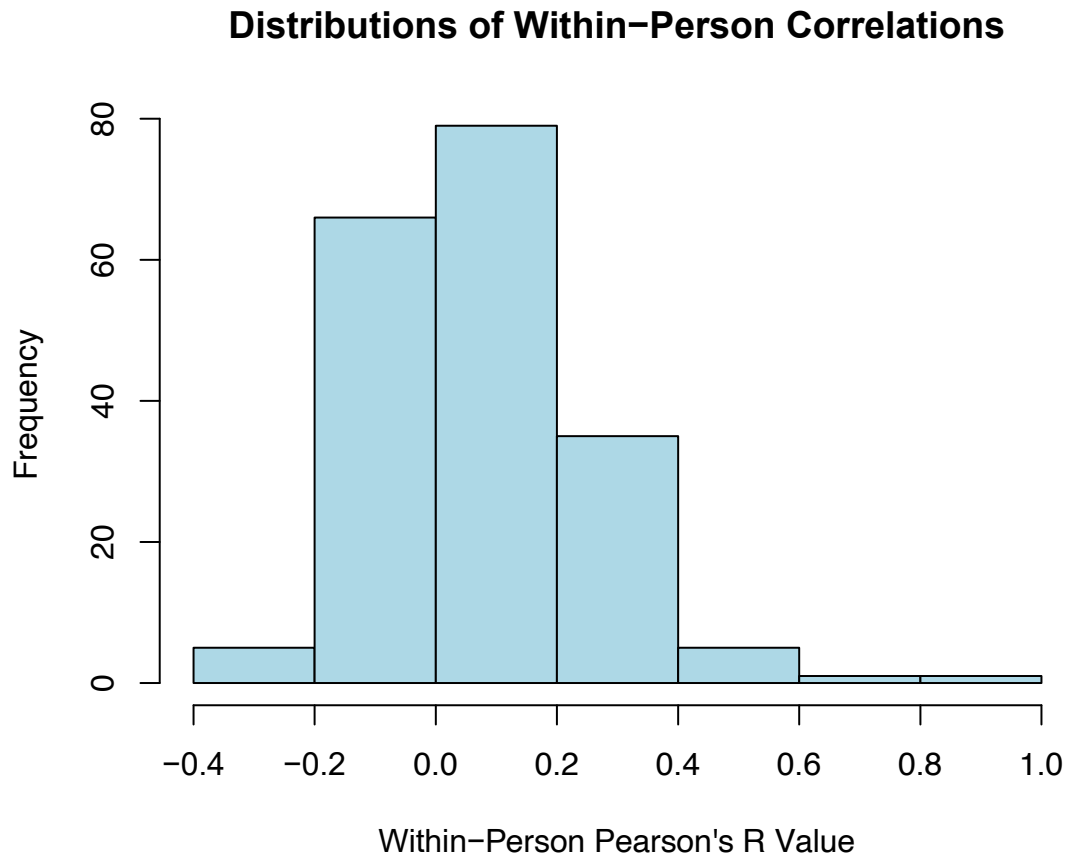


Table 5: Linear models for the moderating effect of diagnoses from the M.I.N.I. on the beta coefficients from idiographic vector autoregressive models between Instagram Use predicting affect, jealousy, and social comparison, respectively.

