

**Identifying mechanisms that explain the relationship between digital technology use
and psychosocial risk factors for suicide**

by

Craig J.R. Sewall

Bachelor of Arts in Sociology, Westmont College, 2009

Master of Social Work, University of Pittsburgh, 2012

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SCHOOL OF SOCIAL WORK

This dissertation was presented

by

Craig J.R. Sewall

It was defended on

April 12, 2021

and approved by

Christina Newhill, PhD, Professor, University of Pittsburgh School of Social Work

Shaun Eack, PhD, Professor, University of Pittsburgh School of Social Work

Tina Goldstein, PhD, Associate Professor, University of Pittsburgh Department of Psychiatry

Dissertation Director: Daniel Rosen, PhD, Professor, University of Pittsburgh School of Social Work

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Identifying mechanisms that explain the relationship between digital technology use and psychosocial risk factors for suicide

Craig J.R. Sewall, PhD

University of Pittsburgh, 2021

The increasing integration of digital technology into our daily lives over the past 20 years, coupled with increasing rates of psychological distress during roughly the same period, especially among young people, have led many to question how these technologies may impact psychosocial risk factors for suicide, such as depression, anxiety, social isolation, and suicidal ideation (SI). Yet, the plethora of research in this field has yielded inconsistent findings due to three prominent limitations: unreliable measurement, lack of longitudinal studies, and lack of research explicating potential mechanisms. Addressing these limitations, the current study aimed to examine (1) the direct, temporal relationships between objectively-measured digital technology use (DTU) and psychosocial risk factors for suicide and (2) the potential mechanisms that mediate or moderate these relationships.

A four-wave panel study of N=384 young adult participants was completed from August-November 2020. Mental health variables included depression, anxiety, social isolation, and SI. Behavioral mechanisms variables included sleep disturbance and number of past-week steps taken. Psychosocial mechanisms included online social comparison as well as five items measuring different aspects of social media use. Objective DTU data were obtained by having participants upload screenshots of their “Screen Time” application which tracks their frequency/duration of iPhone use and duration of social media use. Random intercept cross-lagged panel models (RI-CLPM) and multilevel structural equation models (MSEM) were estimated to investigate aims (1) and (2).

Results of the statistical analyses revealed no significant within- or between-person associations, either temporally or concurrently, between objectively tracked digital technology use and any of the

psychosocial risk factors for suicide. Sleep disturbance and online social comparison were significantly associated with within-person increases in depression, anxiety, and social isolation.

Instead of focusing on simple metrics of frequency or duration of digital technology use, researchers and social work practitioners should take a more person-centered approach whereby details related to who, what, when, why, and how youth use digital technology are carefully assessed to identify whether and how certain specific aspects of DTU are associated with benefits or harms.

Table of Contents

1.0 Introduction.....	<u>1</u>
1.1 Psychosocial Risk Factors for Suicidal Thoughts & Behaviors.....	<u>4</u>
2.0 Background and Significance.....	<u>6</u>
2.1 Amount of Digital Technology Use.....	<u>6</u>
2.1.1 Meta-Analytic Evidence.....	<u>7</u>
2.1.2 Longitudinal Evidence.....	<u>9</u>
2.1.3 Experimental Evidence.....	<u>13</u>
2.2 Evidence for Mechanisms.....	<u>16</u>
2.2.1 Passive Use, Social Comparison, and Social Connectedness.....	<u>17</u>
2.2.2 Sleep Impairment.....	<u>20</u>
2.2.3 Sedentary Behavior.....	<u>21</u>
2.3 Theoretical Frameworks.....	<u>22</u>
2.3.1 Durkheim’s Theory of Suicide.....	<u>22</u>
2.3.2 Social Capital Theory.....	<u>26</u>
2.3.3 Theory Summary.....	<u>29</u>
2.4 Research Methodology.....	<u>30</u>
2.5 Summary of Research Questions.....	<u>33</u>
3.0 Methods.....	<u>37</u>
3.1 Study Design, Setting, and Participants.....	<u>37</u>
3.2 Variables and Measurement.....	<u>37</u>
3.2.1 Outcome Variables.....	<u>38</u>
3.2.2 Predictor Variables.....	<u>39</u>
3.2.2.1 Digital Technology Use.....	<u>39</u>

3.2.2.2 Behavioral Mechanisms.....	40
3.2.2.3 Psychosocial Mechanisms.....	41
3.2.3 Control Variables.....	41
3.2.3.1 COVID-19-Related Distress.....	41
3.3 Data Screening.....	42
3.4. Statistical Analysis.....	43
3.4.1 Random Intercept Cross-Lagged Panel Analysis.....	43
3.4.1 Multilevel Structural Equation Modeling.....	45
3.5 Missing Data.....	47
4.0 Results.....	49
4.1 Descriptive Statistics.....	49
4.2 Results of Random Intercept Cross-Lagged Panel Models.....	51
4.2.1 Within-Person Effects.....	51
4.2.2 Between-Person Effects.....	54
4.3 Results of Multilevel Structural Equation Models.....	56
4.3.1 Direct Effects.....	56
4.3.1.1 Digital Technology Use Variables.....	56
4.3.1.2 Behavioral Mechanism Variables.....	58
4.3.1.3 Psychosocial Mechanism Variables.....	59
4.3.1.4 COVID-19 Related Distress.....	60
4.3.2 Multilevel Moderation.....	61
4.3.2.1 Indirect Effects.....	62
4.3.2.1.1 Behavioral Mechanisms.....	62

4.3.2.1.2 Psychosocial Mechanisms.....	68
4.3.2.1.3 Total Indirect Effects of DTU on SI.....	68
5.0 Discussion.....	74
5.1 Temporal Effects.....	74
5.2 Concurrent Effects and Variance Explained.....	76
5.3 Mechanisms and Indirect Effects.....	78
5.4 Implications for Social Work.....	78
5.5 Limitations.....	81
5.6 Conclusions.....	82
Appendix A Model-Specific RI-CLPM Results.....	84
Bibliography.....	93

List of Tables

Table 1. Definitions for suicidal thoughts and behaviors.....	1
Table 2. Summary of missing data.....	48
Table 3. Sample demographics and summary statistics for study variables.....	50
Table 4. Fit statistics for random intercept cross-lagged panel models.....	51
Table 5. Standardized within-person effects from RI-CLPMs.....	53
Table 6. Standardized between-person effects from RI-CLPMs.....	55
Table 7. Cross-level interaction results from multilevel structural equation models.....	62

List of Figures

Figure 1. Summary of research questions.....	36
Figure 2. Example screenshots of the “Screen Time” application.....	40
Figure 3. Results of depression—screen time random intercept cross-lagged panel model.....	84
Figure 4. Results of depression—social media random intercept cross-lagged panel model.....	85
Figure 5. Results of depression—pickups random intercept cross-lagged panel model.....	86
Figure 6. Results of anxiety—screen time random intercept cross-lagged panel model.....	87
Figure 7. Results of anxiety—social media random intercept cross-lagged panel model.....	88
Figure 8. Results of anxiety—pickups random intercept cross-lagged panel model.....	89
Figure 9. Results of social isolation—screen time random intercept cross-lagged panel model.....	90
Figure 10. Results of social isolation—social media random intercept cross-lagged panel model.....	91
Figure 11. Results of social isolation—pickups random intercept cross-lagged panel model.....	92
Figure 12. Results of the behavioral mechanism multilevel mediation model for depression	64
Figure 13. Results of the behavioral mechanism multilevel mediation model for anxiety.....	65
Figure 14. Results of the behavioral mechanism multilevel mediation model for social isolation	66
Figure 15. Results of the behavioral mechanism multilevel mediation model for suicidal ideation.....	67
Figure 16. Results of the psychosocial mechanism multilevel mediation model for depression	69
Figure 17. Results of the psychosocial mechanism multilevel mediation model for anxiety.....	70
Figure 18. Results of the psychosocial mechanism multilevel mediation model for social isolation	71
Figure 19. Results of the psychosocial mechanism multilevel mediation model for suicidal ideation...	72
Figure 20. Results for total effect of digital technology use on suicidal ideation.....	73

1.0 Introduction

After a period of consistent decline, the suicide rate in the United States has steadily increased since 1999. According to a report by Curtin, Warner, & Hedegaard (2016) with the National Center for Health Statistics, the suicide rate increased 24% from 1999 to 2014, and now is a top ten leading cause of death for people of all ages in the United States, with more than 30,000 suicides taking place every year (Luxton et al., 2012). The problem of suicide is particularly prevalent among young people, where it is the second leading cause of death for adolescents (15-24) and young adults (25-34), and the third leading cause of death for pre-adolescents (10-14; National Center for Injury Prevention and Control, 2015). According to the national Youth Risk Behavior Survey (CDC, 2017), 8.6% of high school-aged youth (9th to 12th grade) report attempting suicide at least once in the past 12 months. Furthermore, 14.6% of high school students report making a suicide plan and 17.7% report seriously considering attempting suicide in the past 12 months (for definitions of suicidal thoughts and behaviors (STBs) see Table 1; Turecki & Brent, 2016).

Table 1. Definitions for suicidal thoughts and behaviors (Turecki & Brent, 2016)

Term	Definition
Suicide/Completed suicide	A fatal self-injurious act with some evidence of intent to die
Suicide attempt	A potentially self-injurious behavior associated with at least some intent to die
Suicidal ideation/thoughts	Thoughts about wanting to die or end one's life, may include identifying a method, plan, or having intent to act

A particularly noteworthy finding in the report by Curtin and colleagues (2016) was that the suicide rate rose by about one percent per year from 1999-2006, but doubled to an annual increase of about two percent per year from 2006 to 2014. In addition to suicide, studies have found that rates of depression and anxiety have increased among youth (Twenge, 2019b). This time span also roughly

correlates with a period of rapid proliferation of digital technology use (Pew Research Center, 2017), as well as the use of social media (SM) and other internet-based communication applications (Perrin, 2015), leading many question whether digital technology use may be the culprit of a nascent mental health crisis among youth.

Throughout this review, I use the phrase digital technology to refer to the physical devices through which users access internet and non-internet-based applications. Here, I define SM as forms of digital communication on internet websites or applications for social networking and microblogging that allow users to create and maintain online communities to share information and content (Merriam-Webster.com, 2019). Common examples of SM include Instagram, Facebook, and Snapchat. Digital technology, internet, and SM form a nested structure of activities that range from broad to narrow, whereby narrower platforms represent subcomponents of larger activities.

One key way that these digital technologies have transformed our lives is the way we interact with each other. Text messaging and other instant messaging services, email, video chat, online forums and SM platforms have allowed for the interactive and synchronous sharing of information formed and controlled by individuals and groups (Luxton et al., 2012). Today, a substantial portion of our social interactions and relationships are mediated by digital technology, especially for youth (Perrin, 2015; Pew Research Center, 2017). How do these technologies affect the way we communicate, relate, and connect with each other? And do these changes have any consequences on the STBs among youth?

Over the last decade there has been a substantial amount of research focusing on how the use of digital technology relates to well-being (for a systematic map of reviews see: Dickson et al., 2018). However, these findings have largely been mixed. Certain studies have found that digital technology use is negatively related to well-being (Booker et al., 2018; Kross et al., 2013; Twenge, 2017; Twenge, Joiner, et al., 2018), while others have found either a positive or no relationship with well-being (Berryman et

al., 2018; Orben & Przybylski, 2019b). Some longitudinal studies found that more digital technology use predicted lower levels of well-being (Booker et al., 2018; Kross et al., 2013), while others found that lower levels of well-being predicted more use of digital technology (Aalbers et al., 2018; Heffer et al., 2019).

Despite these inconsistent findings, studies finding negative associations between digital technology use and well-being tend to gain the most media attention. High impact studies by Twenge and colleagues (Twenge, 2017; Twenge, Joiner, et al., 2018) and other researchers have been featured in popular news outlets like Time magazine, the New York Times, The Atlantic and others with attention-grabbing headlines such as “Have Smartphones Destroyed a Generation?” (Twenge, 2018) and “Is Social Media Contributing to Rising Teen Suicide Rate?” (Chuck, 2017). Roughly half of parents in the U.S. believe their children are addicted to digital technology and are concerned about how the impact they have on their mental health (Common Sense Media, 2018). Hoping to reduce the perceived impact that digital technology have on the well-being of youth, some researchers and stakeholders have recommended school- and family-based policies for how to protect youth from the harms of digital technology use (American Academy of Pediatrics, 2016; Twenge, 2019a).

However, others have argued that the notion that digital technology use is harmful to youth is based more on peoples’ tendency to panic about new technologies than the actual evidence (Ophir et al., 2019). Although research in this area has grown dramatically over the past 10 years, the preponderance of inconsistent findings and methodological concerns undermine any broad conclusions that digital technology usage is negatively impacting the mental health and well-being of U.S. youth. Given the rising rates of STBs among youth, the strong public and academic interest in this topic, as well as potential implications that findings have on policy and practice recommendations, it is crucial to clearly understand whether or in what ways digital technology use impacts risk of STBs. Prematurely or erroneously concluding that digital technology use is harmful, and intervening in the lives of youth at

risk of STBs based on these premature conclusions, may cause youth to be unnecessarily isolated from sources of connectedness and subsequently increase STB risk.

1.1 Psychosocial Risk Factors for Suicidal Thoughts & Behaviors

Despite the concerns about whether digital technology use is associated with the rising rates of STBs among U.S. youth, most research in this area has not examined STB-related outcomes directly. Instead, most studies have examined how digital technology use relates to symptoms of psychopathology (i.e. depression or anxiety), psychological well-being (i.e. life satisfaction, self-esteem, affective stability), or social well-being (i.e. loneliness, belongingness, social connectedness). While previous systematic reviews have summarized the literature on the risks and benefits related to digital technology use and STBs directly (Dyson et al., 2016; Marchant et al., 2017), no study has reviewed how digital technology use is associated with various psychosocial risk factors. Given that STB risk usually occurs as a result of a complex and multifactorial process involving a combination of psychosocial risk factors (O'Connor & Nock, 2014), and that the particular pattern of factors may vary across sociodemographic categories, it is vital to understand whether, how, and for whom digital technology use impacts psychosocial risk factors related to STBs. For comprehensive reviews of psychosocial risk factors for STBs see Franklin et al (2016), O'Connor & Nock (2014), and Turecki & Brent (2016).

In order to limit the scope of this review, I have elected to focus on a subset of risk factors for STBs that focus on common and well-supported psychosocial risk factors that fall into the following categories: psychopathology (i.e. mood disorders, anxiety disorders, substance use disorders), social/interpersonal (i.e. loneliness, social support, interpersonal conflict, belongingness, social transmission), cognitive/psychological well-being (i.e. self-esteem, affective stability, life satisfaction), and sociodemographics (i.e. LGBT status, socioeconomic status, race/ethnicity). Notably, these various

psychosocial risk factors almost always occur in combination to increase STB risk, with certain distal or upstream variables (e.g. social isolation) acting on mediating variables (e.g. personality traits), which, in turn, act on more proximal or downstream variables (e.g. depressive disorder) to increase the likelihood of STBs (Turecki & Brent, 2016).

This interactive scaffolding is important to consider in relation to how digital technology use may be associated with STBs. For instance, digital technology usage may be associated with social isolation, impulsivity, and depression in similar or different ways depending on how and with whom the digital technology is being used. Additionally, youth with higher levels of social isolation, impulsivity, and/or depression may engage and interact with digital technology in ways that are quite different from their peers, potentially exposing them to types of usage that are more harmful. Furthermore, given the interdependent and multilevel nature of psychosocial risk factors for STBs, the ways in which digital technology use may impact upstream psychosocial risk factors may influence a downstream risk factor, which may alter the ways in which youth engage with digital technology, creating a mutually reinforcing cycle. Therefore, it is vital to explicate the ways in which digital technology usage are associated with psychosocial risk factors at upstream, mediating, and downstream levels, and how existing vulnerability to STB risk may predispose youth to certain patterns of digital technology usage.

2.0 Background & Significance

In the following, I review and synthesize the strongest available evidence from systematic reviews and meta-analyses, as well as longitudinal and experimental studies, on the associations between digital technology use and various psychosocial risk factors related to STBs. Studies examining general usage variables (i.e., duration or frequency) are examined first, followed by studies that examine more specific types of digital technology usage, with an emphasis on identifying possible mechanisms and moderators throughout. My analysis and synthesis of the of the evidence is guided by several research questions: a.) How is the amount of digital technology usage related to psychosocial risk factors for STBs?; b.) What variables mediate or moderate the relationship between digital technology use and psychosocial risk factors?; c.) What is the strength of the evidence?; and d.) What are future directions for research in this area?

2.1 Amount of Digital Technology Use

As an indicator of the amount of research in this area, there have been at least 82 systematic reviews or meta-analyses published in the last 10 years examining the relationship between digital technology use and variables relating to psychosocial well-being (Dickson et al., 2019). Frequently examined outcomes include depression (k=41), anxiety (k=34), self-esteem (k=27), well-being (k=19), and social connectedness (k=19). Although the over-abundance of cross-sectional studies present in the extant literature poses challenges, synthesizing evidence from meta-analyses and systematic reviews allows for an understanding of important trends and overall effect sizes across a vast literature. Given the limitations of cross-sectional data with respect to establishing temporal or causal sequence of

effects, I draw on longitudinal and experimental studies to extend the evidence presented in the meta-analyses and systematic reviews.

2.1.1 Meta-Analytic Evidence

Recent meta-analyses examining the association between amount of digital technology use and depression (Huang, 2017; M. Liu et al., 2016; McCrae et al., 2017; Yoon et al., 2019) and anxiety (Prizant-Passal et al., 2016) have found that amount of digital technology use exhibits, on average, a small and positive correlation with both outcomes. However, given the heterogeneity in digital technology measures and samples across these meta-analyses, it is important to examine whether this effect differed depending on type of digital technology platform, the population under study, and other potential moderators. Analyses of SM usage and depression found overall average correlations of $r = .11$ for time spent (Huang, 2019; Yoon et al., 2019) and $r = .10$ for checking frequency (Yoon et al., 2019). One analysis examining total screen time duration and depression found an overall effect of $OR = 1.12$ (M. Liu et al., 2016). Finally, an analysis of total time spent online found and social anxiety found an overall average correlation of $r = .07$ (Prizant-Passal et al., 2016). All these effects were statistically significant at the .05 level.

While three of four three meta-analyses only examined the linear effects of digital technology use, the study by Liu and colleagues (2016) found a non-linear relationship between total screen time usage and depressive symptom severity. Specifically, compared to no screen time, moderate screen time use (about one hour per day) was associated with reduced risk of depression, while heavier use (those with four or five hours of daily use) exhibited the highest risk relative to no use. The resulting j-shaped curve has been found in other studies examining the effects of screen time on mental health problems (Hoare et al., 2016) and given rise to the “Goldilocks Hypothesis” (Przybylski & Weinstein, 2017), which posits that moderate amounts of digital technology use is actually associated with better

outcomes while no digital technology use or extreme amounts of use are associated with poorer outcomes.

Taken together, the effect sizes across different digital technology platforms are relatively consistent, revealing a small and positive association between time spent on digital technology and depression or social anxiety. However, moderation analyses yielded more complicated findings. Yoon et al (2019) and Huang (2017) reported that neither age nor gender significantly moderated the relationship between amount of SNS use and depression, while Liu et al (2016) found that the association between total screen time and depression was stronger in those under the age of 14. For anxiety, Prizant-Passal et al. found that the association between time spent online and social anxiety increased as age increased, with average correlations of $r=.06$ (ns), $r=.10$ ($p<.05$), and $r=.17$ ($p<.05$) for adolescents, young adults, and adults, respectively. Furthermore, while McCrae et al. found that the SM use—depression effect was similar across cross-sectional and longitudinal studies, Liu et al. found significantly different effects for cross-sectional studies (pooled OR=1.19, $p<.05$) versus longitudinal studies (pooled OR=.88, $p=.33$).

In addition to depression and anxiety, other meta-analyses have examined the associations between time spent on digital technology and sleep problems, social support, life satisfaction, self-esteem, loneliness, and personality traits (Carter et al., 2016; Huang, 2017, 2019; D. Liu & Baumeister, 2016; Song et al., 2014). Examining bedtime specific use of digital technology among children and adolescents, Carter et al. found that youth who used mobile devices at bedtime were more than 2.5 times as likely to report inadequate sleep quantity or excessive daytime sleepiness, and almost 1.5 times as likely to report poor sleep quality than youth who did not. However, it is unclear whether this effect varies across age, gender, or digital technology usage measure as moderation was not examined.

Meta-analyses of loneliness and perceived social support, which are strongly negatively correlated (J. Wang et al., 2018), revealed puzzling findings in relation to SM use. Specifically, analyses examining loneliness as an outcome found that general SM (Huang, 2019; D. Liu & Baumeister, 2016) or Facebook (Song et al., 2014) usage was weakly positively associated with loneliness, while another analysis found that SM usage was associated with greater perceived social support (Domahidi, 2018). Other analyses of the association between time spent on SM and self-esteem, life satisfaction, or personality traits showed either null or weak effects (Huang, 2017, 2019; D. Liu & Baumeister, 2016). Overall, SM usage was positively associated with neuroticism, extraversion, and narcissism and unrelated to openness, agreeableness, conscientiousness, self-esteem, and life satisfaction. Moderation analyses of gender and/or age were non-significant.

Given the high degree of heterogeneity between effects from the included studies in these meta-analyses and the relatively weak effect sizes uncovered, the overall picture of whether or how digital technology use is associated with psychosocial factors related to STBs is unclear. Although analyses of psychopathology symptoms (i.e., depression or anxiety) showed significant overall effects, correlates of depression and anxiety, such as self-esteem, life satisfaction, or social support, were either non-significant or in the opposite direction. These seemingly contradictory findings suggest that studies may come to different conclusions regarding the effects of digital technology usage depending on their choice of outcome measures and whether they are expecting the effect to be harmful or beneficial to health outcomes. Furthermore, given the cross-sectional nature of the data included in the meta-analyses, the direction of any association, if any, is indistinguishable.

2.1.2 Longitudinal Evidence

Recent longitudinal studies examining the effects of digital technology use over time have investigated a various psychosocial risk factors, with depression being the most frequently studied.

Comparatively few longitudinal studies have examined STBs as a primary outcome or as a covariate. Perhaps due to the wide variability between study designs, samples, and measures, these longitudinal studies have failed to present a consistent picture regarding the temporal association between digital technology use and psychosocial risk factors. Furthermore, attempting to organize and examine findings by digital technology platform and/or outcome does not yield any meaningful insights into the general or specific relationship between digital technologies and psychopathology or well-being.