| <i>Predictors</i>        | Instagram Use → Affect |              |                | Instagram Use → Jealousy |              |                   | Instagram Use → Social Comparison |              |               |
|--------------------------|------------------------|--------------|----------------|--------------------------|--------------|-------------------|-----------------------------------|--------------|---------------|
|                          | <i>Estimates</i>       | <i>CI</i>    | <i>p</i>       | <i>Estimates</i>         | <i>CI</i>    | <i>p</i>          | <i>Estimates</i>                  | <i>CI</i>    | <i>p</i>      |
| (Intercept)              | 0.02                   | -0.02 – 0.06 | 0.346          | -0.01                    | -0.05 – 0.04 | 0.731             | 0.02                              | -0.04 – 0.07 | 0.570         |
| current depression       | -0.03                  | -0.14 – 0.08 | 0.603          | -0.04                    | -0.15 – 0.08 | 0.546             | -0.04                             | -0.18 – 0.10 | 0.577         |
| current manic            | -0.06                  | -0.27 – 0.15 | 0.591          | 0.11                     | -0.11 – 0.33 | 0.314             | -0.09                             | -0.35 – 0.17 | 0.505         |
| past manic               | -0.26                  | -0.57 – 0.04 | 0.090          | -0.04                    | -0.36 – 0.28 | 0.796             | 0.01                              | -0.37 – 0.39 | 0.965         |
| current panic            | 0.11                   | -0.11 – 0.33 | 0.318          | -0.14                    | -0.37 – 0.08 | 0.213             | -0.04                             | -0.31 – 0.24 | 0.790         |
| current agoraphobia      | 0.18                   | -0.01 – 0.38 | 0.069          | 0.06                     | -0.14 – 0.27 | 0.556             | -0.06                             | -0.30 – 0.19 | 0.654         |
| current social anxiety   | -0.08                  | -0.28 – 0.11 | 0.404          | -0.09                    | -0.29 – 0.12 | 0.400             | -0.03                             | -0.27 – 0.21 | 0.815         |
| current ptsd             | 0.06                   | -0.09 – 0.21 | 0.441          | 0.17                     | 0.01 – 0.33  | <b>0.032*</b>     | 0.08                              | -0.11 – 0.27 | 0.394         |
| current substance use    | 0.82                   | 0.29 – 1.35  | <b>0.003**</b> | 1.32                     | 0.77 – 1.87  | < <b>0.001***</b> | 0.73                              | 0.07 – 1.39  | <b>0.030*</b> |
| current anorexia         | 0.19                   | -0.21 – 0.59 | 0.344          | 0.46                     | 0.04 – 0.87  | <b>0.032*</b>     | 0.35                              | -0.15 – 0.84 | 0.173         |
| current bulimia          | 0.03                   | -0.10 – 0.16 | 0.672          | -0.04                    | -0.18 – 0.09 | 0.541             | 0.09                              | -0.07 – 0.25 | 0.252         |
| current binge eating     | 0.01                   | -0.16 – 0.19 | 0.871          | -0.06                    | -0.24 – 0.12 | 0.530             | -0.03                             | -0.24 – 0.18 | 0.783         |
| current gad              | -0.06                  | -0.17 – 0.05 | 0.287          | 0.03                     | -0.08 – 0.14 | 0.592             | -0.03                             | -0.16 – 0.11 | 0.678         |
| R <sup>2</sup> /adjusted | 0.100 / 0.006          |              |                | 0.204 / 0.118            |              |                   | 0.076 / -0.023                    |              |               |

Note. \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$



Table 6: Linear models for the moderating effect of self-report symptom screeners on the beta coefficients from idiographic vector autoregressive models between affect, jealousy, and social comparison, respectively, predicting Instagram Use

| Predictors               | Affect → Instagram Use |               |               | Jealousy → Instagram Use |              |       | Social Comparison → Instagram Use |              |       |
|--------------------------|------------------------|---------------|---------------|--------------------------|--------------|-------|-----------------------------------|--------------|-------|
|                          | Estimates              | CI            | p             | Estimates                | CI           | p     | Estimates                         | CI           | p     |
| (Intercept)              | 0.02                   | -0.07 – 0.10  | 0.701         | -0.04                    | -0.13 – 0.04 | 0.306 | 0.00                              | -0.08 – 0.09 | 0.952 |
| SLS                      | 0.00                   | 0.00 – 0.00   | <b>0.016*</b> | -0.00                    | -0.00 – 0.00 | 0.589 | 0.00                              | -0.00 – 0.00 | 0.929 |
| PSWQ                     | 0.00                   | -0.00 – 0.00  | 0.337         | 0.00                     | -0.00 – 0.00 | 0.264 | 0.00                              | -0.00 – 0.00 | 0.511 |
| BDI                      | 0.00                   | -0.00 – 0.00  | 0.945         | -0.00                    | -0.00 – 0.00 | 0.342 | 0.00                              | -0.00 – 0.00 | 0.988 |
| ERQ_r                    | 0.00                   | -0.00 – 0.00  | 0.711         | 0.00                     | -0.00 – 0.00 | 0.123 | 0.00                              | -0.00 – 0.00 | 0.171 |
| ERQ_s                    | -0.00                  | -0.00 – 0.00  | 0.522         | 0.00                     | -0.00 – 0.00 | 0.610 | -0.00                             | -0.00 – 0.00 | 0.563 |
| RSES                     | -0.00                  | -0.00 – 0.00  | 0.398         | -0.00                    | -0.00 – 0.00 | 0.908 | -0.00                             | -0.00 – 0.00 | 0.366 |
| INCOM                    | -0.00                  | -0.00 – -0.00 | <b>0.037*</b> | -0.00                    | -0.00 – 0.00 | 0.824 | -0.00                             | -0.00 – 0.00 | 0.465 |
| BDAS                     | 0.00                   | -0.00 – 0.00  | 0.920         | 0.00                     | -0.00 – 0.00 | 0.917 | -0.00                             | -0.00 – 0.00 | 0.868 |
| IAS                      | -0.00                  | -0.00 – 0.00  | 0.943         | 0.00                     | -0.00 – 0.00 | 0.080 | 0.00                              | -0.00 – 0.00 | 0.128 |
| R <sup>2</sup> /adjusted | 0.051 / 0.011          |               |               | 0.049 / 0.007            |              |       | 0.035 / -0.007                    |              |       |