Despite the correlating trends of increased digital technology use and suicidality among youth in the U.S., studies examining the prospective association between digital technology use and STBs have been relatively rare in the empirical literature. Research by Twenge and colleagues (Twenge, 2017; Twenge, Joiner, et al., 2018) has received significant attention in the academic literature and popular press for making the argument that the increase in digital technology use among youth is likely a driver of rising suicidality among youth in the U.S. Using data from the Youth Risk Behavior Surveillance Survey (YRBS) and the Monitoring the Future (MtF) survey, which are nationally representative surveys of U.S. youth, Twenge et al (2018) found that adolescents who reported more time using electronic devices (i.e. video games, computers, cell phones) were more likely to report past year STB-related outcomes. Specifically, after controlling for race, SES, grade, and geographic region, they found that the overall correlation between electronic device use and past-year STBs was $r = .14$ ($p < .001$) for girls and $r = .12$ ($p < .001$) for boys. Furthermore, they found that indicators of economic recession were not positively correlated with suicide-related outcomes among youth when matched by year, but electronic device use was.

However, given the time-lag design of the YRBS and MtF surveys, these associations represent general between-person trends rather than within-person effects, as new participants are surveyed at each wave. Therefore, it is unclear whether increases in digital technology use are temporally or causally associated with increases in STBs. A study by Kim (2017) analyzed two waves from a nationally

representative sample of Korean youth that followed the same participants over time and found that SM use in Wave 1 was positively related to SI in Wave 5 (OR= 1.36, 95% CI 1.10-1.67). Furthermore, this relationship was robust to multiple covariates including sociodemographics, cyberbully victimization, sleep issues, and lagged SI. However, the study failed to control for participants' prior SM use, so it is unclear if within-person increases in SI were preceded by within-person increases in SM use. Therefore, like the study by Twenge et al. (2018) above, the temporal and causal association of the digital technology use—STB effect remains unclear.

The results of these studies are hampered by certain limitations. First, their measures of digital technology use combine a wide array of different types of platforms and uses, which precludes the ability to infer whether certain types of digital technology use are more harmful, and whether this varies across sub-groups. Second, like most research examining the link between time spent on digital technology and health-related outcomes, they rely upon self-reported estimates of digital technology use.

One longitudinal study of Californian adults using objective measures of Facebook use found that various types of Facebook activity were actually associated with reduced risk of suicide mortality (Hobbs et al., 2016). Specifically, after tracking Facebook use for six months, they found that the number of Facebook friends, received messages, and received photo tags were significantly associated with reduced risk of suicide mortality over two years of follow-up. This suggests that SM use is largely reflective of peoples' offline social networks (Hobbs et al., 2016), where those with more active online social networks experience more social support and connectedness, which protects against suicide risk. However, this study only examined one specific platform (Facebook) among a large sample of adults in California. So, the results may not generalize to different types of uses on different platforms across different ages, particularly youth.

Prospective studies of digital technology usage and depression have also yielded inconsistent results. Studies have found that screen time predicts worsening depression (Twenge, Joiner, et al., 2018), that depression predicts more screen time (Zink et al., 2019) or less smartphone usage (Elhai et al., 2018), that depression and screen time exhibit a reciprocal relationship (Houghton et al., 2018), or that there is no prospective relationship between digital technology use and depression (George et al., 2018; Rozgonjuk et al., 2018). Importantly, the direction and significance of this association may vary by age and gender, as amount of SM use predicted depression among adolescent males, while among adolescent females this association was reversed (Heffer et al., 2019). Furthermore, the same study by Heffer et al. found no prospective relationship between SM use and depression among young adults.

Investigations into other outcomes related to psychopathology have focused on anxiety disorders (George et al., 2018; Rozgonjuk et al., 2018), ADHD (George et al., 2018), general mental health problems (van der Velden et al., 2019), and (serious) psychological distress (Hampton, 2019). Specifically, two studies employing more reliable measures of digital technology use (George et al., 2018; Rozgonjuk et al., 2018) found no effects with anxiety, while a study using retrospective self-reports of digital technology use found a reciprocal association with anxiety. One of the only studies to include ADHD as an outcome found that increase in daily ADHD symptoms were associated with increases in next time digital technology use (George et al., 2018). Finally, studies that focused on psychological distress more broadly found that SM use was either associated with reduced risk of serious psychological distress over time (Hampton, 2019) or had no association with psychopathology over time, once prior mental health problems were taken into account (van der Velden et al., 2019).

In addition to outcomes related to psychopathology, other longitudinal studies have examined the prospective association between digital technology usage and psychological well-being as a composite construct or as an umbrella term applied to similar constructs such as emotional wellness, self-esteem, happiness, and life satisfaction. As above, the findings are mixed, with evidence variably

suggesting that digital technology usage predicts lower psychological well-being (Babic et al., 2017; Kross et al., 2013; Twenge, Martin, et al., 2018) or that greater loneliness (Kross et al., 2013) predicts more digital technology usage, or that higher self-esteem predicts more digital technology use (Valkenburg et al., 2017), or that psychological well-being and digital technology use reciprocally reinforce each other over time (Orben et al., 2019). Furthermore, in the only study that tested for moderation by gender, Orben et al. (2019) found that the reciprocal relationship between digital technology use and life satisfaction was slightly stronger in females than males.

2.1.3 Experimental Evidence

While the results from the longitudinal studies provide mixed findings regarding the association between digital technology use amount and psychosocial risk factors, results from five recent experimental studies suggest that digital technology use may be driving this effect. Four of the five experiments compared the effects of Facebook (Allcott et al., 2020; Mosquera et al., 2019; Tromholt, 2016) or SM (Hunt et al., 2018) restriction on outcomes related to psychosocial risk factors. The three most robust experiments objectively verified compliance with Facebook/SM restriction. All three experiments found that Facebook deactivation (Allcott et al., 2020; Mosquera et al., 2019) or SM use reduction (Hunt et al., 2018) led to small but significant improvements in depression compared to the control group (i.e. regular use). In addition to depression, Facebook deactivation led to significant gains in happiness, life satisfaction, and anxiety in the study by Allcott and colleagues, and SM use reduction led to significant reductions in loneliness in the study by Hunt et al. However, despite a remarkably similar study design to that of Allcott et al., the study by Mosquera et al. found that Facebook deactivation did not significantly affect life satisfaction, happiness, or worry. Furthermore, only two of the seven outcomes tested by Hunt and colleagues were significant, while effects for self-esteem, psychological well-being, social support, fear of missing out (i.e. FOMO), and anxiety were not.

Although the experiment by Tromholt et al. did not verify compliance with Facebook deactivation, similar to Allcott et al., they found that subjects in the treatment group reported significantly higher life satisfaction and better moods than the control group, and that the effects were moderated by intensity of Facebook usage at baseline, with Facebook deactivation exhibiting no effects for light users but significant effects for heavy users. Similarly, in another Facebook experiment, participants who used Facebook reported lower positive affect compared with those that browsed the internet (control group; Yuen et al., 2018).

So what did participants do with their “extra” time that they would have spent using Facebook or SM? Two dominant hypotheses represent opposite effects. The displacement hypothesis (Kraut et al., 1998) suggest that digital technology crowds-out other forms of communication that are considered more meaningful and important, such as in-person and telephone interactions. While the reinforcement hypothesis (Dienlin et al., 2017) suggests that digital technology provide more avenues for people to establish new connections and maintain old ones, thus providing additional resources to strengthen or maintain relationships. Findings from the only two studies that tracked this kind of data (Allcott et al., 2020; Mosquera et al., 2019) provides some evidence in support of the displacement hypotheses. Specifically, compared to baseline, participants randomized to the restricted Facebook use condition reported engaging in significantly less time on other online activities and devoting more time to offline activities such as spending time with friends and family and exercising. Still, some evidence suggests that participants significantly increased time spent in other sedentary behaviors, such as watching TV alone (Allcott et al., 2020). However, the measures used in these studies to track time spent may reveal researcher bias, as nearly all items were phrased in a way that did not allow for increases in unhealthy behavior to be tracked.

This is an important area for future research, as the causal picture of the effects of digital technology use on psychosocial well-being remains unclear. For instance, if the finding by Mosquera et

al (2019) is replicated in other populations and other digital technology platforms, then evidence would suggest that digital technology use displaces engagement in healthier activities, lending support for the claim that digital technology use increases depression, which may increase risk of STBs. However, if depression increases digital technology use, then we may find that depressed individuals replace their extra time with other similar sedentary-type behaviors (i.e. watching TV, sleeping). Therefore, future experimental studies should examine the effect of digital technology restriction on depression across various platforms and populations, while also tracking what participants did with the time that would have been spent on digital technology.

The results from these experimental studies are somewhat inconsistent. Interestingly, the findings that restrictions in Facebook or SM use leads to significant declines in depression appear to be consistent across three different studies. On the other hand, other outcomes related to psychosocial well-being that tend to strongly correlate with depression, such as anxiety, life satisfaction, happiness, and mood, show more inconsistent results. Possible explanations for these inconsistencies include heterogeneity across studies in sample sizes (range = 143-2743), constructs, measures, and exposure periods (range: 20 minutes to four weeks). It is possible that different exposure periods may have variable effects on different outcomes, or that the effects may not follow a linear trend over time. For instance, it may be that Facebook or SM use restriction follows a quadratic trend, whereby people experience improvements in well-being during the initial period, then deterioration over the subsequent period. Notably, these inconsistent results may also suggest that amount of digital technology usage in and of itself is not inherently good or bad, and that there are important mechanisms that mediate the relationship between digital technology use and psychosocial well-being.

2.2 Evidence for Mechanisms

The accumulated evidence suggests that digital technology usage in and of itself does not increase or decrease psychosocial risk factors related to STBs. Rather, it depends on a complex interaction involving what particular digital technology platform is being used, how it is being used, what it is being used for, and with whom it is being used (Best et al., 2014; Keles et al., 2019; Seabrook et al., 2016; Verduyn et al., 2017; Wu et al., 2016). Digital technologies offer many potential benefits that may increase psychosocial well-being and protect against risk of STBs, such as providing an avenue for social support, maintaining relationships, and establishing new relationships, and reducing social isolation. Digital technology may be especially beneficial for those struggling with more severe forms of depression or anxiety in which they find it difficult to engage in the face-to-face interactions and are afforded the opportunity to access some form of interaction and potential social connectedness. Furthermore, digital technology may be more beneficial to certain groups at higher risk of STBs due to family or social ostracism, such as LGBT youth, who may find an online community that fosters the acceptance, belonging, and support that they may not receive from family and friends in offline settings (Escobar-viera et al., 2018). On the other hand, digital technologies also present potential harms that may decrease psychosocial well-being and increase risk of STBs, such as negative social comparison.

Numerous studies have examined how different types of digital technology usage are associated with outcomes related to psychosocial well-being, identifying mechanisms that may mediate this relationship. However, because digital technology captures a range of different types of platforms, from specific applications like SM to broad platforms like smartphones or internet use, the types of behaviors one engages in may differ significantly across platforms. This may lead to exposure to different mechanisms depending on the type of digital technology platform being used and, in turn, have varied impact on outcomes.

2.2.1 Passive Use, Social Comparison, and Social Connectedness

A substantial amount of research has focused on the mechanisms of passive use, social comparison, and social connectedness as important processes that help explain the relationship between SM use and psychosocial risk factors related to STBs. The broadest of these categories, passive vs. active use, refers to the different ways in which people may engage on SM, with active use connoting direct interaction with others (e.g. commenting or direct messaging) and passive use connoting the non-interactive viewing of others' SM profiles (e.g. browsing through Facebook or Instagram).

Most research suggests that passive SM use is negatively related to well-being outcomes, while active use is positively related to well-being (Frost & Rickwood, 2017; Verduyn et al., 2017). Whether passive SM use predicts poorer well-being over time, or vice versa, is somewhat unclear. Some experimental and longitudinal evidence suggests that passive use predicts lower well-being over time, but not vice versa (Shakya & Christakis, 2017; Verduyn et al., 2015). Others have found that lower well-being predicts more passive use (Aalbers et al., 2018; Frison & Eggermont, 2015) or is bi-directional over time (J. L. Wang et al., 2018).

Explanations for why active and passive SM use are oppositely associated with well-being have focused on the mechanisms of social comparison and social support/social connectedness. Human beings have a fundamental need for belongingness (Baumeister & Leary, 1995) and a drive to evaluate their abilities and experiences to others (Festinger, 1954) which motivate many behaviors related to social connectedness and social comparison. The wide availability of SM, which contains vast amount of information about friends, acquaintances, and strangers, makes it a prime ground for social comparisons. However, as people typically present only their best or most glamorous sides on SM, it is more likely that people will make upward social comparisons, in which they negatively evaluate themselves in relation to others. These upward social comparisons can have negative impacts on well-being (Verduyn et al., 2015).

Studies have consistently shown that social comparisons on SM are associated with poorer well-being. Specifically, a meta-analysis found that the amount of time spent on SM was weakly positively associated with depression ($r=.11$), but the association between social comparisons made on SM and depression was more than twice as strong ($r=.23$; Yoon et al., 2019). Furthermore, evidence from longitudinal and experimental studies support the assertion that negative comparisons on SM leads to poorer well-being (de Vries et al., 2018; Frison & Eggermont, 2016; Tromholt, 2016; Vogel et al., 2015; Weinstein, 2017). Given that passive use of SM predominantly involves browsing through others profiles, it is plausible that those that use SM more passively most likely engage in more social comparisons compared to active users (Verduyn et al., 2015).

Aside from differences in level of exposure to social comparisons, engaging in active vs. passive SM use also may impact the level of social connectedness people derive from their SM engagement. Evidence from an experimental (Große Deters & Mehl, 2012) and longitudinal study (Frison & Eggermont, 2015) of Facebook use found that those who increased active Facebook engagement reported enhanced perceptions of social connectedness, while passive use decreased perceptions of social connectedness. Additionally, with whom people are interacting online may play an important factor in whether the active or passive engagement leads to significant changes in well-being. Longitudinal studies using objective Facebook data (Burke & Kraut, 2014, 2016) found that active engagement from strong ties was significantly associated with enhanced well-being and perceived relationship quality, while active engagement from weak ties had no effect.

The accumulated evidence suggests that the positive effects of SM are predominantly mediated by enhanced social connectedness such as feelings of social support and positive quality interactions (Waytz & Gray, 2018). However, there are concerns that youth at higher risk of STBs, due to experiencing various psychosocial impairments, may be less likely to experience the positive effects of SM and more likely to experience the negative effects. Those struggling with lower levels of psychosocial

well-being likely engage in types of SM activity and perceive their SM interaction differently than those with higher levels of psychosocial well-being. These behaviors and perceptions may be influenced by symptoms of psychopathology that affect cognition, motivation, mood, and energy. For instance, those struggling with depression are more likely to negatively compare themselves to others' SM profiles and more likely to perceive their online interactions as poor in quality than those without depression (Seabrook et al., 2016). Therefore, whether SM use is positively or negatively related to well-being may depend in many ways on the level of social connection and support derived online (Clark et al., 2018; Yoo & Jeong, 2017).

This suggests that youth who are at higher risk for STBs vis-à-vis their levels of psychopathology, well-being, or social connectedness may be more likely to engage in passive SM use and less likely to engage in active SM use. The proclivity for passive use may then increase the likelihood that they engage in potentially harmful online behaviors like negative social comparison and less likely to access the types of online interactions that may be associated with enhanced social connectedness. However, even if these youth do engage in more active uses, they are more likely to perceive their interactions and social support as negative which may, in turn, further undermine well-being and subsequently increase risk of STBs. The phenomenon that those with lower well-being are more likely to have poorer outcomes associated with their SM use, and those with higher well-being are more likely to have better outcomes associated with theirs, is known as the poor-get-poorer and rich-get-richer effects. Additionally, there is some evidence for a poor-get-richer effect, namely that those with lower well-being may experience improvements over time associated with their SM use (Frison & Eggermont, 2015). These effects have been uncovered in numerous studies attempting to understand how and for whom SM use benefits or harms (Best et al., 2014; de Vries et al., 2018; Frison & Eggermont, 2015; Weinstein, 2017; Yoo & Jeong, 2017).

2.2.2 Sleep Impairment

Evidence suggests that sleep impairment may be implicated as a mediator in either a directional (i.e. higher digital technology use leads to worse sleep) or bidirectional (i.e. digital technology use and sleep pathology mutually impact each other) causal process (Elhai et al., 2017; Keles et al., 2019). It may be that digital technology use at bedtime may impair sleep, exacerbating psychopathology which, in turn, may further fuel problematic digital technology use. On the other hand, youth already experiencing sleep psychopathology may turn to digital technology at night as a result of not being able to fall asleep, which further exacerbates their sleep problems.

Evidence from cross-sectional studies indicate that digital technology use before bed is associated with sleep impairment among youth. Results of a meta-analysis (Carter et al., 2016) found that, across 17 studies, those that used a mobile device at bedtime were more than 2.5 times as likely to report inadequate sleep quality and excessive daytime sleepiness compared to those that did not use digital technology at bedtime. Furthermore, just having access to a mobile device during bedtime was also significantly associated with increased likelihood of sleep impairment when compared to those that did not have access.

Furthermore, longitudinal studies suggest that digital technology use is prospectively associated with sleep disturbances over time (Thomée et al., 2011; Twenge et al., 2017; van der Velden et al., 2019; Vernon et al., 2017). This finding appears to be robust across age and country of origin (samples from the U.S., the Netherlands, and Sweden), type of digital technology measure (i.e. general electronic device use, problematic digital technology use, SM use), as well as random (Thomée et al., 2011; Twenge et al., 2017; van der Velden et al., 2019) and convenience samples (Vernon et al., 2017). Although sleep disturbance itself is considered a risk factor for STBs, it may also mediate the relationships between digital technology usage and other psychosocial risk factors for STBs such as

depression or psychological well-being. This is evidenced in two prospective studies that found that changes in sleep problems explained more than half of the variation in the problematic SM use--depression effect (Vernon et al., 2017), and that the SM use no longer significantly predicted psychopathology over time once sleep problems was taken into account (van der Velden et al., 2019).

Taken together, evidence suggests that digital technology use at bedtime is associated with sleep problems, and that sleep disturbance may mediate the relationship between digital technology use and psychosocial well-being. However, it remains unclear to what extent digital technology use causes those with no pre-existing sleep pathology to begin experiencing sleep problems or whether youth with pre-existing sleep pathology use their digital devices more at night because they already cannot sleep. Disentangling these scenarios is an important area for future research. Notably, these findings are limited by their reliance upon self-report measures of digital technology use and sleep impairment, both of which are highly prone to inaccuracy (Boase & Ling, 2013; Lauderdale et al., 2008). To better understand the nature of the association between digital technology use and sleep, prospective and/or experimental designs utilizing objective measures should be considered.

2.2.3 Sedentary Behavior

There is strong evidence indicating that higher levels of sedentary behaviors are associated with increased risk of poor health outcomes and mortality (Chau et al., 2013; Thorp et al., 2011), including psychopathology (Bélair et al., 2018; Hoare et al., 2016). Given that use of digital technologies such as computers, tablets, and smartphones tend to be sedentary activities, it is possible that the significant rise in digital technology use among youth may relate to poorer health outcomes via the mechanism of increased time spent in sedentary activities. However, few investigations of the link between digital technology use and outcomes related to STBs have considered sedentary behavior as a mechanism or even a covariate (Hoare et al., 2016). An experimental study (Mosquera et al., 2019) found that adults

who were randomized to the Facebook restriction condition reported significantly increasing their physical activity as a result of less time spent using Facebook and other SNS.

More experimental and prospective studies are needed to see how digital technology use and sedentary behavior relate to each other and unfavorable health outcomes over time among youth. It is important to ascertain the temporal sequence of effects and to determine whether digital technology use supplements or substitutes total time spent in sedentary activities. For instance, the ubiquity and portability of digital technology devices such as smartphones and other mobile devices may exert a stronger influence toward sedentary behaviors than comparable activities (e.g. TV watching), thereby displacing time spent in physical activities, which is protective against unfavorable health outcomes (Dohrn et al., 2018). Therefore, digital technology may indirectly exacerbate the severity of STB related risk factors such as depression, which already predisposes individuals toward physical inactivity due to impaired behavioral activation (American Psychiatric Association, 2013), by increasing sedentary time. Alternatively, digital technology may impart no additional effect on sedentary behavior for youth but merely serve as a substitute for other sedentary activities. Experimental studies that induce reductions in digital technology usage and gauge effects on sedentary behaviors and other health-related outcomes may provide valuable insight into these questions.

2.3 Theoretical Frameworks

2.3.1 Durkheim's Theory of Suicide

The major theoretical concepts that emerged from Durkheim's theory of suicide center on a four-way classification of suicides that result from mutable degrees of regulation and integration that exist in the political, social, and religious groups of which individuals are a part. Integration—which describes the level of connectedness, belonging, and acceptance that an individual derives from a group

(Durkheim, 1962/1897; Wray et al., 2011)—at the extreme low and high ends of the continuum can both lead to suicide, with egoistic suicide resulting from lack of integration, and altruistic suicide from over-integration. Similarly, regulation—which refers to the moral and normative demands that an individual is subject to as a member of a group (Bearman, 1991; Durkheim, 1962/1897)—can produce suicide at the extremes of the continuum. With lack of regulation leading to anomic suicide and over-regulation resulting in fatalistic suicide. Of the four types, Durkheim focused primarily on egoistic and anomic suicides, as these were more representative of suicide in modern society (Durkheim, 1962/1897).

Generally, the notion of social integration has been the focus of a significant amount of research and theorization. Conceptual fields that utilize social integration as a foundational idea have developed into significant areas of study, such as social isolation, social cohesion, social networks, and social connectedness (Pescosolido & Georgianna, 1989; Wray et al., 2011). The links between social relationships and various measures of well-being as well as suicide have been consistently supported (Holt-Lunstad et al., 2010; Van Orden et al., 2010). Results from multiple experimental and quasi-experimental studies have shown that interventions specifically designed to improve social integration led to a reduction in suicidality (Fässberg et al., 2012).

Although Durkheim and many of his subsequent contributors could have never imagined a world in which a substantial portion of human interaction is mediated by digital devices, the theory retains valuable explanatory power for interpreting suicidality in modern times. The foundational concepts of social integration and regulation, as well as the fourfold typology of suicide, offer a useful cognitive scaffolding from which to analyze the problem. Because the theory is so expansive, only two of the many possible interpretations of the problem of and suicidality will be presented.

The first perspective posits that while the suicide rate has climbed steadily since the late 1990s, it is due to factors not relating to the growth of digital technology. In fact, digital technology has likely

kept the suicide rate from being even higher. This perspective asserts that digital technology permits people to have unprecedented connection to others. The wide range of devices and applications that individuals can use to connect with each other allows for new relationships to be initiated, and existing relationships to be maintained. This ubiquity and potentiality of connection fosters social integration and social cohesion (Schroeder & Ling, 2014).

The enhancement of social integration that digital technology affords directly and indirectly reduces the individual's suicide risk. Due in large part to digital technology, it is now possible to exist in a nearly constant state of both simultaneous and delayed connection. Although separated by space and time, individuals can connect face-to-face by video, or by voice via phone call, or by text or photo via any number of applications such as instant messaging, email, Facebook, Instagram, Twitter, and so on. This constant connection fosters relational familiarity, which can buffer individuals against the risk of egoistic suicide that comes from a lack of social integration.

The second perspective interprets the problem of suicide in modern times being exacerbated by digital technology. Whereas the first perspective argued for a reduction in suicide because of increased social integration, this perspective posits an increase in suicidality resulting from anomie, or a state of normlessness. Seeing the social forces of integration and regulation as interdependent and dynamic rather than distinct and static, Bearman (1991) posits that the modern anomic state can be characterized by significant social integration across multiple groups. This gives way to a normative dissonance that, like the traditional understanding of normlessness, equates to anomie.

This interpretation implies that while digital technology allows for constant and ubiquitous communication across an array of social groups, the exposure to the disparate norms and customs that regulate individuals gives way to normative and moral confusion. This confusion, or dissonance, leaves the individual in a deregulated state with no solid normative or moral scaffolding to guide them or offer

purpose and meaning, and thus makes them prone to suicide when confronted with crises and tribulations.

The view of integration and regulation as interdependent and dynamic provides a useful analysis of the potentially harmful impact of SM applications such as Facebook, Instagram, and Twitter. While it is true that, like the first perspective asserted, SM can foster connection and integration among individuals, it can also do the opposite. It is common practice to present a highly curated, idealized version of oneself on SM that minimizes blemishes while magnifying various accomplishments and positive character traits. The individual perusing the SM profiles of friends and acquaintances, rather than feeling more connected, is likely to feel alienated as they compare their blemished self to the idealized self of others. This alienation breeds a sense of social disintegration, prompting the individual to feel a lack of meaningful or intimate connection and thus at increased risk of suicide.

Overall, this theoretical perspective has strengths and limitations when applied to the issue of digital technology and STBs in the modern world. By focusing on the broader social forces at work, this theory can be utilized to analyze how rapid transformations, such as technological change, alter the structures and functions of society that integrate and regulate the lives of individuals. These alterations in the social structures and functions of society can influence the suicide rate for better or for worse. However, macro sociological interpretations of suicide like Durkheim's theory are apt to neglect proximate causes of suicide, such as mental illness, in favor of distal causes, such as social integration (Stack, 2000). This leads to a potential confounding effect that misattributes to variations in social integration what ought to be attributed to predispositions of mental illness (or other more proximal factors). This limitation advises caution when studying this relationship in the online world, underlining the importance of controlling possible confounding proximal variables that are associated with suicide.

Additionally, social integration is prone to variation in conceptualization, operationalization, and measurement. This prompts questions about whether social integration is best captured by measures of belongingness, social isolation, social cohesion, social connectedness, or none of the above. Whether digital technology influences suicide through social integration can only be adequately answered to the degree that reliable and valid measures of the construct of social integration are used across multiple studies.

2.3.2 Social Capital Theory

According to Putnam (1995) social capital is understood as the “features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit” (p. 67). Focusing his explication of social capital at the societal level, Putnam is perhaps best known for his popular book *Bowling Alone* (2000), which introduced the concept of social capital to a much wider general audience.

In this book, Putnam details the decline of social capital in American society, evidenced by precipitating rates of civic engagement and associational involvement—which he attributes primarily to the “technological transformation of leisure” (Putnam, 1995, p. 75). Two key concepts emerged from Putnam’s work in *Bowling Alone* (2000): bonding and bridging social capital. Bonding social capital is typified by the ties of friends and family members, as well as close community organizations or groups. Bonding social capital networks are more exclusive and inward-looking, reinforcing a specific set of norms, customs, and homogenous identities. Bridging social capital are the ties that connect different groups of people and tend to be outward-looking. Bonding social capital is helpful for getting by, while bridging social capital is useful for getting ahead (Putnam, 2000).

Recent investigations have found that areas high in social capital are correlated with less psychological distress, mental illness, hospitalization, and STBs (Recker & Moore, 2016; Scheffler et al.,

2010). Examining social capital in the context of the online world, a systematic review analyzing the relationship between digital technology and well-being among adolescents found, generally, that both bonding and bridging social capital are enhanced by SM and other online communication (Best et al., 2014). However, whether this enhancement in social capital was subsequently associated with changes in well-being yielded mixed results.

An analysis of the problem of suicide in modern times from a social capital perspective treats digital technology as basically neutral. That is, the degree to which digital technology contributes positively or negatively to STBs depends on the particular type of application being used as well as how it is being used. If the idiosyncratic use of particular digital technology applications leads to enhanced social capital, then the risk of STBs diminishes, and vice versa.

The plethora of digital technology applications has tremendous potential to enhance both the bonding and bridging social capital of individuals and groups. As mentioned previously, the ability to maintain a nearly constant connection across multiple devices and applications offers a heretofore unequalled opportunity to stay linked with loved ones. These familial or close-friend relationships make up a predominant portion of bonding social capital, which provides individuals with emotional and intimate support and generally help people get by in life (Putnam, 2000). This potentiality of emotional support by close connections serves as an important buffer against risk of STBs.

In addition to bonding social capital, the use of these applications can also enhance bridging social capital. Most SM sites have features that assist users in making connections with acquaintances outside of their primary network. While these connections do not provide the emotional support that is derived from bonding social capital, they broaden and diversify the individual's network, thereby potentially increasing the amount and quality of social capital to which they can gain access. These

resources can then be employed to augment the person's life situation, or be utilized as a safety net if crises strike.

Although not approaching their investigation from a social capital perspective, recent research has indicated that well-being can either be enhanced or diminished depending on the way in which the digital technology is being used. For instance, active uses of Facebook, such as sending or receiving personalized messages, have been found to improve well-being (Burke & Kraut, 2016), whereas passive use, such as scrolling through profiles without interacting, have been found to decrease well-being (Seabrook et al., 2016). From a social capital perspective, these findings illustrate how digital technology has the potential to strengthen social bonds by providing an avenue for active connection (i.e. direct interaction), or weaken social bonds by fostering non-interactive, passive comparison (i.e. scrolling through Instagram or Facebook profiles). This potential undermining of social capital due to weakened social bonds may increase STB risk for individuals by reducing social connectedness and social trust. This alienates individuals from the bonding social ties, therefore creating barriers to accessing the social and emotional support that can safeguard against suicide risk.

Studies by Chan (2015) and Burke & Kraut (2016) suggest that digital technology use with strong ties (bonding social capital) may maintain or enhance social connectedness, whereas interaction with weak ties (bridging social capital) may diminish it. When extrapolated to the problem of STBs, the improvement or undermining of social capital has potentially significant implications for suicide risk and mental illness. The finding pertaining to weak ties is particularly interesting, as one would expect that weak-tie interaction would enhance bridging social capital, which would increase overall levels of social capital. One explanation for this finding is that digital technology affords individuals opportunities to interact on a near-constant basis with a wide range of social ties, some strong and some weak. Given that strong ties, like bonding social capital, provide the social and emotional support that help individuals get through life, individuals that interact more frequently with weak ties may neglect their

strong ties, thereby diminishing the sense of support and belonging that come from bonding social capital. The expectation of obtaining from weak ties the functions of strong ties (i.e. emotional support), may lead to the result of undermining social capital and engendering a sense of social isolation, which may increase risk of STBs.

Social capital theory has strengths and limitations when applied to the issue of suicide and digital technology. Of particular use are the concepts of bonding and bridging social capital, which provide a lens through which to interpret how different forms of interactions afford different types of value to the individual or group. The ways in which digital technology instigates or protects against risk of STBs depends in large part on how the technology is being utilized, and whether that use enhances or diminishes social capital. However, methodological and measurement concerns arise from the wide variation in how social capital has been defined (De Silva et al., 2005; Scheffler et al., 2010). Additionally, conceptualizations of social capital are limited by difficulties in distinguishing between what it is from what it does (Woolcock, 1998). For instance, is civic engagement an element of social capital, or is it a by-product of social capital? The lack of conceptual clarity has led to numerous measures of social capital that are applied at different levels of measurement in various contexts. This has produced findings that are at times contradictory, triggering criticisms that the measurements of social capital do not actually capture the phenomenon of social capital (De Silva et al., 2005).

2.3.3 Theory Summary

Together, these theoretical perspectives provide valuable insight into the modern problem of suicide in an age wherein so much of our social interactions are mediated by digital technology. By elucidating the important role that social integration plays in STBs, Durkheim's theory of suicide offers a lens through which to examine how modern technology is adding to or detracting from our social integration. However, while Durkheim's theory of suicide overlooks the importance of the content of

the social relationship and interaction, imitation theory and social capital theory can provide powerful explanations for why, in certain instances, the social integration afforded by digital technology ends up increasing risk of STBs. Future research should focus on further elucidating the mechanisms present in each of these theoretical perspectives in order to test them against empirical data.

2.4 Research Methodology

Nested within the general question of whether and how digital technology usage impacts risk factors related to STBs are methodological concerns that challenge the reliability and validity of empirical findings. Generally, research on the effects of digital technology on STB-related outcomes and risk factors are undermined by several primary limitations: a.) over-abundance of cross-sectional studies; b.) small effect sizes; c.) high levels of analytical flexibility that inflate false positive rates (i.e. researcher degrees of freedom; Simmons, Nelson, & Simonsohn, 2011); and d.) measurement issues that challenge the reliability and validity of uncovered associations.

As noted elsewhere in this review, cross-sectional data preclude any temporal or causal inferences concerning associations between variables. The saturation of cross-sectional studies and lack of longitudinal data were nearly universal concerns expressed across a host of systematic reviews and meta-analyses examining the potential association between digital technology and psychosocial outcomes (Dickson et al., 2019). While useful for other purposes, cross-sectional studies are unable to identify whether usage amount or levels of well-being are driving the association, or whether the association is reciprocal in nature. However, because digital technology usage is typically considered the independent or predictor variable in analyses, coupled with peoples' propensity to treat new technologies as probable causes of nascent societal ills (Ophir et al., 2019), researchers and consumers

of academic articles may improperly speculate or conclude that digital technology usage is the likely culprit.

Highlighted by Orben, Przybylski and colleagues (Orben et al., 2019; Orben & Przybylski, 2019a, 2019b; Przybylski & Weinstein, 2017), findings in this area of research are limited by concerns related to small effect sizes and high levels of researcher degrees of freedom. Researcher degrees of freedom refers to the myriad choices that researchers make when collecting and analyzing data. Typical examples include whether or how to exclude observations, how to deal with missing data, which control variables should be considered, whether or how data should be transformed, and so on. As it is likely impossible to think of every instantiation of possible analytic decisions beforehand, researchers often explore different options post hoc. Due to uncertainty about how best to make these decisions and (unconscious) motivated reasoning, researchers may search for a combination that yields a statistically significant result and then only report this finding while neglecting to report other combinations that were non-significant (Simmons et al., 2011).

Studies using large, nationally representative surveys of youth such as the YRBS or MtF may be particularly prone to false positive findings due to a combination of small effect sizes, large sample sizes, and high levels of researcher degrees of freedom. Utilizing a new and powerful statistical technique called specification curve analysis, which allows for testing a wide range of analytical specifications (Simonsohn et al., 2015; Steegen et al., 2016), Orben, Przybylski, and colleagues uncovered the ways in which researcher degrees of freedom may bias findings. Across 372 reasonable specifications for the YRBS and close to 50,000 specifications for the MtF, they found the median digital technology use—well-being effect was $\beta = -.035$ for the YRBS dataset and $\beta = -.005$ for the MtF dataset. These median effects are smaller than those reported in oft-cited work by Twenge and colleagues (Twenge et al., 2017; Twenge, Joiner, et al., 2018; Twenge, Martin, et al., 2018), who used the same datasets but only reported the results from a few specifications. Although some of these associations may register as

statistically significant, the small sizes of effects begs the question of whether they are clinically or scientifically meaningful, especially in light of other variables that displayed much stronger associations with well-being (Orben & Przybylski, 2019a). For instance, the median effects of bullying and smoking marijuana were three to four times as large as the median effect of digital technology use. Comparatively, eating potatoes and wearing glasses—seemingly benign activities---had roughly the same effect size as digital technology use (Orben & Przybylski, 2019b).

Finally, given that most studies in the area have relied upon self-report measures of digital technology use, the reliability of results may be questionable. Self-report measures of media use are consistently inaccurate when compared against more objective measures such as passive sensing, usage meters, or provider logs (see Parry et al. (2020) for a recent meta-analysis). Importantly, studies have shown that inaccuracies in estimates of media use are not solely due to random error, but are often related to individual characteristics that are fundamental to the relationship being investigated, such as amount of use (Kobayashi & Boase, 2012) and level of psychosocial well-being (Sewall et al., 2020). These errors in estimation can have significant consequences when attempting to detect associations and can lead to type I and/or type II errors (Kobayashi & Boase, 2012). To illustrate, Sewall and colleagues (2020) recently found that participants with higher levels of depressive symptomology provided estimates of iPhone and social media use that were more inaccurate than those with lower levels of depressive symptomology.

Additionally, aside from concerns regarding misestimating digital technology usage in self-reports, numerous studies rely upon measures of types of digital technology usage (e.g. passive use) or psychosocial outcomes that are of questionable psychometric validity. Use of one-item measures of different types of digital technology usage and psychosocial outcomes that have not been psychometrically tested are common across studies. Furthermore, although some measures of types of

digital technology use exist, there is wide variability in the measures used across studies, which makes comparisons difficult.

These methodological concerns pose serious threats to the reliability and validity of findings in the digital technology use research. In general, studies employing random samples that may generalize to the general population are limited by their use of self-report measures that may lack validity and reliability. On the other hand, while experimental studies have high internal validity, their highly controlled conditions, narrow focus on particular platforms, and convenience-based samples challenge the notion that any uncovered effects may generalize to other platforms, uses, and/or populations.

2.5 Summary of Research Questions

Overall, my review of the evidence suggests that the relationship between digital technology use and psychosocial risk factors for STBs is a complex process that implicates multiple mediating and moderating mechanisms. Mediating mechanisms can be crudely categorized into behavioral and psychosocial. The behavioral mechanisms—sleep disturbance and sedentariness—are generally a byproduct of digital technology use, while the psychosocial mechanisms—social comparison and passive vs. active use—occur directly on digital technology platforms. For instance, a teenager passively scrolling through Instagram at bedtime may be directly engaging in social comparison, a psychosocial mechanism, and experiencing sleep impairment, a behavioral mechanism, as a byproduct of bedtime digital technology use. Since multiple mechanisms at different levels may be implicated at the same time, it is important for future studies to simultaneously examine behavioral as well as psychosocial mechanisms to better account for possible confounding between the two. Additionally, patterns of effects are heterogeneous across groups, particularly groups defined by age and gender. Thus, it is important to not

only examine various potential mechanisms, but also how these mechanisms may differ for people of different ages and/or genders.

To address the limitations and complexities described above, the current study will address the following research questions, which are visually depicted in Figure 1 (below):

Q1a: What are the temporal associations between different types of DTU (screen time, social media, pickups) and psychosocial risk factors for suicide (depression, anxiety, social isolation)?

Q1b: How much within- and between-person variance do the DTU variables explain in depression, anxiety, and social isolation?

Q2a: What are the within- and between-person direct effects of the DTU variables on suicidal ideation?

Q2b: How much within- and between-person variance do the DTU variables explain in suicidal ideation?

Q3a: What are the indirect effects of the DTU variables on depression, anxiety, and social isolation via the behavioral mechanism variables?

Q3b: How much within- and between-person variance do the behavioral mechanism variables explain in depression, anxiety, and social isolation?

Q4a: What are the indirect effects of the DTU variables on depression, anxiety, and social isolation via the psychosocial mechanism variables?

Q4b: How much within- and between-person variance do the psychosocial mechanism variables explain in depression, anxiety, and social isolation?

Q5a: What are the indirect effects of the DTU variables on suicidal ideation via the behavioral mechanism variables?

Q5b: How much within- and between-person variance do the behavioral mechanism variables explain in suicidal ideation?

Q6a: What are the indirect effects of the DTU variables on suicidal ideation via the psychosocial mechanism variables?

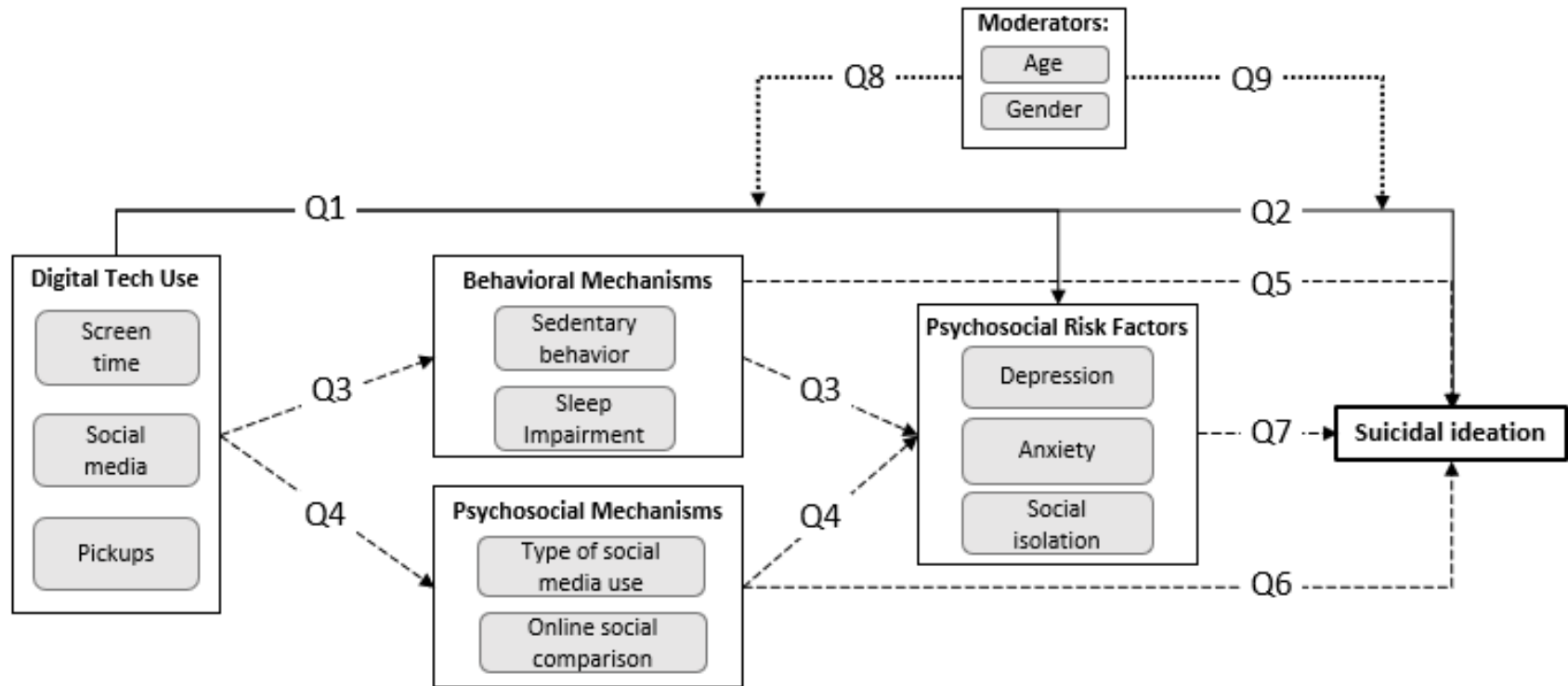
Q6b: How much within- and between-person variance do the behavioral mechanism variables explain in suicidal ideation?

Q7: What is the total effect of the DTU variables on suicidal ideation via their impact on depression, anxiety, and social isolation?

Q8: Does the DTU—psychosocial risk factors direct effect vary by gender or age?

Q9: Does the DTU—suicidal ideation direct effect vary by gender or age?

Figure 1. Summary of research questions



Note. Solid lines represent direct effects. Dashed lines represent indirect effects. Dotted lines represent moderation effects.

3.0 Methods

3.1 Study Design, Setting, and Participants

To address the research questions described above, I completed a four-wave online panel study tracking participants' objectively-measured DTU and well-being over time. Data were collected from August through November of 2020, with waves of data collection occurring approximately one month apart. Participants were recruited via Prolific (<https://www.prolific.co/>)—an online participant recruitment platform. Participants were eligible if they were: U.S. residents, 18-35 years old, iPhone users, and had ≥ 10 previous submissions on Prolific with approval rating $\geq 95\%$. Eligible participants who agreed to participate in the study were routed to the online Qualtrics (Qualtrics, Provo, UT) survey hosted by the University of Pittsburgh for data collection. Those who successfully completed the wave 1 survey were followed-up for the remaining waves. Participants were compensated \$4.00 for wave one and \$3.00 each for waves two through four. Those who completed all four waves received a \$2.00 bonus compensation.

3.2 Variables and Measurement

Data were gathered using a combination of objective and self-report measures. Objective measures comprised screenshots of device-tracked behaviors (i.e., time spent using iPhone, number of steps taken) uploaded to Qualtrics by the participant. Self-report measures comprised the mental health outcome variables, the behavioral and psychosocial mechanism variables, as well as COVID-19 related distress control variables.

3.2.1 Outcome Variables

Mental health outcomes were suicidal ideation (SI), depressive symptom severity, anxiety symptom severity, and social isolation. I used item nine from the Patient Health Questionnaire (Kroenke et al., 2001) to measure SI. Response choices ranged from “Not at all” to “Nearly every day.” For the statistical analyses, I dichotomized the SI variable into presence/absence of SI (0 = “Not at all” and 1 = “One or two days” or more). To be consistent with other measures, which focused on past-week behaviors and/or symptoms, I adapted the item slightly to cover the past week rather than the past two weeks.

I used Patient-Reported Outcomes Measurement Information System (PROMIS™) six-item adult short form instruments to measure depressive and anxiety symptoms (Pilkonis et al., 2011) and social isolation (Hahn et al., 2014). For both the depression and anxiety measures, respondents were asked to rate their symptom severity over the past seven days using a five-point Likert-style scale ranging from “Never” to “Always.” Specific items for the depression measure included: “I felt worthless,” “I felt helpless,” “I felt depressed,” “I felt hopeless,” “I felt like a failure,” and “I felt unhappy.” Specific items for the anxiety measure included: “I felt fearful,” “I found it hard to focus on anything other than my anxiety,” “My worries overwhelmed me,” “I felt uneasy,” “I felt nervous,” and “I felt like I needed help for my anxiety.” For the social isolation measure, respondents were asked to rate how often they experience the following items using a five-point Likert-style scale ranging from “Never” to “Always”: “I feel left out,” “I feel that people barely know me,” “I feel isolated from others,” “I feel that people are around me but not with me,” “I feel isolated even when I am not alone,” and “I feel that people avoid talking to me.” The PROMIS measures are scored using an Item Response Theory (IRT) approach and are calibrated to be representative of the general adult U.S. population. I used the HealthMeasures Scoring Service ([HealthMeasures.net](https://healthmeasures.net))—which encompasses the PROMIS measures—to transform participants’ raw scores into standardized T-scores (with mean [SD] = 50 [10]). A T-score of 50 represents the average

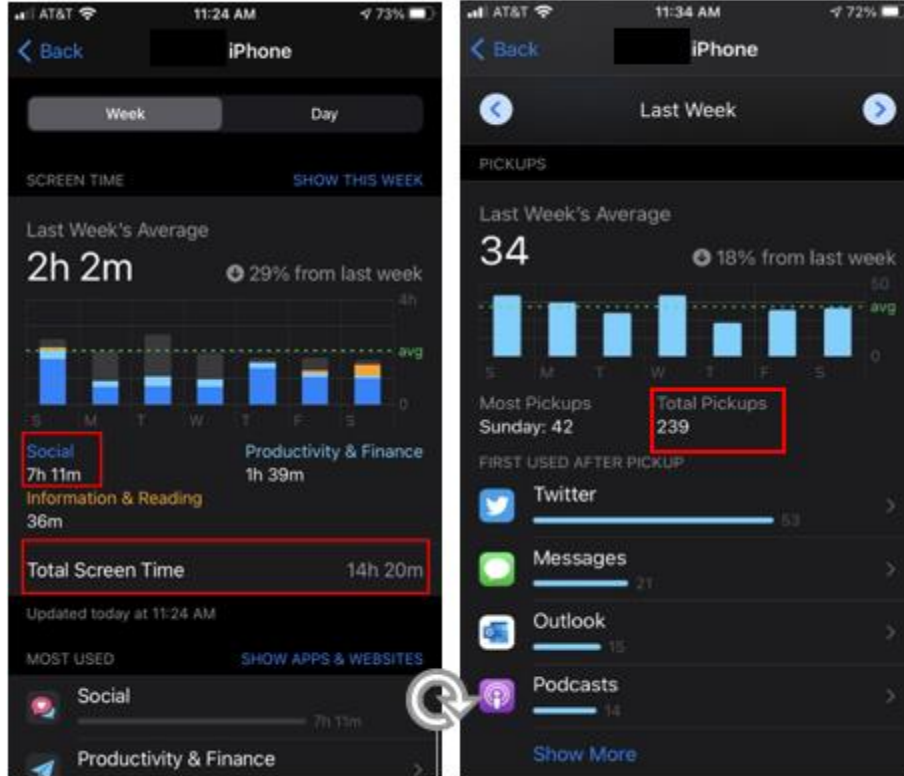
level of depression, anxiety, or social isolation among the general adult U.S. population (range 38.4-80.2).

3.2.2 Predictor Variables

3.2.2.1 Digital Technology Use

To obtain objective data on time spent using DTU, participants uploaded screenshots from their Apple “Screen Time” iPhone application, which passively tracks a variety of device use metrics and comes pre-installed on all iPhones running iOS version 12 or later. I provided participants detailed instructions for how to navigate to the application and take and upload the screenshots. To ensure that I obtained a full week of device-logged data, I had participants upload screenshots from the past week. I manually extracted two pieces of data from the first screenshot (Figure 2, left panel): 1.) “Total Screen Time”—the total duration of time that the device was engaged; and 2.) total “Social” time—the total duration of time spent on applications categorized by Apple as social networking and/or social media (e.g., Facebook, Instagram, Snapchat, Messages). From the second screenshot (Figure 2, right panel), I extracted the total number of past-week pickups—which is the number of times the device was unlocked and engaged with. To reduce the variance/scale of the *pickups* variable, the raw totals were divided by 100 when running the statistical analyses.

Figure 2. Example screenshots of the “Screen Time” application. Portions outlined in red were extracted and used as predictors.



3.2.2.2 Behavioral Mechanisms

Behavioral mechanism variables included past-week steps taken, as a proxy for sedentariness, and sleep disturbance. Like the DTU variables, the *steps* data were gathered via iPhone screenshot. Participants uploaded a screenshot from their iPhone “Health” application—which automatically tracks the number of steps users take (when the iPhone, or a linked device such as an Apple Watch, are on their person)—and I manually extracted the number of steps taken over the past week from the screenshots. Like the *pickups* variable, the *steps* variable was divided by 100 to reduce the variance/scale when estimating the statistical models.

Sleep disturbance was measured using the PROMIS six-item adult short form for assessing sleep disturbance (Yu et al., 2012). For item one, respondents were asked to rate their sleep quality over the past seven days using a five-point Likert-style scale ranging from “Very poor” to “Very good.” For the

remaining items, respondents rated their sleep disturbance over the past seven days using a Likert-style scale ranging from “Not at all” to “Very much.” These items included “My sleep was refreshing,” “I had a problem with my sleep,” “I had difficulty falling asleep,” “My sleep was restless,” “I tried hard to get to sleep.” Like the PROMIS *depression* and *anxiety* measures described above, the *sleep disturbance* raw scores were converted into T-scores using the HealthMeasures Scoring Service and have a minimum/maximum T-score of 38.4/80.3.

3.2.2.3 Psychosocial Mechanisms

To capture how participants were using social media, participants reported on five distinct behaviors on social media. These items related to *posting content* (“Post content that all my contacts can view (e.g. status updates, pictures, videos)”), *video chatting* (“Interact with others on video chat”), *passive browsing* (“Scroll through my feed without writing comments or interacting”), *direct messaging* (“Send or receive direct messages (including text messages)”), *read news* (“Read news stories posted on social media”). Participants rated how frequently they engaged in these behaviors over the past week using a five-point Likert-style scale ranging from “Never” to “Always.”

To capture how frequently participants engaged in *social comparison* online, I adapted the Facebook Social Comparison measure (Lee, 2014) to cover all social media platforms rather than just Facebook. Participants rated how strongly they agreed/disagreed with the following four items using a five-point Likert-style scale ranging from “strongly disagree” to “strongly agree”: “I often compare myself with others,” “I often think that others have a better life than me,” “I often think that others are doing better than me,” “I often think that I am isolated from others.” Responses are summed across items, with higher scores indicating more social comparison (range 5-20). To evaluate the reliability of the *social comparison* measure, I calculated McDonald’s (McDonald, 1999) Omega (ω) by fitting a unidimensional multilevel confirmatory factor analysis (CFA) at the within- and between-person levels .

ω is calculated as the ratio of “true score” variation over the total variation, which reflects the amount of total variability accounted for by the latent factor at each level of analysis (i.e., within-person and between-person). Results of this procedure indicated good reliability at the within ($\omega = 0.76$) and between ($\omega = 0.95$) levels.

3.2.3 Control Variables

3.2.3.1 COVID-19-related Distress

Participants were prompted to “Please rate how much the following items have contributed to any distress you may be experiencing due to the Covid-19 outbreak over the past month.” The response scale for each item ranged from 0 “Not at all” to 10 “A great deal.” Stressors included: “lost job or income,” “loved one got sick or passed away,” “not having enough money,” “not seeing friends in person,” “not seeing family in person,” “worried I might get sick,” “living alone,” “conflict with people I’m living with,” “childcare responsibilities,” and “difficulty getting food, medications, or other necessities.” Items were summed to create a *total COVID-19 related distress* variable (range 0-100).

3.3 Data Screening

I implemented robust data screening procedures to ensure high-quality data were collected. The most robust check on data quality was the requirement to upload multiple screenshots. This allowed me to check each screenshot for internal consistency (i.e., that the time of day and data provider listed at the top of each screenshot matched for each participant). This also made it very difficult for participants to upload inauthentic screenshots (i.e., images download from the internet), as it is almost impossible to find publicly available “Screen Time” screenshots that a.) are internally consistent and b.) contain the exact data we requested for the study.

Additionally, I included three attention checks at each wave of data collection. Participants who failed two or more attention checks during a single wave were excluded. However, there was only one instance of this (at wave one).

3.4. Statistical Analysis

Descriptive statistics for all variables were calculated. Additionally, intraclass correlation coefficients (ICCs) were calculated to assess the level of within- and between-person variance in the time-varying variables.

3.4.1 Random Intercept Cross-Lagged Panel Analysis

I estimated random intercept cross-lagged panel models (RI-CLPM; Hamaker et al., 2015) to examine how within-person changes in DTU impacted within-changes in mental health, or vice versa. Models were estimated using maximum likelihood with robust standard errors with Mplus (Muthen & Muthen, 2017). RI-CLPMs are well-suited for testing the bidirectional relations between two constructs of interest and overcome many of the limitations of the traditional cross-lagged panel model. Specifically, the RI-CLPM separates the variance of the time-varying observed variables into a stable, between-person component—which reflects trait-like individual differences in average mental health status and/or DTU—and a varying, within-person component reflecting state-like deviations from one's expected level of mental health status and/or DTU given. Failing to account for the between-person and within-person effects in these way can lead to substantial bias of the within-person effects (Hamaker et al., 2015).

Nine RI-CLPMs were estimated consisting of the three objective measures of DTU (screen time, social media, pickups) paired with the three continuous mental health variables (depression, anxiety,

and social isolation). RI-CLPMs have not yet been extended to accommodate categorical variables, so the SI mental health outcome was examined with another method (see below). For each model, between-person (i.e., trait-like) differences were accounted for by regressing the observed DTU and mental health variables onto their respective random intercept latent factors and fixing the factor loadings to one. These random intercepts capture the trait-like individual differences in average levels of DTU and mental health (e.g., some people are more depressed than others, on average). Then, the within-person (i.e., state-like) variability were created by specifying a latent variable for each measurement occasion and constraining the factor loadings to one. The error variances of the observed variables were constrained to zero so that all between- and within-person variance would be captured by the trait-like and state-like latent factors, respectively. Cross-sectional correlations, autoregressive paths, and cross-lagged paths were specified between the latent factors to investigate the within- and between-person dynamics of DTU and mental health. Additionally, the *total COVID-19 related distress* variable and sociodemographic variables were included as predictors of the DTU and mental health random intercepts to examine whether these variables predicted individual differences in average levels of DTU and mental health. Finally, in line with the recommendations of Orth and colleagues (2020), given the equal intervals between measurement occasions, the autoregressive and cross-lagged paths were constrained to equality over time.

To aid in the interpretation of the results, the RI-CLPM parameters are briefly explained. The correlation between the random intercept latent factors shows how DTU and mental health are associated with each other at the between-person level, e.g., do those with higher average social media use have higher average depression? The within-person autoregressive paths reflect the level of inertia of the DTU or mental health variables over time, e.g., does an individual who experiences elevated depression relative to their own expected score at time t more likely to also experience elevated depression at time $t + 1$? The within-person cross-lagged paths represent the spillover effect from one

dynamic variable to the other, e.g., does experiencing elevated depression at time t predict elevated social media use at time $t + 1$? The within-person correlations at wave one show how an individual's deviation from their expected score on DTU is associated with deviation from their expected score on mental health. The within-person correlated residual correlations at waves two through four reflect how they are associated due to unmeasured state-like effects.

Model fit was evaluated using the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the standardized root-mean-square residual (SRMR). Per Hu & Bentler (1999), RMSEA values $< .08$, CFI and TLI values $> .90$, and SRMR values $< .08$ reflect acceptable fit to the data.

3.4.2 Multilevel Structural Equation Modeling

Multilevel structural equation models (MSEM) were used to supplement the information from the RI-CLPMs regarding the DTU—mental health direct effects and to investigate the role of the potential behavioral and psychosocial mechanisms in mediating the association between DTU and mental health. MSEM is a flexible statistical method that combines the advantages of multilevel modeling (MLM) and structural equation modeling (SEM) into one generalized approach (for introductions to MSEM see Mehta & Neale, 2005; Muthen & Asparouhov, 2011; Sadikaj et al., 2021) and is well-suited for evaluating complex patterns of effects at the within- and/or between-person levels. Several types of MSEM models were specified across the mental health outcomes to address various related research questions: (1) Multilevel direct effects models, (2) Multilevel moderation models, and (3) Multilevel mediation models.

Multilevel direct effects models were estimated in the following sequence. First, the mental health variable was regressed on the DTU variables at the within- and between-person level (slopes estimated as fixed effects). Then, the behavioral and psychosocial mechanism variables were added as

fixed effects alongside the DTU variables. Finally, the DTU and behavioral/psychosocial direct effects were estimated as random slopes to examine whether there are between-person differences in the within-person effects. Two measures of effect size were evaluated for each model *at each level of analysis* (i.e., within- vs. between-person): (1) unstandardized betas, representing the strength of each individual direct effect; (2) variance explained (R^2), representing the amount of within- or between-person outcome variance explained by the group of predictors (i.e., DTU variables, psychosocial mechanism variables, behavioral mechanism variables); and (3) change in variance explained (ΔR^2), representing the amount of additional outcome variance explained by the addition of the psychosocial/behavioral mechanism variables.

Multilevel moderation models were estimated to evaluate whether variance in within-person processes (e.g., the within-person association between social media use and depression) is explained by between-person variables (*age* (at baseline) and *gender*; see Preacher et al. (2016) for introduction to multilevel moderation). This was done by specifying a random slope at the within-person level (e.g., depression regressed on social media), which allows the depression—social media within-person effect to vary at the between-person level, and then regressing the depression—social media slope on age and gender.

Finally, multilevel mediation models were estimated to examine whether the psychosocial and/or behavioral mechanism variables explained the association between DTU and mental health. As opposed to the direct effects model described above, this allows for the assessment of whether the DTU variables exert an indirect effect on the mental health outcomes via their impact on one or more of the psychosocial/behavioral mechanism variables. Additionally, to examine the total effect of the DTU variables on SI via their impact on the mental health outcome variables, a multilevel mediation model was specified whereby SI was regressed on depression, anxiety, and social isolation which, in turn, were regressed on the DTU variables.

All MSEM models were estimated in Mplus (Muthen & Muthen, 2017) with Bayesian estimation (see Asparouhov & Muthén, 2010). I used diffuse conjugate priors, the default in Mplus (Zyphur & Oswald, 2015), which leads to asymptotically equivalent results to frequentist maximum likelihood estimates with increasing sample sizes (Asparouhov & Muthén, 2010a). The models were estimated using a Markov Chain Monte Carlo (MCMC) algorithm based on the Gibbs sampler (Gelfand, 2000). For each model, eight Markov chains were used, each with at least 2,500 burn-in iterations. Convergence was assessed using the Gelman-Rubin convergence criterion based on the potential scale reduction (PSR) factor each model parameter (Gelman & Rubin, 1992). When using multiple Markov chains, the PSR is a comparison of within- and between-chain variation and, generally, PSR values $\leq .05$ are recommended (Muthen & Muthen, 2017). I specified a PSR convergence criterion of $\leq .01$ in all MSEM models and visually inspected trace plots for all model parameters to ensure good mixing of the Markov Chains.

3.5 Missing Data

See Table 2 for summary of missing data. Data were missing at random; thus, I used full information maximum likelihood for missing data when estimating the models (Asparouhov & Muthén, 2010; Muthén & Muthén, 2017).

Table 2. Missing data summary

	Wave 1	Wave 2	Wave 3	Wave 4
	<i>Complete rate</i>	<i>Complete rate</i>	<i>Complete rate</i>	<i>Complete rate</i>
Screen time	0.87	0.86	0.82	0.79
Social media	0.76	0.74	0.74	0.73
Pickups	0.83	0.84	0.81	0.78
Depression	1.00	0.88	0.83	0.80
Anxiety	1.00	0.88	0.83	0.80
Social isolation	1.00	0.88	0.83	0.80
Suicidal ideation	1.00	0.88	0.83	0.80
Sleep disturbance	1.00	0.88	0.83	0.80
Steps taken	0.99	0.86	0.81	0.78
Online social comparison	1.00	0.88	0.83	0.80
Post content	1.00	0.88	0.83	0.80
Videochat	1.00	0.88	0.83	0.80
Passive browse	1.00	0.88	0.83	0.80
Direct message	1.00	0.88	0.83	0.80
Read news	1.00	0.88	0.83	0.80
Total COVID distress (sum)	1.00	0.88	0.83	0.80

Note. Sociodemographic variables were complete

4.0 Results

A total of 396 participants completed the wave one survey. However, twelve participants were excluded due to submitting inauthentic screenshots, failing multiple attention checks, and/or failing to submit the correct Prolific authentication code (which proves that participants completed the survey), leaving a final wave one sample of $N_1=384$. Retention for waves two through four were $N_2=337$, $N_3=318$, and $N_4=308$.

4.1 Descriptive Statistics

Table 3 provides summary statistics for all study variables. The sample ($N=384$) had a mean (SD) age of 24.5 (5.1), was 57% female, 54% white, and 48% had a Bachelor's degree education or above. Overall, over the past week, participants averaged 47.5 hours of Screen Time, 15.5 hours of social media, and 677 pickups (i.e., opening/unlocking the device). On average, participants reported experiencing between 4-5 pandemic-related stressors per wave. Mean depression and anxiety T-scores were 54.6 and 56.7, respectively, and nearly 29% of participants reported past-week SI at least once—indicating that this sample had higher than average rates of psychological distress.

Intraclass correlation coefficients (ICCs) for the time-varying variables ranged from 0.45 to 0.79, indicating that at least 20% of the variance in these variables was attributable to within-person variation. See Table 3 for full ICC results.

Table 3. Sample (N=384) demographics and summary statistics for study variables

<i>Variable</i>	<i>Mean (SD) or N(%)</i>	<i>Intraclass Correlation Coefficient</i>
Sociodemographics		
<i>Age (years)</i>	24.5 (5.1)	--
<i>Race</i>		--
White	208 (54%)	--
Asian	114 (30%)	--
Black	28 (7%)	--
Multiracial	18 (5%)	--
Other	16 (4%)	--
<i>Hispanic</i>	57 (15%)	--
<i>Gender</i>		--
Female	217 (57%)	--
Male	161 (42%)	--
Other	6 (2%)	--
<i>Education level</i>		--
Graduate degree	61 (16%)	--
Bachelor's degree	122 (32%)	--
Some college	131 (34%)	--
High school	70 (18%)	--
Objective Tech Use		
<i>Screen Time (hours)</i>	47.5 (25.0)	0.75
<i>Social Media (hours)</i>	15.5 (11.5)	0.74
<i>Pickups (x100)</i>	6.78 (3.3)	0.71
Mental Health Outcomes		
<i>Depression</i>	54.6 (9.9)	0.79
<i>Anxiety</i>	56.6 (9.8)	0.73
<i>Social isolation</i>	49.6 (10.1)	0.77
<i>Suicidal Ideation</i>	110 (29%)	0.91 ^a
Behavioral Mechanisms		
<i>Sleep disturbance</i>	52.0 (8.6)	0.64
<i>Steps taken (x100)</i>	30.5 (30.0)	0.78
Psychosocial Mechanisms		
<i>Online social comparison</i>	12.4 (4.3)	0.72
<i>Social Media uses</i>		
Post content	2.1 (1.1)	0.61
Videochat	2.5 (1.1)	0.54
Passive browse	3.9 (1.0)	0.45
Direct message	3.6 (1.0)	0.45
Read news	3.1 (1.0)	0.54
COVID-19 Stressors		
<i>Lost job/income</i>	1.8 (3.1)	--
<i>Loved one sick/died</i>	0.7 (1.9)	--
<i>Insufficient money</i>	2.7 (3.3)	--
<i>Not seeing friends in person</i>	4.7 (3.2)	--
<i>Not seeing family in person</i>	3.4 (3.3)	--
<i>Worried I'll get sick</i>	4.1 (3.2)	--
<i>Living alone</i>	0.6 (1.7)	--
<i>Conflict with co-residents</i>	2.2 (2.9)	--
<i>Childcare responsibilities</i>	0.6 (1.8)	--
<i>Difficulty getting necessities</i>	1.2 (2.1)	--
<i>Total COVID distress (sum)</i>	22.0 (14.4)	0.73

Note. ^a ICC for binary variable was calculated using the formula $ICC = \tau^2 / (\tau^2 + \pi^2/3)$, where τ^2 represents the level-2 residual variance

4.2 Results of Random Intercept Cross-Lagged Panel Models

I fit RI-CLPMs to investigate the temporal within-person associations between the objective DTU variables and the mental health outcomes. All nine RI-CLPMs demonstrated acceptable fit to the data (CFIs/TLIs $\geq .94/.92$, RMSEAs $\leq .06$, SRMRs $\leq .08$; see Table 4 for complete fit statistics for all models). Tables 5 and 6 provide standardized estimates for all within-person and between-person parameters. For illustrations of model-specific results see Figures 3 through 11 of the Appendix. Overall, results indicate that, despite ample within-person variance in the DTU and mental health variables (as evidenced by the ICCs), within-person fluctuations in DTU had little to no impact on within-person fluctuations in mental health, or vice versa.

Table 4. Fit indices for the RI-CLPMs

Model	CFI/TLI	RMSEA [95% CI]	SRMR
Depression and screen time	.971/.962	.044 [.033, .055]	.068
Depression and social media	.961/.949	.053 [.042, .063]	.071
Depression and pickups	.957/.944	.052 [.041, .062]	.070
Anxiety and screen time	.958/.946	.051 [.041, .062]	.078
Anxiety and social media	.954/.940	.056 [.046, .067]	.081
Anxiety and pickups	.939/.920	.060 [.050, .070]	.080
Social isolation and screen time	.955/.942	.054 [.044, .065]	.076
Social isolation and social media	.947/.931	.062 [.052, .072]	.079
Social isolation and pickups	.937/.917	.062 [.052, .072]	.078

Note. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root-mean-square residual.

4.2.1 Within-Person Effects

Of the 54 cross-lagged paths estimated across the nine models, only two had standardized effects $\beta > 0.10$ and only one (wave 1 screen time $\rightarrow$ wave 2 anxiety) was statistically significant ($\beta = 0.115$, $p = 0.032$). Overall, total screen time had an average effect of $\beta = -0.01$ on depression, $\beta = 0.10$ on anxiety, and $\beta = 0.04$ on social isolation; social media had an average effect of $\beta = 0.02$ on depression, β

= 0.10 on anxiety, and $\beta = 0.06$ on social isolation; and pickups had an average effect of $\beta = 0.04$ on depression, $\beta = 0.09$ on anxiety, and $\beta = -0.08$ on social isolation. Conversely, depression had an average effect of $\beta = 0.05$ on screen time, $\beta = 0.02$ on anxiety, and $\beta = 0.06$ on social isolation; anxiety had an average effect of $\beta = 0.03$ on screen time, $\beta = 0.03$ on social media, and $\beta = 0.10$ on pickups; and social isolation had an average effect of $\beta = -0.02$ on screen time, $\beta = 0.03$ on social media, and $\beta = 0.06$ on pickups. In summary, results of the cross-lagged effects indicates that higher (or lower) than usual DTU over a given week did not predict higher (or lower) than usual mental health distress the next month, nor vice versa.

As opposed to the cross-lagged paths, all autoregressive paths aside from *screen time* were moderate in size and statistically significant. Overall, *screen time* had an average autoregressive effect of $\beta = 0.06$, *social media* had an average autoregressive effect of $\beta = 0.45$, *pickups* had an average autoregressive effect of $\beta = 0.30$, *depression* had an average autoregressive effect of $\beta = 0.22$, *anxiety* had an average autoregressive effect of $\beta = 0.19$, and *social isolation* had an average autoregressive effect of $\beta = 0.16$. Thus, results suggest that, of the DTU variables, *social media* use and *pickups* are relatively persistent over time, while *screen time* fluctuates from wave to wave. Similarly, all mental health variables were relatively persistent over time.

Table 5. Standardized model coefficients for within-person effects from RI-CLPMs

Model	Screen time			Social media			Pickups		
	Depression	Anxiety	Social Isolation	Depression	Anxiety	Social Isolation	Depression	Anxiety	Social Isolation
Cross-lagged effects									
Media use 1 -> Mental distress 2	-0.006	.115*	.045	.017	.104	.069	.037	.093	-.085
Media use 2 -> Mental distress 3	-0.005	.099	.043	.015	.085	.062	.036	.089	-.085
Media use 3 -> Mental distress 4	-0.004	.082	.030	.018	.097	.060	.037	.083	-.069
Mental distress 1 -> Media use 2	0.048	.033	-.020	.019	.028	.038	.053	.097	.058
Mental distress 2 -> Media use 3	0.062	.039	-.023	.018	.024	.032	.060	.100	.058
Mental distress 3 -> Media use 4	0.04	.028	-.015	.017	.025	.029	.056	.099	.052
Autoregressive effects									
Media use 1 -> Media use 2	0.055	.079	.067	.512***	.517***	.515***	.300	.327	.296
Media use 2 -> Media use 3	0.059	.087	.073	.385**	.392**	.391**	.301	.351	.297
Media use 3 -> Media use 4	0.032	.048	.040	.421**	.429**	.427**	.269	.311	.265
Mental distress 1 -> Mental distress 2	.209**	.197**	.165	.197**	.189**	.174	.212***	.201**	.164
Mental distress 2 -> Mental distress 3	.226**	.180**	.165	.211**	.173**	.173	.233**	.185**	.164
Mental distress 3 -> Mental distress 4	.241**	.193**	.133	.224**	.185**	.142	.248**	.193**	.133
Within-wave correlations									
Media use 1 with Mental distress 1	0.061	-.027	.026	-.008	.066	.004	.012	.142	-.092
Media use 2 with Mental distress 2	-0.007	.118	.042	.123	.184*	.090	.000	.035	-.004
Media use 3 with Mental distress 3	0.051	.029	.144	-.002	.023	.063	-.105	-.080	.050
Media use 4 with Mental distress 4	-0.159*	-.093	-.080	-.048	-.016	-.074	.028	.149*	.062

Note. Regression paths are indicated by "->". * $p < .05$, ** $p < .01$, *** $p < .001$.

4.2.2 Between-Person Effects

Correlations between the screen time and social media random intercepts with the mental health random intercepts were very small ($r < .10$) and not statistically significant. Those who, on average, had higher amounts of screen time over the course of the study did not exhibit higher average levels of depression ($r = .03, p > .05$), anxiety ($r = .08, p > .05$), or social isolation ($r = .05, p > .05$). Similarly, those who, on average, had higher amounts of social media use over the course of the study did not exhibit higher average levels of depression ($r = -.04, p > .05$), anxiety ($r = -.02, p > .05$), or social isolation ($r = -.02, p > .05$). Alternatively, those who, on average, had higher number of pickups had *lower* average depression ($r = -.21, p < .05$), anxiety ($r = -.20, p > .05$), and social isolation ($r = -.14, p > .05$). These results suggest that higher average amounts of DTU were not related to higher average levels of mental health distress, and that those who averaged more pickups reported lower levels of mental health distress.

Age was not significantly associated with average levels of depression ($\beta = 0.05$), anxiety ($\beta = -0.02$), or social isolation ($\beta = 0.01$) but was negatively associated with average levels of screen time ($\beta = -0.14, p < .05$), pickups ($\beta = -0.25, p < .05$), and social media ($\beta = -0.12, p > .05$); that is, younger participants evidenced higher levels of DTU, on average. Females were more likely than males to have higher average anxiety ($\beta = 0.13, p < .05$), screen time ($\beta = 0.21, p < .05$), and social media use ($\beta = 0.28$), but no significant differences with respect to depression ($\beta = 0.08$), social isolation ($\beta = -.04$), or pickups ($\beta = 0.07$).

Table 6. Standardized between-person effects from RI-CLPMs

Regressions						
<i>Time-invariant predictor</i>	Depression	Anxiety	Social isolation	Screen time	Social media	Pickups
COVID impact on mental health	.74***	.73***	.65***	.04	.06	-.03
COVID-related distress (sum)	.08	.18***	.12*	.05	.13*	.09
Age	.05	-.02	.01	-.14*	-.11	-.25
Female	.08	.13**	.04	.21***	.28***	.07
Person of color	.03	.02	.05	.10	-.00	-.20***
Hispanic	-.03	-.03	-.06	.11*	.17*	.02
Bachelor's degree	-.10*	-.03	-.14**	.03	-.07	.03
Correlations						
Screen time with Depression	0.026					
Screen time with Anxiety	.078					
Screen time with Social isolation	.049					
Social media with Depression	-.037					
Social media with Anxiety	-.016					
Social media with Social isolation	-.020					
Pickups with Depression	-.206*					
Pickups with Anxiety	-.202					
Pickups with Social isolation	-.139					

Note. Effects for regressions are standardized betas (β); effects for correlations are Pearson correlations (r). * $p < .05$, ** $p < .01$, *** $p < .001$.

The COVID-19 related variables had, by far, the largest associations with average levels of mental health distress but were mostly unrelated to average levels of DTU. Those who reported a greater negative impact on their well-being due to the pandemic had significantly higher average levels of depression ($\beta_s \approx 0.74$, $p < .05$), anxiety ($\beta_s \approx 0.73$, $p < .05$), and social isolation ($\beta_s \approx 0.65$, $p < .05$). Those who reported experiencing a greater number of pandemic-related stressors had significantly higher average levels of anxiety ($\beta_s \approx 0.18$, $p < .05$) and social isolation ($\beta_s \approx 0.12$, $p < .05$) but not depression ($\beta_s \approx 0.85$, $p > .05$). Average levels of screen time and pickups were unrelated to COVID-19 related distress variables ($\beta_s \leq 0.10$, $ps > 0.05$). Higher average levels of social media use were positively related to experiencing more pandemic-related stressors ($\beta_s \approx 0.13$, $ps < .05$) but unrelated to perceived pandemic-related impact on well-being ($\beta_s \approx 0.6$, $p > .05$).

4.3 Results of Multilevel Structural Equation Models

4.3.1 Direct Effects

4.3.1.1 Digital Technology Use Variables

At the within-person level, none of the objective DTU variables were related to any of the mental health outcomes. Inspection of the Bayesian posterior distributions reveals that all the within-person direct effects (unstandardized) of DTU on mental health distress centered around zero. Specifically, given the observed data, results indicate that there is a 95% probability that the within-person effect of screen time is between $-.034$ and $.019$ for depression, between $-.050$ and $.009$ for anxiety, between $-.024$ and $.031$ for social isolation, and between $-.010$ and $.019$ for SI. For social media, there is a 95% probability that the within-person effect is between $-.048$ and $.073$ for depression, between $-.018$ and $.117$ for anxiety, between $-.054$ and $.072$ for social isolation, and between $-.037$ and

.024 for SI. For pickups, there is a 95% probability that the within-person effect is between -.274 and .082 for depression, between -.143 and .250 for anxiety, between -.192 and .182 for social isolation, and between -.069 and .036 for SI. As elucidated in the Discussion section below, the credibility intervals are relatively narrow and bound around zero, indicating a high degree of plausibility that these effects are very small, whatever their direction.

Together, the DTU variables explained 0.5% (95% CrI: 0.1%, 1.8%) of the within-person variance in depression, 0.6% (95% CrI: 0.1%, 1.9%) of the within-person variance in anxiety, 0.3% (95% CrI: 0.0%, 1.2%) of the within-person variance in social isolation, and 2.1% (95% CrI: 0.2%, 8.1%) of the within-person variance in SI.

At the between-person level, screen time and social media were unrelated to any of the mental health outcomes (including SI), while pickups were *negatively* associated with depression, anxiety, social isolation, and SI. Specifically, given the observed data, results indicate that there is a 95% probability that the between-person effect of screen time is between -0.058 and 0.059 for depression, between -0.034 and 0.074 for anxiety, between -0.045 and 0.075 for social isolation, and between -0.023 and 0.025 for SI. For social media, there is a 95% probability that the between-person effect is between -0.137 and .136 for depression, between -0.145 and 0.108 for anxiety, between -0.151 and 0.129 for social isolation, and between -0.053 and 0.056 for SI. For pickups, there is a 95% probability that the between-person effect is between -0.730 and -0.043 for depression, between -0.568 and 0.075 for anxiety, between -0.728 and -0.026 for social isolation, and between -0.137 and -0.006 for SI.

Together, the DTU variables explained 3.9% (95% CrI: 0.9%, 9.2%) of the between-person variance in depression, 5.0% (95% CrI: 1.4%, 10.8%) of the between-person variance in anxiety, 3.3% (95% CrI: 0.6%, 8.1%) of the between-person variance in social isolation, and 4.0% (95% CrI: 0.6%, 10.3%) of the within-person variance in SI.

4.3.1.2 Behavioral Mechanism Variables

At the within-person level, increases in sleep disturbance were associated with increases in depression ($b = .226$, 95% CrI: .171, .280), anxiety ($b = .276$, 95% CrI: .216, .336), social isolation ($b = .099$, 95% CrI: .039, .157), but not SI ($b = .010$, 95% CrI: -.017, .038). Number of past week steps taken was unrelated to depression ($b = .002$, 95% CrI: -.018, .023), social isolation ($b = .006$, 95% CrI: -.016, .029), and SI ($b = .004$, 95% CrI: -.009, .018), but was slightly positively related to anxiety ($b = .029$, 95% CrI: .006, .052).

Combined, the behavioral mechanism and DTU variables explained 7.7% (95% CrI: 4.7%, 11.2%) of the within-person variance in depression, 9.6% (95% CrI: 6.2%, 13.4%) of the within-person variance in anxiety, 1.8% (95% CrI: 0.6%, 3.7%) of the within-person variance in social isolation, and 3.8% (95% CrI: 0.8%, 10.9%) of the within-person variance in SI. Calculating the ΔR^2 (i.e., the difference in R^2 for the DTU model and the DTU + behavioral mechanisms model), which allows us to contrast the influence of the DTU variables as a group against other variables, reveals that the behavioral mechanisms accounted for 7.2% of the within-person variance in depression, 9.0% in anxiety, 1.5% in social isolation, and 1.7% in SI.

At the between-person level, those with higher average levels of sleep disturbance also had higher average levels of depression ($b = .693$, 95% CrI: .572, .814), anxiety ($b = .607$, 95% CrI: .490, .722), social isolation ($b = .653$, 95% CrI: .521, .783), and SI ($b = .093$, 95% CrI: .049, .137). Average number of daily week steps taken was unrelated to average levels of depression ($b = -.022$, 95% CrI: -.051, .008), anxiety ($b = -.003$, 95% CrI: -.031, .026) and social isolation ($b = -.014$, 95% CrI: -.046, .019), but was slightly negatively related to SI ($b = -.022$, 95% CrI: -.039, -.007).

Combined, the behavioral mechanisms and DTU variables explained 39.6% (95% CrI: 30.6%, 48.7%) of the between-person variance in depression, 36.8% (95% CrI: 27.6%, 45.9%) of the between-

person variance in anxiety, 33.3% (95% CrI: 24.3%, 42.5%) of the between-person variance in social isolation, and 19.2% (95% CrI: 10.4%, 30.4%) of the between-person variance in SI. Calculating the ΔR^2 (i.e., the difference in R^2 for the DTU model and the DTU + behavioral mechanisms model) reveals that the behavioral mechanisms accounted for 35.7% of the between-person variance in depression, 31.8% in anxiety, 30.0% in social isolation, and 15.2% in SI.

4.3.1.3 Psychosocial Mechanism Variables

At the within-person level, increases in online social comparison were associated with increases in depression ($b = .322$, 95% CrI: .196, .447), anxiety ($b = .315$, 95% CrI: .174, .457), social isolation ($b = .485$, 95% CrI: .351, .617), and SI ($b = .107$, 95% CrI: .037, .183). None of the social media uses variables (post content, videochat, passive browse, direct message, and reading news) were significantly associated with any of the mental health outcomes.

Combined, the psychosocial mechanisms and DTU variables explained 4.4% (95% CrI: 2.4%, 7.1%) of the within-person variance in depression, 3.6% (95% CrI: 1.8%, 6.0%) of the within-person variance in anxiety, 6.9% (95% CrI: 4.2%, 10.1%) of the within-person variance in social isolation, and 12.6% (95% CrI: 5.3%, 22.6%) of the within-person variance in SI. Calculating the ΔR^2 reveals that the psychosocial mechanisms accounted for 3.9% of the within-person variance in depression, 3.0% in anxiety, 6.6% in social isolation, and 10.5% in SI.

At the between-person level, those with higher average levels of online social comparison also had higher average levels of depression ($b = 1.553$, 95% CrI: 1.327, 1.780), anxiety ($b = 1.262$, 95% CrI: 1.038, 1.496), social isolation, ($b = 1.572$, 95% CrI: 1.344, 1.807), and SI ($b = .400$, 95% CrI: .266, .570). Those who, on average, had higher levels of videochatting had lower average levels of depression ($b = -1.900$, 95% CrI: -2.936, -.893), anxiety ($b = -1.385$, 95% CrI: -2.428, -.361), social isolation, ($b = -1.744$,

95% CrI: -2.783, -.686), and SI ($b = -.886$, 95% CrI: -1.467, -.331). None of the other social media uses variables were significantly associated with any of the mental health outcomes.

Combined, the psychosocial mechanisms and DTU variables explained 54.7% (95% CrI: 46.2%, 62.7%) of the between-person variance in depression, 46.0% (95% CrI: 36.8%, 55.1%) of the between-person variance in anxiety, 54.1% (95% CrI: 45.5%, 62.0%) of the between-person variance in social isolation, and 41.3% (95% CrI: 28.0%, 54.0%) of the between-person variance in SI. Calculating the ΔR^2 reveals that the psychosocial mechanisms accounted for 50.8% of the between-person variance in depression, 41.0% in anxiety, 50.8% in social isolation, and 37.3% in SI.

4.3.1.4 COVID-19 Related Distress

At the within-person level, increases in pandemic-related distress were associated with increases in depression ($b = .094$, 95% CrI: .056, .132), anxiety ($b = .049$, 95% CrI: .006, .092), social isolation ($b = .126$, 95% CrI: .085, .166), but not SI ($b = .016$, 95% CrI: -.004, .036).

Combined, the DTU and COVID-19 related distress variables explained 3.0% (95% CrI: 1.3%, 5.5%) of the within-person variance in depression, 1.3% (95% CrI: 0.3%, 3.0%) in anxiety, 4.2% (95% CrI: 2.0%, 7.0%) in social isolation, and 4.1% (95% CrI: 0.7%, 11.0%) in SI. Calculating ΔR^2 reveals that the psychosocial mechanisms accounted for 2.5% of the within-person variance in depression, 0.7% in anxiety, 3.9% in social isolation, and 2.0% in SI.

At the between-person level, those with higher average pandemic-related distress reported higher average levels of depression ($b = .293$ 95% CrI: .215, .396), anxiety ($b = .313$, 95% CrI: .240, .385), social isolation ($b = .273$, 95% CrI: .193, .351), and SI ($b = .058$, 95% CrI: .029, .093).

Combined, the DTU and COVID-19 related distress variables explained 21.1% (95% CrI: 13.1%, 29.5%) of the between-person variance in depression, 26.3% (95% CrI: 17.8%, 35.3%) in anxiety, 19.6%

(95% CrI: 11.8%, 28.2%) in social isolation, and 14.3% (95% CrI: 6.6%, 24.7%) in SI. Calculating ΔR^2 reveals that the psychosocial mechanisms accounted for 17.2% of the within-person variance in depression, 21.3% in anxiety, 16.3% in social isolation, and 10.3% in SI.

4.3.2 Multilevel Moderation

Multilevel moderation models—also known as cross-level interactions—were estimated to examine whether the variation in the within-person direct effects described above (e.g., social media use predicting anxiety) varied by gender and age. This was done by specifying the within-person direct effects as random slopes and then using gender and age to predict the random slope at the between-person level (i.e., a “slopes-as-outcomes” approach; Preacher et al., 2016). Results across all models revealed that none of the cross-level interactions were statistically significant (see Table 7). This was due, in part, to the fact that there was generally a small amount of variance in the random slopes, meaning that there was little variance for the gender and age variables to explain.

Table 7. Results of cross-level interactions

Random Slope	Female	Age
<i>DTU direct effects</i>		
Screen time > Depression	.024 (-.039, .092)	-.003 (-.009, .004)
Social media > Depression	-.058 (-.240, .125)	.003 (-.014, .020)
Pickups > Depression	.205 (-.231, .612)	.035 (-.006, .077)
Screen time > Anxiety	.035 (-.036, .108)	-.001 (-.008, .006)
Social media > Anxiety	-.124 (-.302, .052)	.010 (-.006, .026)
Pickups > Anxiety	.021 (-.450, .453)	.007 (-.037, .054)
Screen time > Social isolation	-.001 (-.067, .062)	.000 (-.007, .007)
Social media > Social isolation	-.075 (-.244, .085)	.005 (-.010, .023)
Pickups > Social isolation	-.256 (-.746, .270)	.000 (-.048, .049)
<i>Psychosocial mechanisms</i>		
Social comparison > Depression	.174 (-.114, .470)	-.002 (-.031, .027)
Social comparison > Anxiety	.163 (-.162, .508)	-.020 (-.053, .013)
Social comparison > Social isolation	.128 (-.220, .463)	-.003 (-.034, .029)
Screen time > Social comparison	.022 (-.010, .053)	.002 (-.002, .005)
Social media > Social comparison	-.054 (-.141, .039)	-.001 (-.009, .008)
<i>Behavioral mechanisms</i>		
Sleep disturbance > Depression	-.002 (-.137, .131)	.000 (-.014, .013)
Sleep disturbance > Anxiety	.070 (-.073, .210)	.007 (-.006, .020)
Sleep disturbance > Social isolation	-.102 (-.232, .034)	.003 (-.010, .016)
Steps taken > Depression	.012 (-.034, .057)	-.001 (-.006, .003)
Steps taken > Anxiety	.033 (-.022, .085)	-.002 (-.006, .004)
Steps taken > Social isolation	.000 (-.058, .057)	-.003 (-.009, .003)
Screen time > Sleep disturbance	.002 (-.071, .076)	-.003 (-.011, .004)
Social media > Sleep disturbance	-.001 (-.186, .180)	-.005 (-.019, .010)
Pickups > Sleep disturbance	.323 (-.143, .757)	.045 (-.001, .094)
Screen time > Steps taken	-.150 (-.358, .060)	.015 (-.007, .034)
Social media > Steps taken	-.108 (-.580, .446)	-.017 (-.056, .020)
Pickups > Steps taken	-.763 (-2.398, .739)	-.030 (-.188, .111)

Note. The variable to the right of the ">" symbol is regressed on the variable to the left. The effects displayed represent the effect of the level-2 (time-invariant) variables Female and Age predicting the random slope. Parameter estimates represent the (unstandardized) median effect of the posterior distribution and the 95% credibility interval in parentheses.

4.3.2.1 Indirect Effects

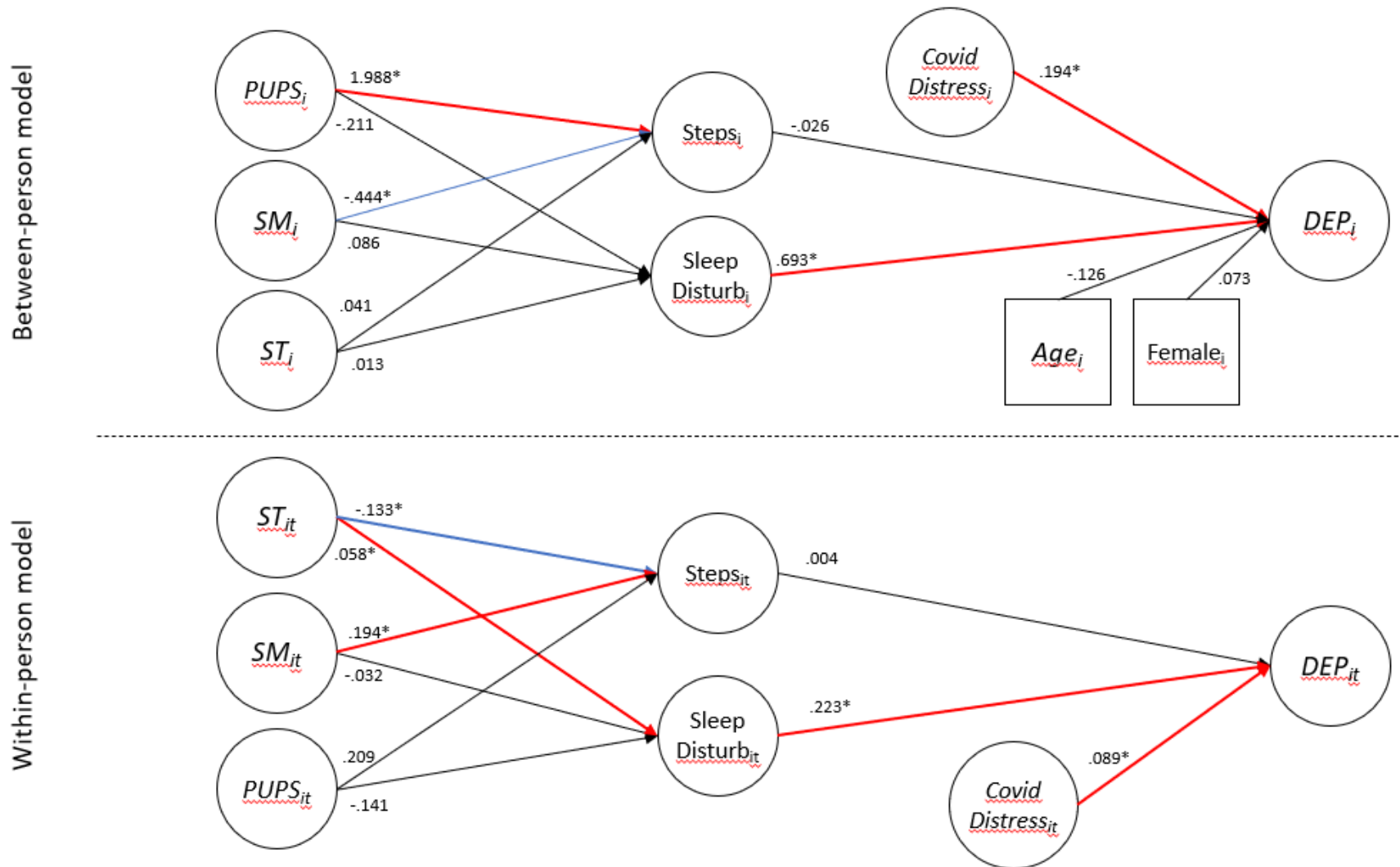
4.3.2.1.1 Behavioral Mechanisms

Results of the behavioral mechanism multilevel mediation models are illustrated in Figures 12 through 15. At the within-person level, increases in screen time were associated with increases in sleep

disturbance ($b's \approx .06, p < .05$) and decreases in number of steps taken ($b's \approx -.13, p < .05$). Increases in social media use were associated with increases in number of steps taken ($b's \approx .19, p < .05$) and unrelated to sleep disturbance ($b's \approx -.03, p > .05$). Although not statistically significant, pickups were positively associated with steps ($b's \approx .22, p > .05$) and negatively associated with sleep disturbance ($b's \approx -.14, p > .05$). At the between-person level, those with higher average levels of social media use averaged less past-week steps ($b's \approx -.44, p < .05$), and those who averaged more pickups also averaged more steps over the past week ($b's \approx 1.98, p < .05$).

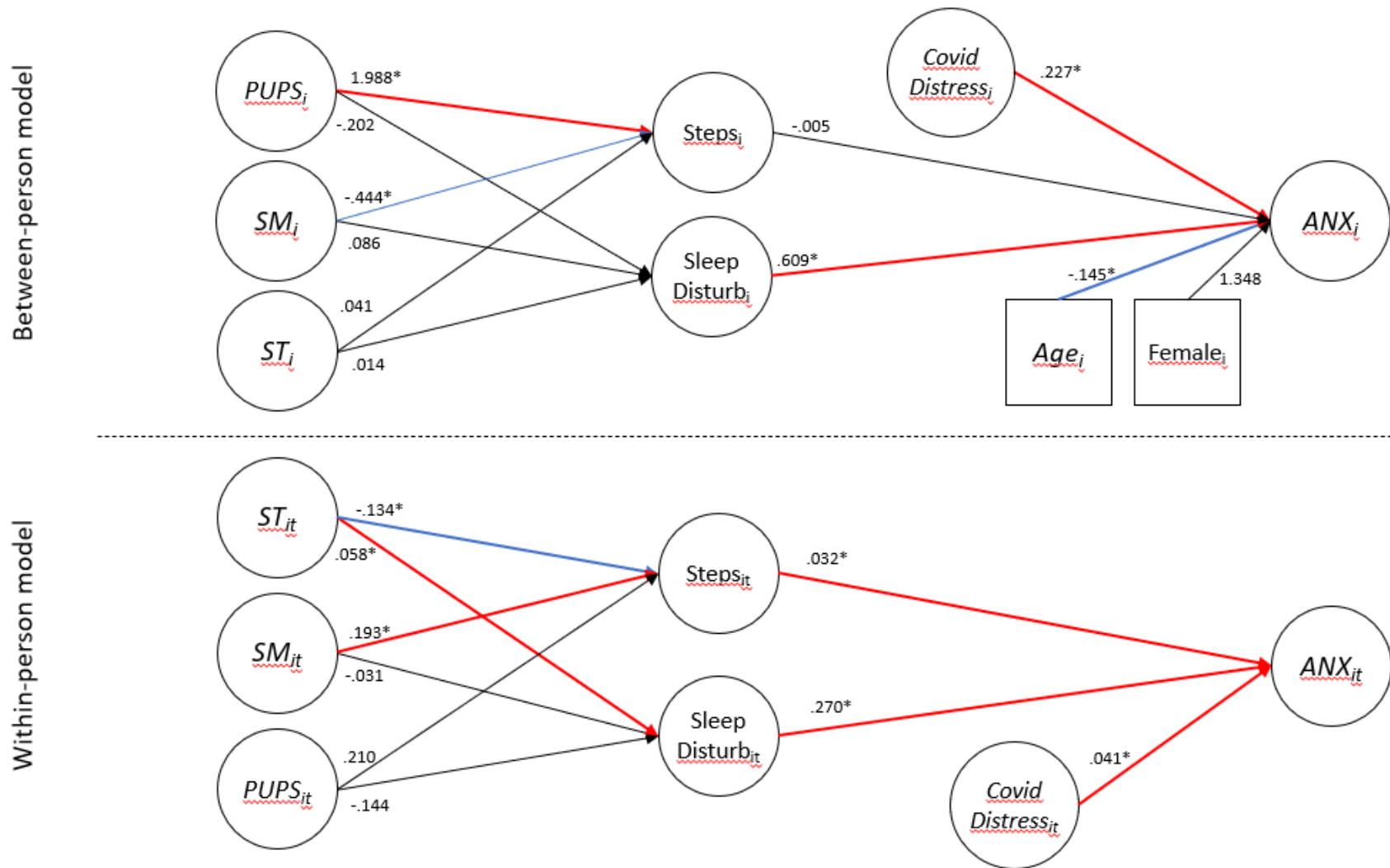
Six indirect effects were estimated in each outcome model: 1.) screen time > sleep disturbance > MH outcome, 2.) screen time > steps > MH outcome, 3.) social media > sleep disturbance > MH outcome, 4.) social media > steps > MH outcome, 5.) pickups > sleep disturbance > MH outcome, 6.) pickups > steps > MH outcome. In the depression model, only the screen time > sleep disturbance > depression indirect effect was statistically significant ($b = .013$, 95% CrI: .006, .021). In the anxiety model, the screen time > sleep disturbance > anxiety indirect effect ($b = .015$, 95% CrI: .007, .025), the screen time > steps > anxiety indirect effect ($b = -.004$, 95% CrI: -.009, -.001), and the social media > steps > anxiety indirect effect ($b = .006$, 95% CrI: .000, .015) were statistically significant. In the social isolation model, only the screen time > sleep disturbance > social isolation indirect effect was statistically significant ($b = .005$, 95% CrI: .002, .011). Finally, none of the indirect effects in the SI model were significant. In summation, these results indicate that within-person increases in screen time were associated with depression, anxiety, and social isolation via sleep disturbance. In addition, increases in screen time were associated with very small decreases in anxiety via steps, and increases in social media were associated with very small increases in anxiety via steps. However, all indirect effects, even those deemed statistically significant, were very small.

Figure 12. Results of the behavioral mechanism multilevel mediation model for depression



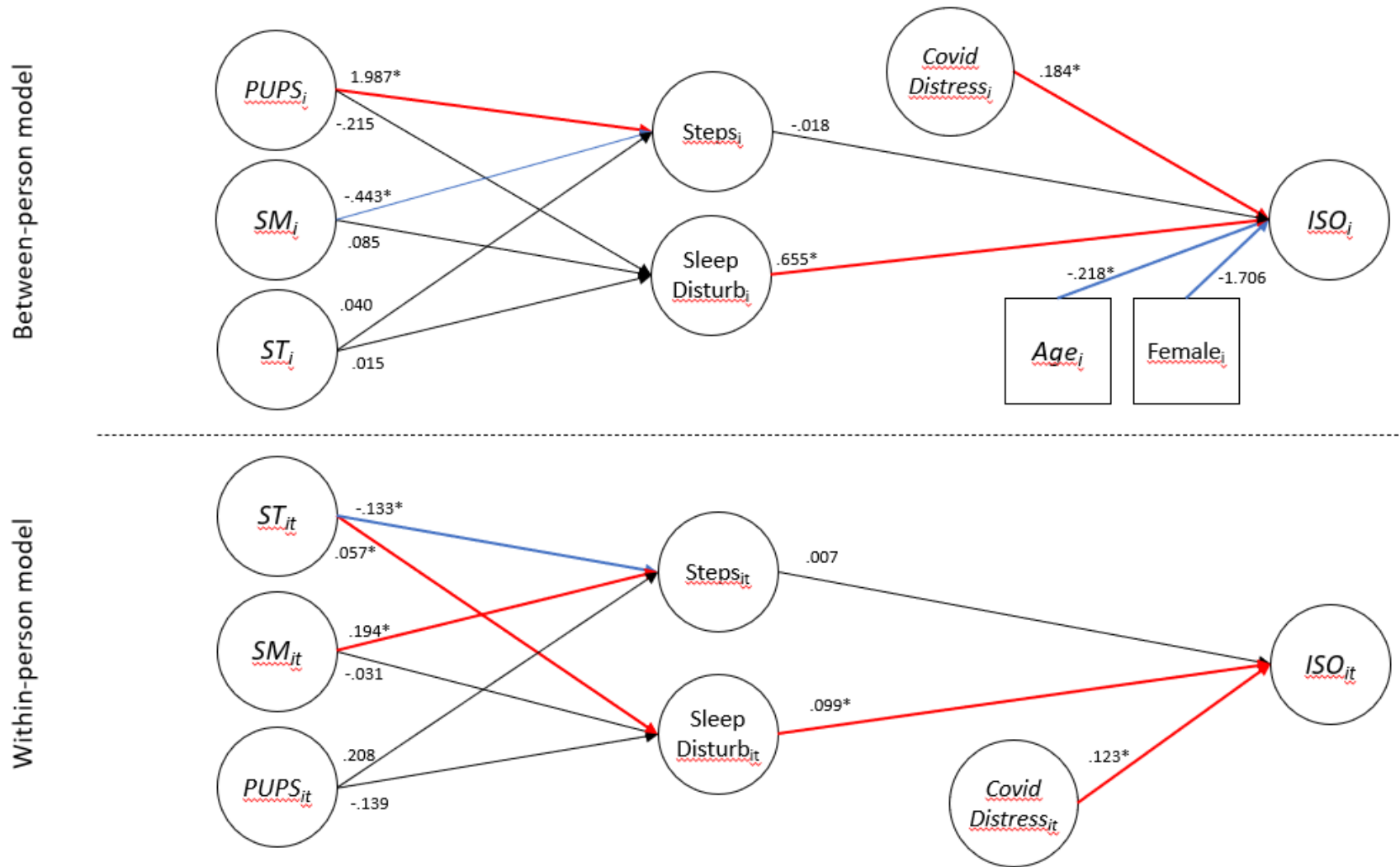
Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

Figure 13. Results of the behavioral mechanism multilevel mediation model for anxiety



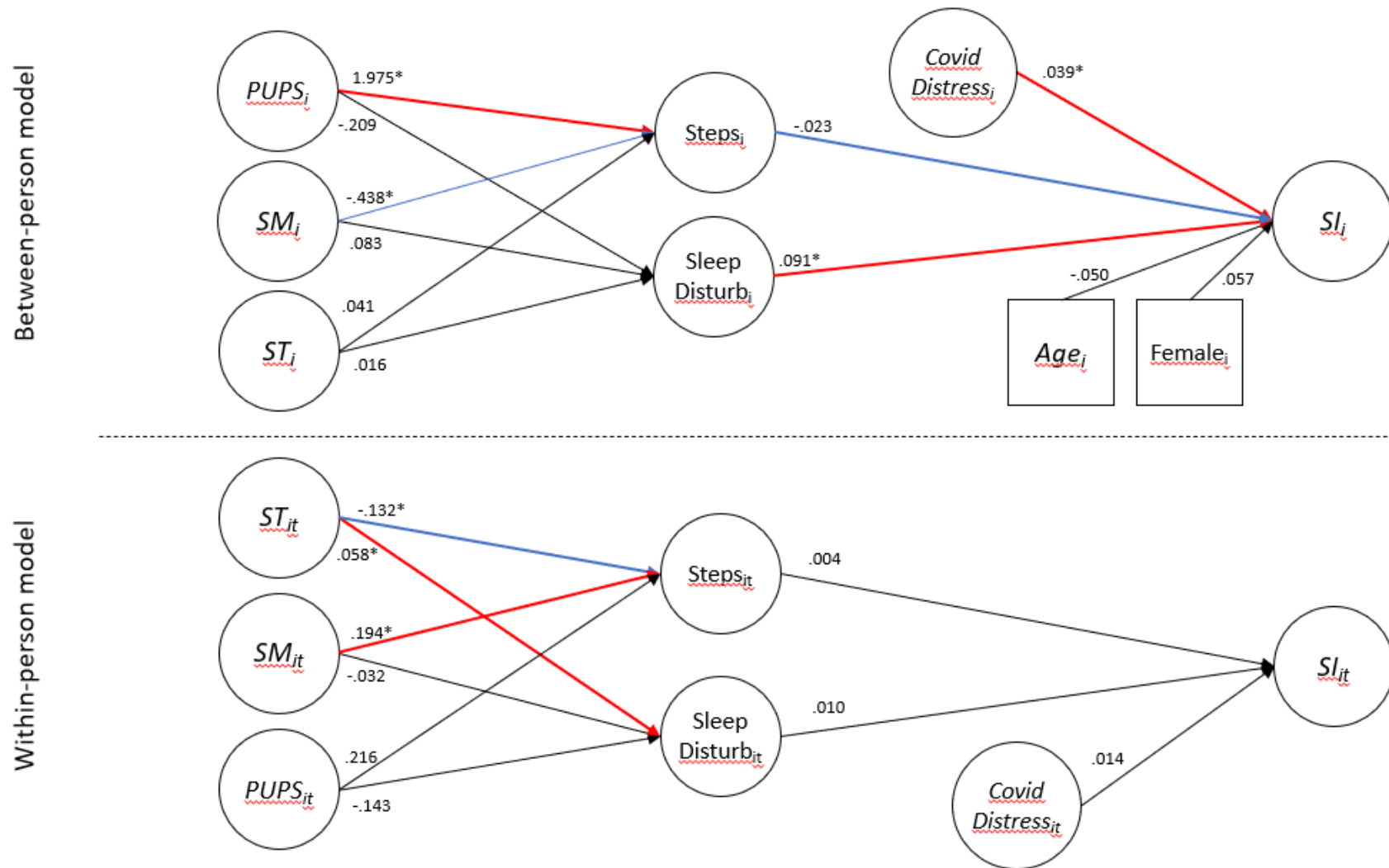
Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

Figure 14. Results of the behavioral mechanism multilevel mediation model for social isolation



Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

Figure 15. Results of the behavioral mechanism multilevel mediation model for suicidal ideation



Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

4.3.2.1.2 Psychosocial Mechanisms

Results of the psychosocial mechanism multilevel mediation models are illustrated in Figures 16 through 19. At the within-person level, increases in social media use were associated with slight increases in videochat frequency ($b = .012, p < .05$), and increases in online social comparison were associated with increases in depression ($b = .325, p < .05$), anxiety ($b = .314, p < .05$), social isolation ($b = .486, p < .05$), and SI ($b = .101, p < .05$). All other within-person effects were non-significant. Given that most of the within-person effects of DTU on social media uses and online social comparison were close to zero and non-significant, only the social media use > video chat > MH outcomes and social media use > online social comparison > MH outcomes indirect effects were calculated. However, all indirect effects were closer to zero and not statistically significant. In summary, these results indicate that within-person increases in DTU do not exert an indirect effect on mental health distress via their associations with the psychosocial mechanism variables.

4.3.2.1.3 Total Indirect Effects of DTU on SI

Results of the total indirect effect model are illustrated in Figure 20. At the within-person level, increases in depression ($b = .096, p < .05$) or anxiety ($b = .055, p < .05$) were associated with increases in SI. However, none of the DTU variables were significantly associated with depression, anxiety, or social isolation, so the indirect effects were not calculated. At the between-person level, depression ($b = .205, p < .05$) and social isolation ($b = .063, p < .05$) were positively related to SI, but anxiety ($b = -.086, p < .05$) was negatively related to SI. Of the nine DTU → mental health paths, only one was significant: those with higher average levels of weekly pickups had lower average depression ($b = -.376, p < .05$).

Figure 16. Results of the psychosocial mechanism multilevel mediation model for depression

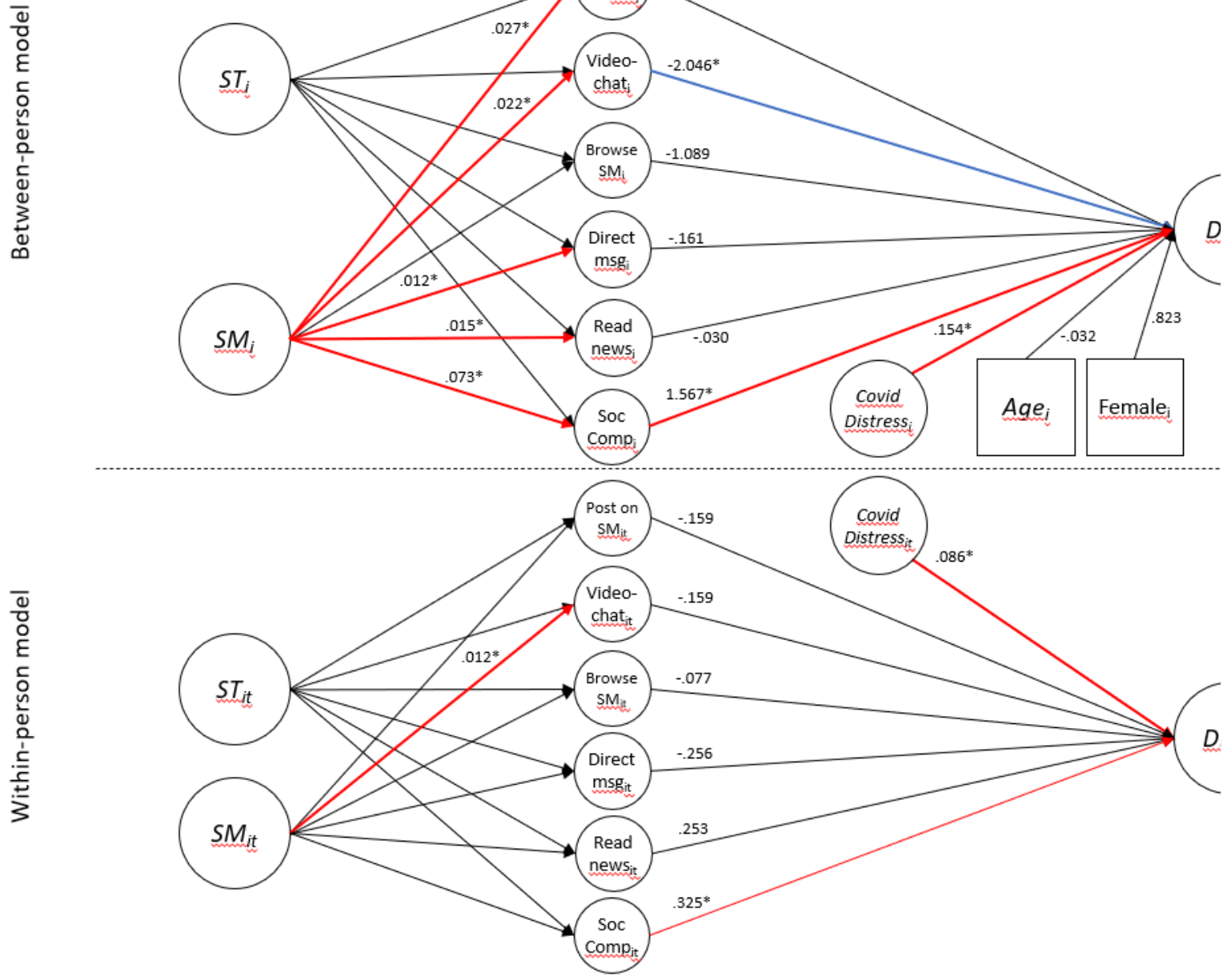
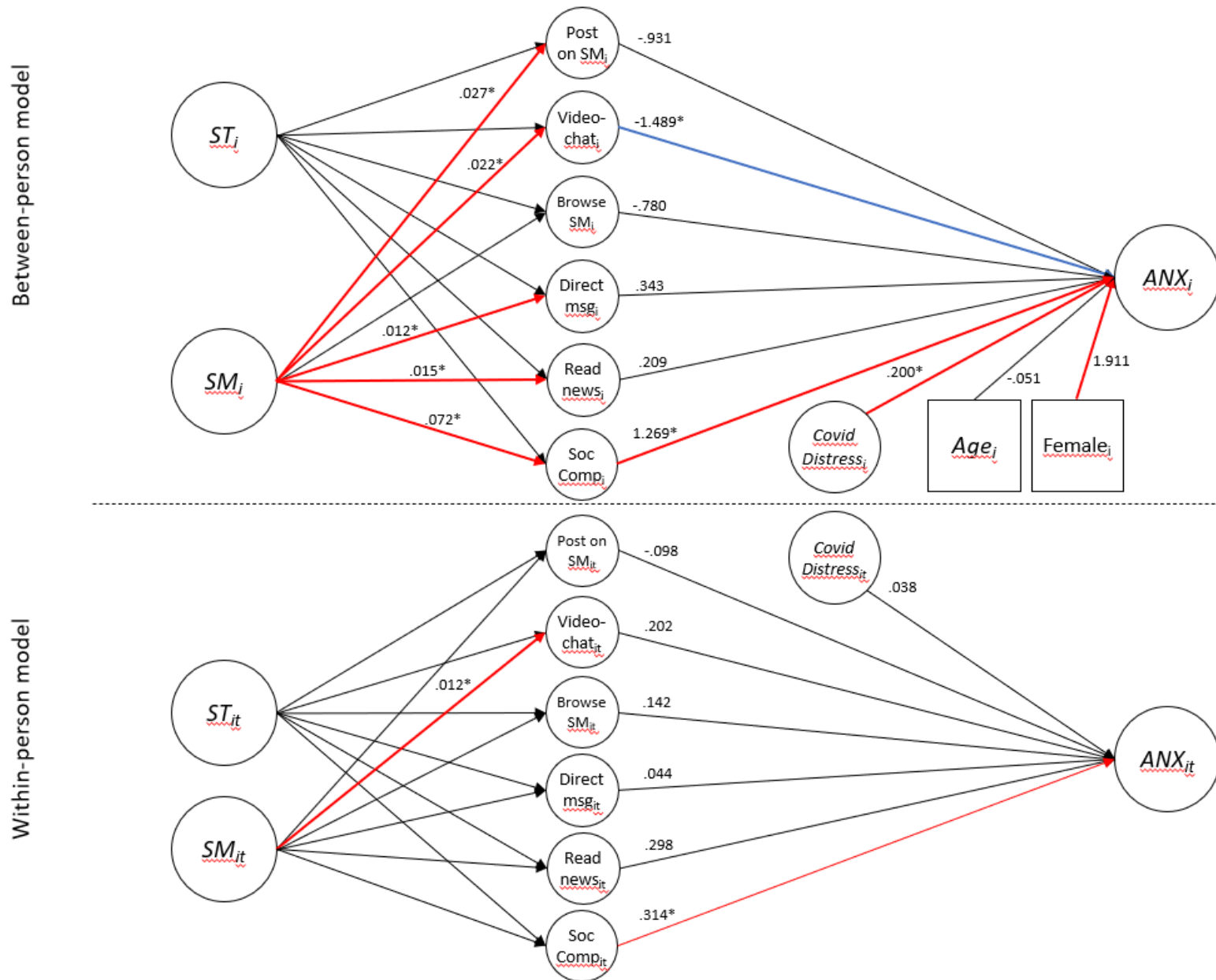
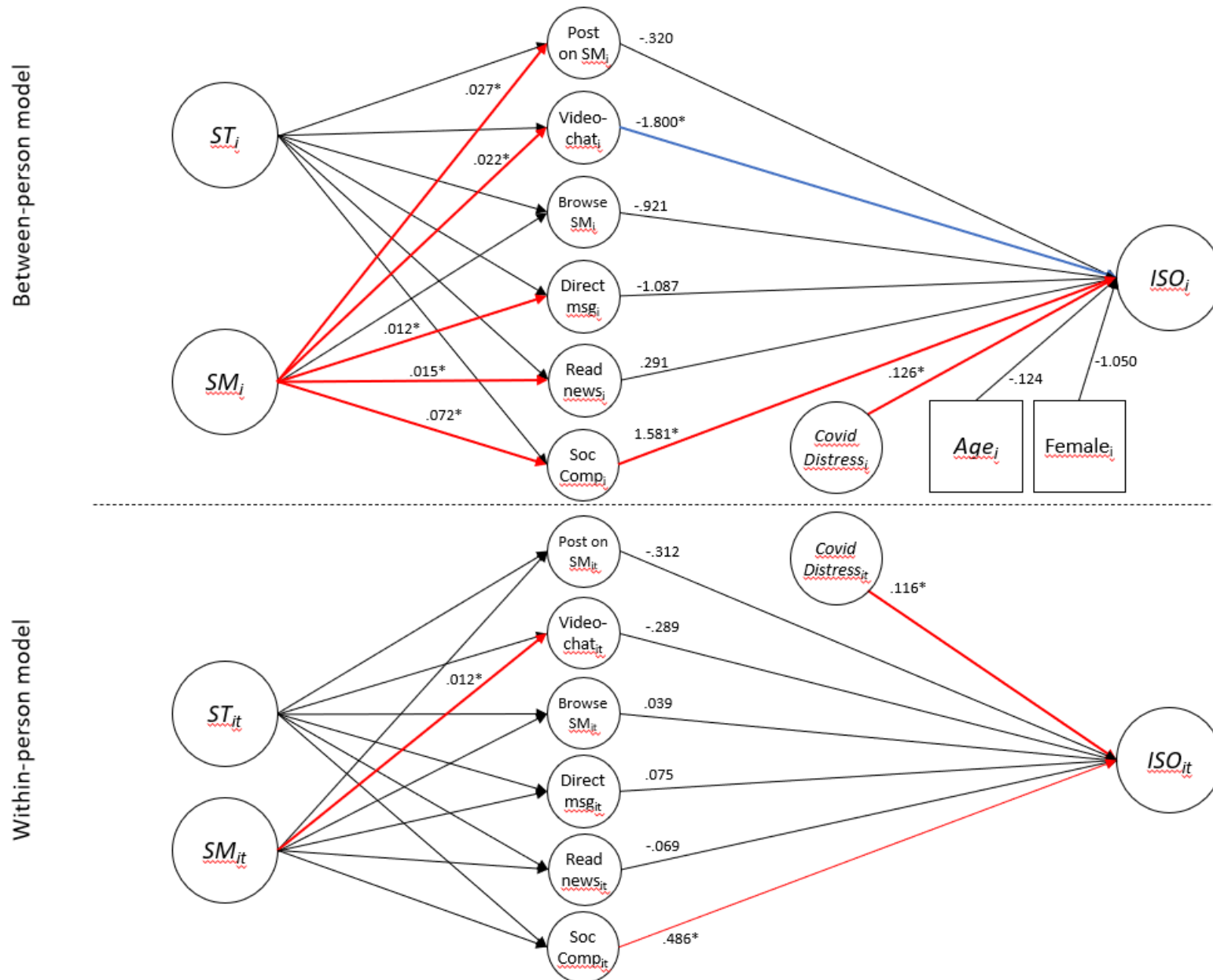


Figure 17. Results of the psychosocial mechanism multilevel mediation model for anxiety



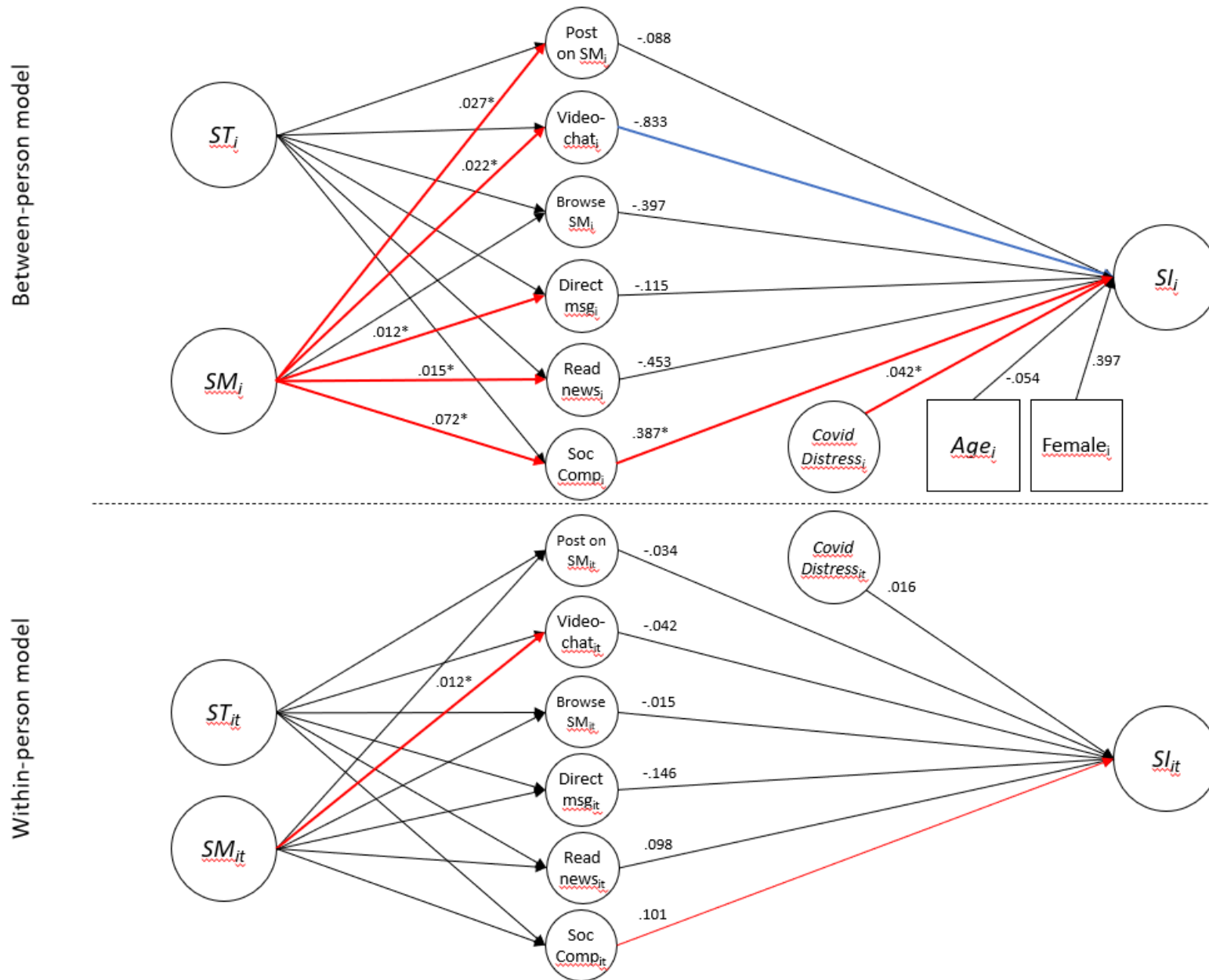
Note. *p < .05; **p < .01; ***p < .001. Red paths represent significant positive associations; blue paths represent significant negative associations.

Figure 18. Results of the psychosocial mechanism multilevel mediation model for social isolation



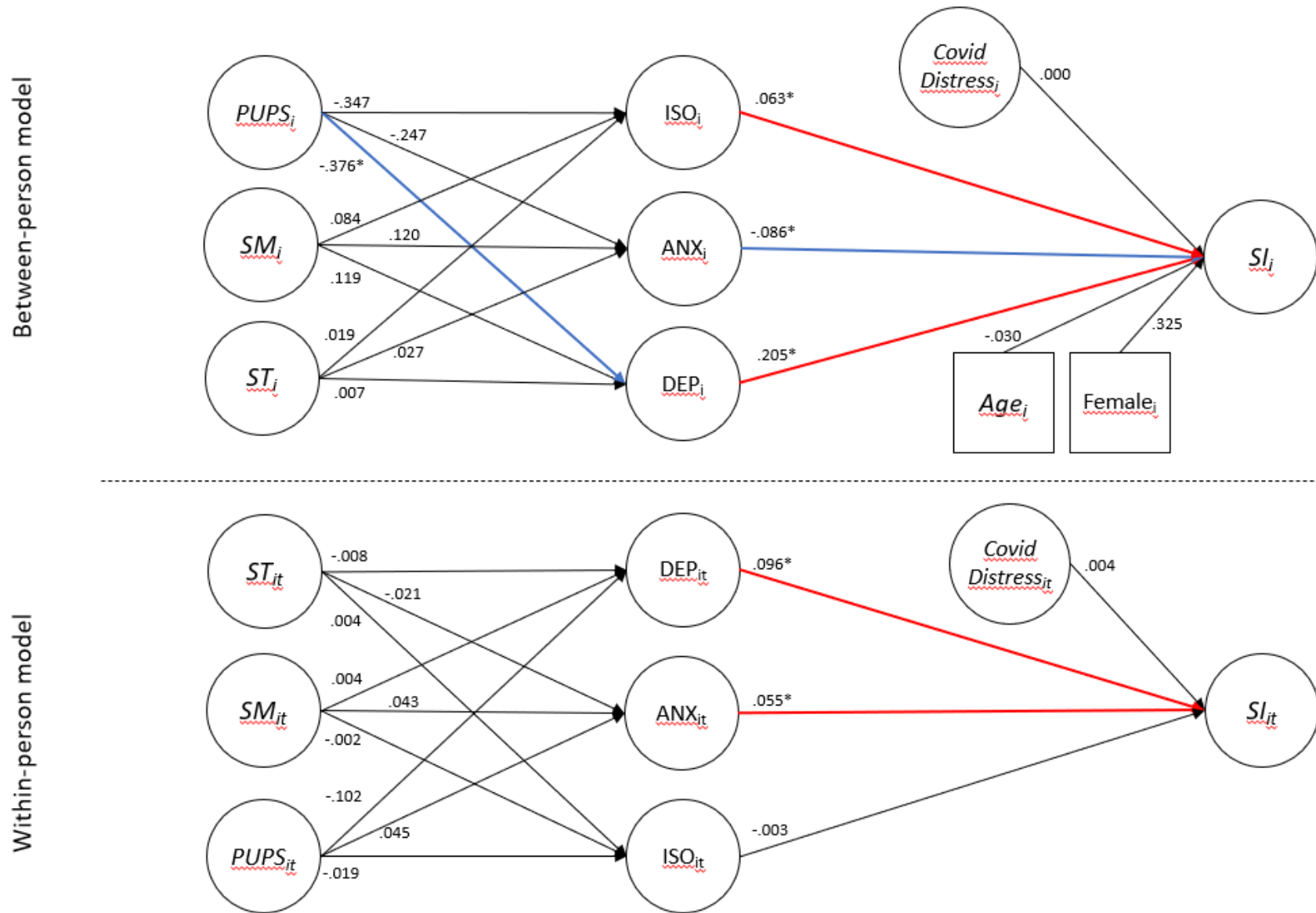
Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

Figure 19. Results of the psychosocial mechanism multilevel mediation model for suicidal ideation



Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

Figure 20. Results of multilevel mediation model for total effect of DTU on suicidal ideation



Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Red paths represent significant positive associations; blue paths represent significant negative associations.

5.0 Discussion

5.1 Temporal Effects

Despite the plethora of research on the putative effects of DTU on well-being and mental health conducted over the past decade, there have been relatively few longitudinal studies examining the within-person temporal precedence of these effects over time, which is imperative for establishing even a weak argument for causality. The few studies that have done so have come to conflicting results. Some found that within-person increases in DTU predicted within-person increases in depression (Boers et al., 2019; Primack et al., 2020) or anxiety (Boers et al., 2020), leading to the conclusion that DTU may be a driver of increased psychological distress. Others found the converse effect—that within-person increases in psychological distress predicted increases in DTU (Puukko et al., 2020)—leading to the conclusion that psychological distress is a driver of increased DTU. Finally, several recent longitudinal studies found no within-person temporal effects between DTU and psychological distress (Coyne et al., 2020; Orben et al., 2019; Schemer et al., 2020). This inconsistency is due to many factors, such as the length of the study, the characteristics of the sample, the type(s) of DTU being measured, and many others. However, because the studies cited above—as well as the overwhelming majority of studies in the field of digital health effects research (Griffioen et al., 2020)—relied upon self-report measures of DTU, and because measurement is fundamental to the reliability of results (Flake & Fried, 2020), it has remained unclear whether these inconsistencies are due to actual, substantive differences in the DTU—mental health effects, or rather measurement error.

As the first longitudinal study to employ objective measures of DTU to examine the within-person temporal effect between DTU and mental health, the present study overcomes this major limitation. Of the 27 DTU → mental health cross-lagged paths, only one was statistically significant and

all effect sizes ranged from small (i.e., $\beta \approx .10$) to very small (i.e., $\beta \approx .05$). Similarly, of the 27 mental health $\rightarrow$ DTU cross-lagged paths, none were statistically significant and effect sizes were similar in size. The lack of statistically significant cross-lagged paths and prevalence of small effect sizes is similar to findings from an eight year longitudinal study of adolescents (Coyne et al., 2020), which found that only one of the 14 social media $\rightarrow$ mental health cross-lagged paths, only one was significant and all effects were $|\beta| \leq 0.10$. Similarly, a study by Orben and colleagues (2019) that employed a robust statistical analysis technique called specification curve analysis (Simonsohn et al., 2015), which analyzes thousands of different model specifications and how this impacts the results, found that the median social media $\rightarrow$ life satisfaction cross-lagged effect was trivial in size $\beta = -0.05$.

The fact that the using objective measures of DTU yielded within-person effects similar to other recent studies that used self-report measures of DTU does not mean that the two measurement methods are equivalent. As mentioned above, several other studies employed similar statistical analysis methods, but also relied on self-reported DTU, and came up with considerably different results. The substantial variance observed across these studies is likely due, at least in part, to random and systematic error inherent to self-report measures of DTU. A recent meta-analysis based on 106 effect sizes found that self-reported DTU was only moderately correlated ($r = .38$) with objectively measured DTU. Though this correlation would be of substantial size if comparing two distinct constructs, such as depression and age, the fact that self-report measures of DTU are designed to measure actual DTU means that one would expect extremely high convergent validity (i.e., $r > .75$). That this is not the case strongly suggests that self-report measures of DTU cannot be relied upon as a proxy measure of actual DTU and, importantly, are likely measuring constructs that are unrelated to the construct that they are designed to measure, such as attitudes, beliefs, and cognitive-affective state (Ellis, 2019). This construct contamination and measurement error make it impossible to conclude whether the effects observed using these measures are attributable to actual DTU or something else, yielding inconsistent results that

could be artificially inflated or attenuated. Thus, to improve the reliability of results in digital health effects research, it is imperative that researchers utilize objective measures of DTU.

5.2 Concurrent Effects and Variance Explained

Two measures of effect size were included in the current study to get a sense of how each individual predictor was associated with the outcome (unstandardized betas) and how groups of conceptually similar variables explained variance in the outcome (R^2). Beginning with the DTU variables, all of the DTU variables had very small (and statistically non-significant) associations with each of the mental health outcomes. Most of the posterior distributions centered around zero, meaning that within-person changes in depression, anxiety, social isolation, or SI had close to nothing to do with within-person changes in DTU. To illustrate how small these effects are, the largest within-person effect for social media was in the anxiety model. Even though the 95% credibility interval included effects ranging from $b = -.018$ to $b = .117$, the point estimate—which represents the midway point (median) of the posterior distribution—was $b = 0.05$. If we assume $b = 0.05$ is the most plausible within-person effect size for the social media—anxiety association, then a participant would have to increase their social media use by 20 hours above their usual amount to increase their depression severity by one point above their average. Given that the within-person standard deviation for social media is 6.0 hours, this level of increase is very unlikely.

In contrast to the small effects of the DTU variables, two mechanism variables exhibited much more robust within-person associations with the mental health outcomes. The point estimate for the within-person effect of sleep disturbance was $b = .28$ for the anxiety model. Thus, a within-person increase of only one standard deviation in sleep disturbance (about 5.0 points on the sleep disturbance scale) has a stronger effect on anxiety than more than a three standard deviation increase in social

media use. The point estimate for the psychosocial mechanism *online social comparison* had a within-person effect of $b = .32$ for the anxiety model, meaning that a within-person increase of one standard deviation in social comparison (2.3 points on the *online social comparison* scale) had roughly the same effect on anxiety as more than a two standard deviation increase in social media.

Given the small individual effects of the DTU variables, it should be unsurprising that, as a group, the DTU variables explained a very small amount ($< 2.1\%$) of the within-person variance in the mental health outcomes. In contrast, the behavioral mechanisms (number of steps taken, sleep disturbance) explained twice as much within-person variance in SI, 6 times as much in social isolation, 15 times as much in depression, and 16 times as much in anxiety. The psychosocial mechanisms (social media uses, online social comparison) explained 6 times as much within-person variance in anxiety and SI, 9 times as much in depression, and 23 times as much in social isolation.

The take home message from these results is that simply spending more time on DTU (as indicated by total screen time, social media use, and/or device pickups) is not inherently harmful to mental health. This finding is consistent with an emerging consensus among digital health effects researchers (Kaye et al., 2020; Odgers, 2018; Odgers & Jensen, 2020; Orben, 2020) who have, based on the disparate results from studies using self-reports of DTU, encouraged the field to move beyond simple questions of duration/frequency toward more nuanced approach considering who, what, where, why, and when DTU are being used. The above results indicate that sleep disturbance and online social comparison are significantly associated with increases in mental health distress, both of which have been consistently observed in the digital health effects literature (Biernesser et al., 2020; Carter et al., 2016; Li et al., 2019; Seabrook et al., 2016; Viner et al., 2019). However, just because sleep disturbance and online social comparison exhibit a direct association with mental health outcomes, as described above, does not necessarily mean that they act as a mechanism for any kind of DTU—mental health effect.

5.3 Mechanisms and Indirect Effects

Even though the DTU variables exhibited no meaningful within-person associations with the mental health variables, it is possible that they may influence these outcomes indirectly via their impact on variables that, in turn, impact mental health. However, while there were indications that some DTU variables were associated with either sleep disturbance or social comparison at the within-person level, only a few indirect effects, i.e., DTU → Mechanism → Mental health, were statistically significant and all were very small in size. The two largest indirect effects were the effect of screen time on depression ($b = .013$) and anxiety ($b = .015$) via sleep disturbance. Taking $b = .015$ as the most plausible value for the indirect effect, in order to increase depression by one point via sleep disturbance, a person would need to increase their screen time by 77 hours above their baseline, which is more than six standard deviations above the average within-person change. This illustrates that even the largest of the DTU indirect effects would have a small to negligible influence on mental health at the within-person level.

5.4 Implications for Social Work

The results of the current study have important implications for social work practice and research. Digital technology use is ubiquitous accounts for a substantial amount of time spent, especially among young adults (Pew Research Center, 2020). It is important that social workers working with young adults and/or their families, whether in schools, clinical settings, or other environments, are knowledgeable of the evidence, or lack thereof, of the associations between different types of DTU and mental health. This is quite difficult given that research discussing the putative negative effects of DTU on mental health are frequently highlighted by the popular media (e.g., Richtel, 2021), leading to the commonly held belief among parents that DTU is harmful to well-being (Common Sense Media, 2018). However, DTU is frequently (especially during the pandemic) young peoples' primary avenue for crucial

activities such as social connection and relationship maintenance, educational and informational outlets, creative expression, and entertainment. Forcing young people to eliminate or drastically reduce their DTU in the misguided hope that it will lead to improved well-being could very well backfire, further exacerbating pre-existing mental health distress.

An evidence-based approach to social work practice with young adults relating to DTU comprises several key elements. First, given the importance of digital technology and its varied uses, it is crucial that social workers speak with their clients about their DTU. Second, in assessing DTU, social workers should take an idiographic, person-centered approach. That is, rather than assume that a certain type or form of DTU is inherently harmful/beneficial, social workers should assess their clients' specific digital context. This means asking questions that go beyond simple frequencies or durations of use. Rather, social workers should assess what specific apps are being used, why they are being used, who they are being used with, how the client feels before/during/after they are used, when they are being used, and what sort of content they seek out/are exposed to while online. This process can identify whether clients are, for instance, engaging in social comparison on social media that causes feelings of inadequacy, or using DTU late at night and undermining sleep hygiene. Third, because beliefs about the putative harms of DTU are commonly held, especially among parents, social workers should caution parents and caregivers against overly negative views about DTU and highlight the various ways that young people may use DTU to meet their needs and goals. Fourth, social workers should advise against unnecessarily restricting or eliminating use of DTU in toto. Rather, specific aspects of DTU should first seek to be understood, then, if a particular aspect of DTU poses a risk of harm to the young person (i.e., involvement in an online group that glorifies self-harm), the social worker should work with the client and family member to find feasible replacements so that the harmful DTU use can be reduced or eliminated.

This study also has implications for social work research. Methodologically, social work researchers interested in investigating digital health effects, whether as a primary or secondary interest, should be aware of the limitations of self-report measures of frequency/duration of DTU and, if feasible, obtain objective DTU data instead. However, given that the field of digital health effects is moving toward identifying how specific aspects of DTU relate to various aspects of well-being, rather than on general measures of frequency/duration, researchers should focus more on including a range of measures that would allow them to capture various characteristics of DTU. These aspects include elements related to (1) the *medium*, which comprises the type of digital technology (e.g. smartphone or social media) and/or platform (e.g. Twitter or Snapchat); (2) the *operations*, which comprise the different types of specific uses of digital technology (e.g., direct messaging, reading news, entertainment, scrolling feeds, etc.); (3) the *content*, which comprises the experiences and material participants are exposed to while using digital media; and (4) the *operator*, which are the characteristics of the person using digital technology. Lastly, researchers should endeavor to measure these aspects of DTU repeatedly, preferably using ecological momentary assessment methods to capture the dynamic, everyday fluctuations of these phenomena over time and how they relate to health outcomes.

Substantively, social work researchers should leverage their knowledge and experience working with vulnerable groups to investigate digital health effects among these populations. Research suggests that those who are most vulnerable to harms in offline contexts are also most vulnerable to harms in online contexts (Escobar-viera et al., 2018; Sage et al., 2020). Given the general nature of the sample for the current study, it is unclear whether or how the results generalize to members of different vulnerable populations. For instance, although levels of mental health distress were high in current sample, it is possible that a different pattern of results would emerge if the study were to be replicated among a clinical population of young adults. Although lacking consensus in the literature, there are indications that youth with psychiatric disorders are more likely to experience aspects of DTU frequently associated

with poorer well-being, such as online social comparison, cybervictimization, and exposure to harmful content (Biernesser et al., 2020; Odgers, 2018; Seabrook et al., 2016). As another example, LGBTQ+ youth may benefit more from online social connection, especially if they are in unaccepting families, where they can connect with peers who accept and validate their experiences, but at the same time may be more susceptible to online cybervictimization (Escobar-viera et al., 2018). However, these issues are understudied among vulnerable populations, so research is relatively premature in this area. Thus, social work researchers could help fill these gaps and make valuable contributions to the digital health effects literature.

5.5 Limitations

There are several limitations to the current study. First, the generalizability of the findings is constrained by the convenience-based sample of participants. Only people who used Prolific, owned iPhones, were between 18-35 years of age, and lived in the U.S. were able to participate. Although the racial/ethnic makeup of the current sample was more diverse than typical University-based convenience samples, it is not clear how the results generalize to non-iPhone users, youth < 18 years old or adults > 35 years old, non-Prolific users, and/or non-U.S. residents. Future research should attempt to replicate these findings, especially those related to objective DTU, among these populations to investigate the transferability of results. Second, although objective measures of DTU are superior to self-reported estimates, they are not perfect (Jürgens et al., 2019). To illustrate, multiple participants did not have their “Screen Time” app enabled or experienced other complications that led to inaccurate tracking of device usage. Furthermore, the measure of objective social media used in this study relied upon how Apple classifies applications. For instance, during the course of the study, Apple classified a popular app called “TikTok” as belonging to the “creative” category rather than their “social media” category. So,

time spent on TikTok was not included in the calculations of total social media time. Third, the lag of one month between data collections may not be the ideal timeframe to capture within-person dynamics. Although the ideal timeframe for panel studies of this nature is unknown, recent research suggests that digital effects may be highly dynamic, occurring over short periods of time (Vanden Abeele, 2020). This is an important area of ongoing and future work. Finally, although this study captured several potential mediators/moderators of the DTU—mental health effects, not all variables of import could be included. For example, this study did not collect data on what participants were exposed to while online (e.g., cybervictimization, suicide-related content, etc.).

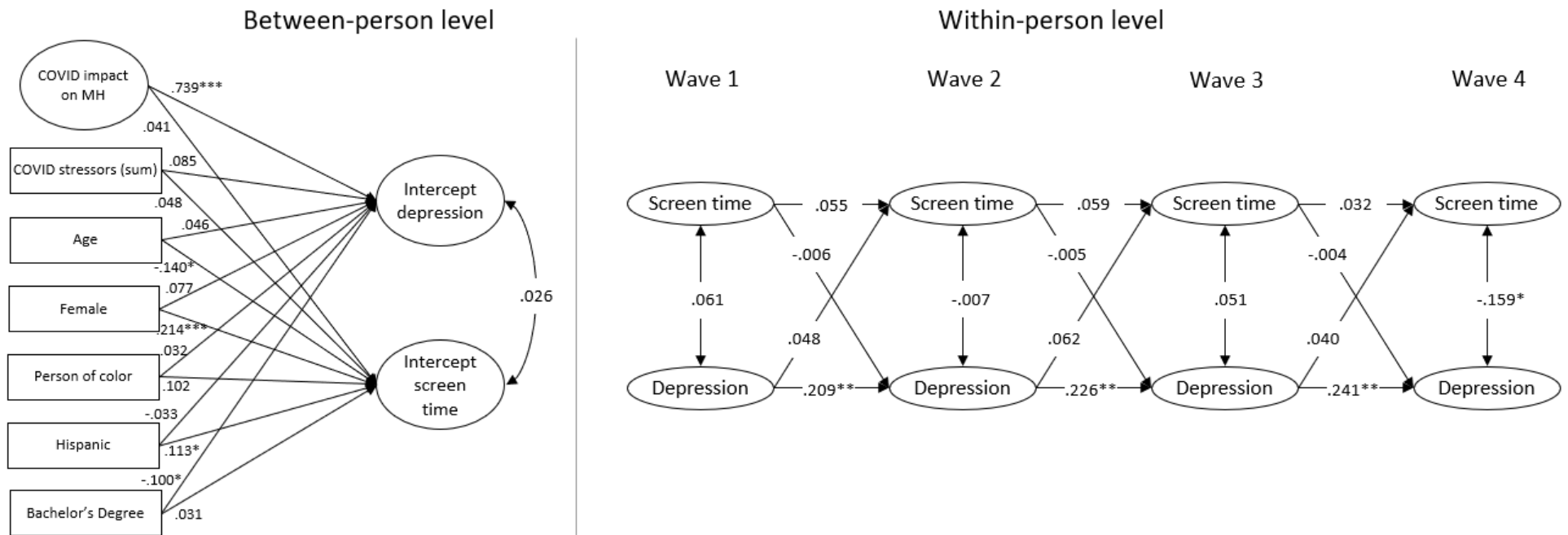
5.6 Conclusions

This longitudinal study examined two overarching questions related to DTU and psychosocial risk factors for suicide: (1) What are the direct, temporal relationships between different types of DTU (total screen time, social media use, and pickups) and certain psychosocial risk factors for suicide (depression, anxiety, social isolation, and SI)? and (2) What mechanisms potentially mediate or moderate these relationships? This study addressed important methodological limitations that frequently undermine results in this arena of research, such as the use of self-report measures of DTU, the lack of longitudinal studies, failing to separate within- vs. between-person effects, focusing on a restricted set of mental health outcomes, and failing to examine various potential mediators or moderators of the DTU—mental health effect. The overarching findings were: (1) the objectively-measured DTU variables were not temporally associated with any of the mental health variables and explained a negligible portion of the within-person variance in these outcome; (2) only the sleep disturbance and online social comparison mechanisms were reliably associated with increased mental health distress at the within-person level; and (3) the within-person effects of the DTU and mechanism

variables did not vary significantly across age or gender. Social work practitioners should employ a person-centered, idiographic approach when assessing their clients' DTU and endeavor to dispel commonly held misconceptions regarding the putative harms of DTU. Social work researchers are uniquely positioned to attempt to investigate and replicate these results among vulnerable populations.

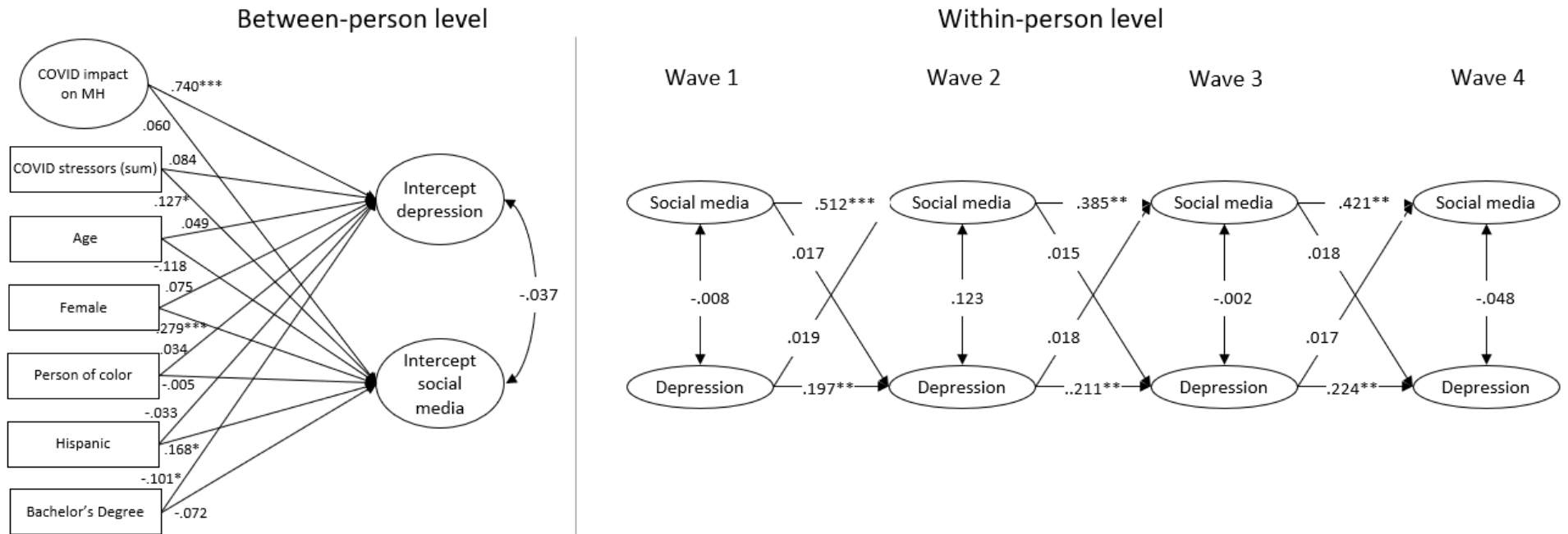
Appendix A Model-Specific RI-CLPM Results

Figure 3. Results of depression—screen time RI-CLPM



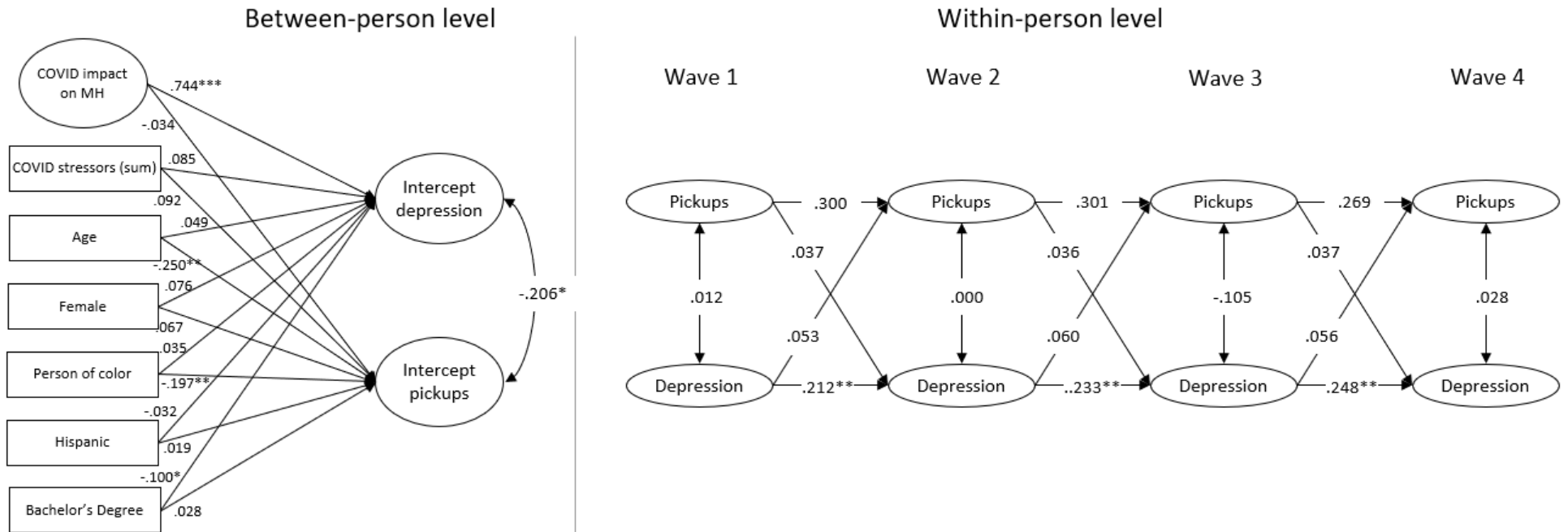
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 4. Results of depression—social media RI-CLPM



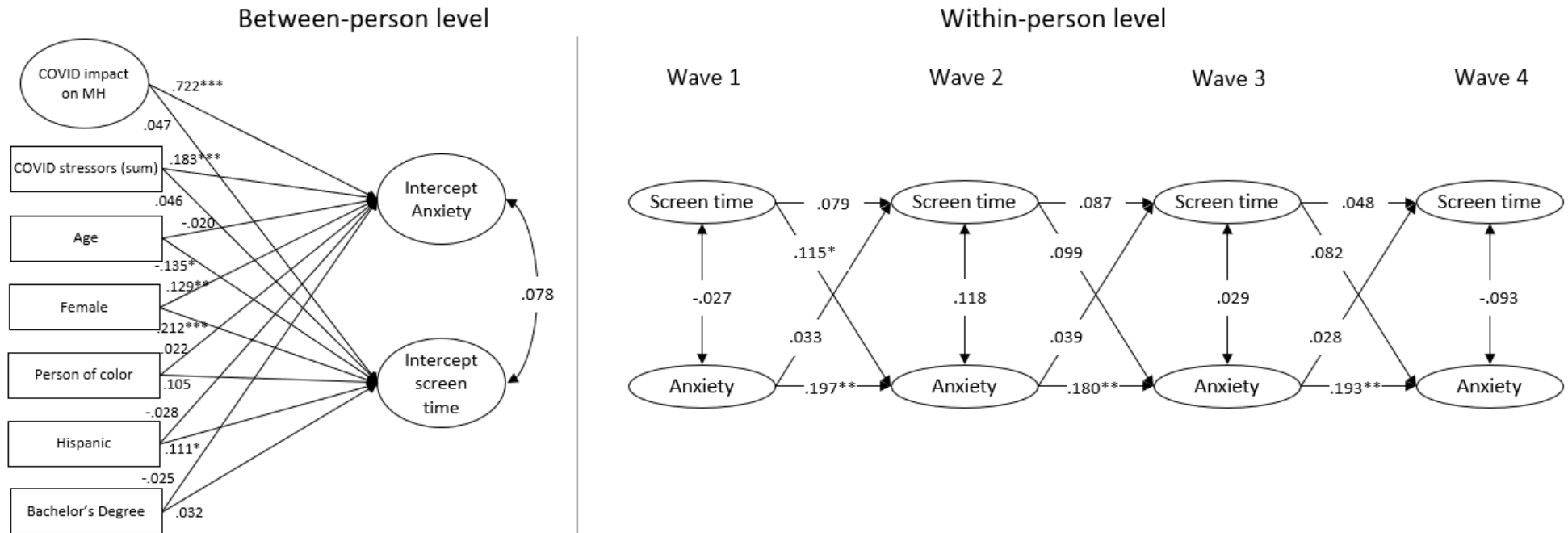
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 5. Results of depression—pickups RI-CLPM



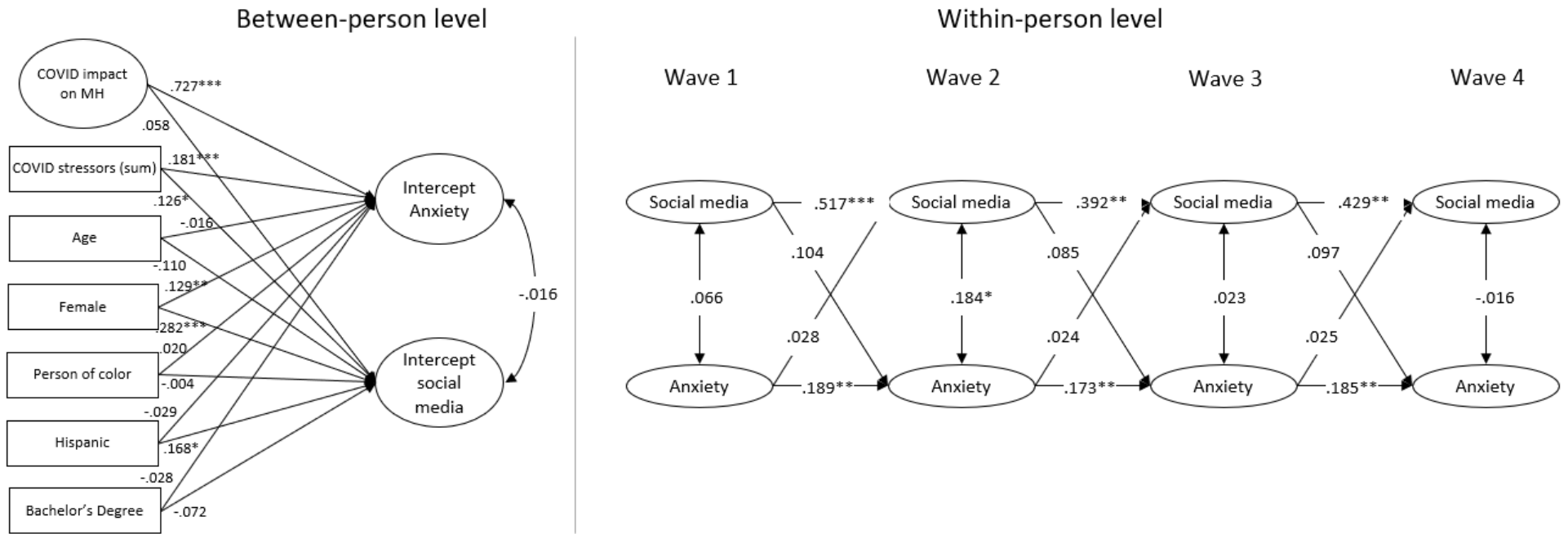
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 6. Results of anxiety—screen time RI-CLPM



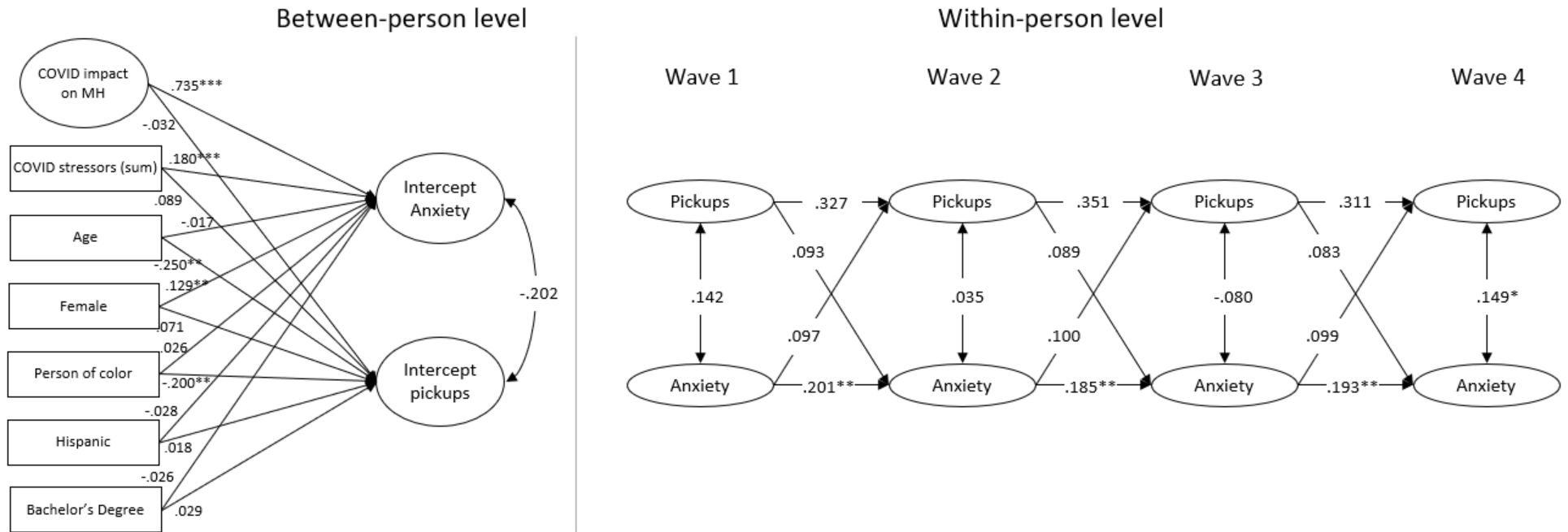
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 7. Results of anxiety—social media RI-CLPM



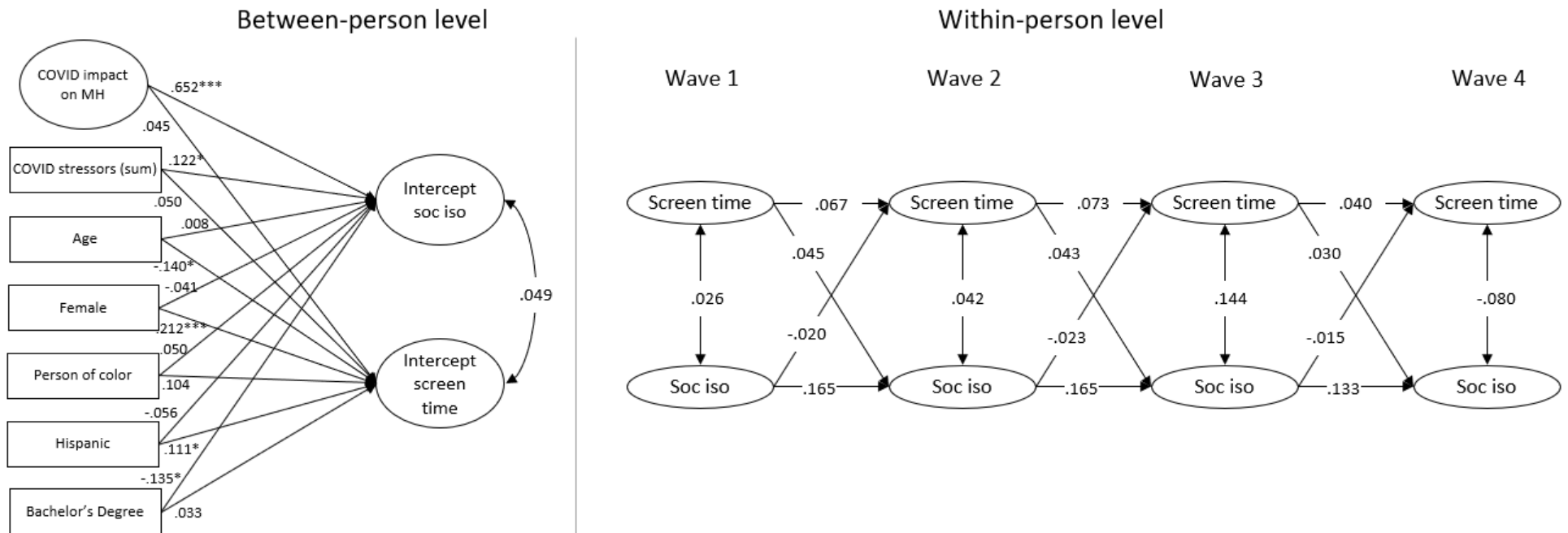
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 8. Results of anxiety—pickups RI-CLPM