Note. SLS = Satisfaction with Life Scale; PSWQ = Penn State Worry Questionnaire; BDI = Beck Depression Inventory; ERQ\_r = Emotion Regulation Questionnaire Reappraisal Subscale; ERQ\_s = Emotion Regulation Questionnaire Suppression Subscale; RSES = Rosenberg Self-Esteem Scale; INCOM = Iowa-Netherlands Comparison Orientation Measure; BDAS = Bergen Facebook Addiction Scale; IAS = Instagram Addiction Scale. \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

Table 7: Linear models for the moderating effect of clinical diagnoses on the idiographic contemporaneous correlation coefficients between Instagram use and avoidance

| <b>Correlation between Instagram Use &amp; Avoidance</b> |                  |              |                     |
|--|------------------|--------------|---------------------|
| <i>Predictors</i>  | <i>Estimates</i> | <i>CI</i>    | <i>p</i>            |
| intercept  | 0.08             | 0.04 – 0.11  | <b>&lt;0.001***</b> |
| current depression                                       | 0.00             | -0.08 – 0.09 | 0.932               |
| current manic  | 0.02             | -0.13 – 0.17 | 0.823               |
| past manic   | 0.06             | -0.16 – 0.28 | 0.594               |
| current panic  | 0.01             | -0.15 – 0.17 | 0.900               |
| current agoraphobia                                      | 0.03             | -0.11 – 0.17 | 0.668               |
| current social anxiety                                   | 0.13             | -0.01 – 0.27 | 0.068               |
| current ocd  | 0.00             | -0.10 – 0.10 | 0.998               |
| current ptsd   | 0.02             | -0.09 – 0.14 | 0.676               |
| current alcoholism                                       | 0.04             | -0.08 – 0.15 | 0.507               |
| current stimulants                                       | -0.16            | -0.32 – 0.01 | 0.060               |
| current opiates  | 0.03             | -0.08 – 0.14 | 0.581               |
| current hallucinogens                                    | 0.18             | 0.02 – 0.34  | <b>0.029*</b>       |
| current inhalants  | 0.41             | 0.03 – 0.78  | <b>0.036*</b>       |
| current cannabis   | -0.10            | -0.21 – 0.01 | 0.074               |
| current tranquilizers                                    | -0.26            | -0.56 – 0.03 | 0.077               |
| current miscellaneous                                    | -0.16            | -0.34 – 0.01 | 0.068               |
| current psychotic  | -0.02            | -0.11 – 0.06 | 0.582               |
| current anorexia   | 0.01             | -0.28 – 0.29 | 0.956               |
| current bulimia  | 0.02             | -0.08 – 0.11 | 0.707               |
| current binge eating                                     | 0.14             | 0.02 – 0.27  | <b>0.022*</b>       |
| current gad  | -0.07            | -0.16 – 0.01 | 0.092               |
| Observations   | 192              |              |                     |
| R <sup>2</sup> / R <sup>2</sup> adjusted                 | 0.136 / 0.030    |              |                     |

Note. \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .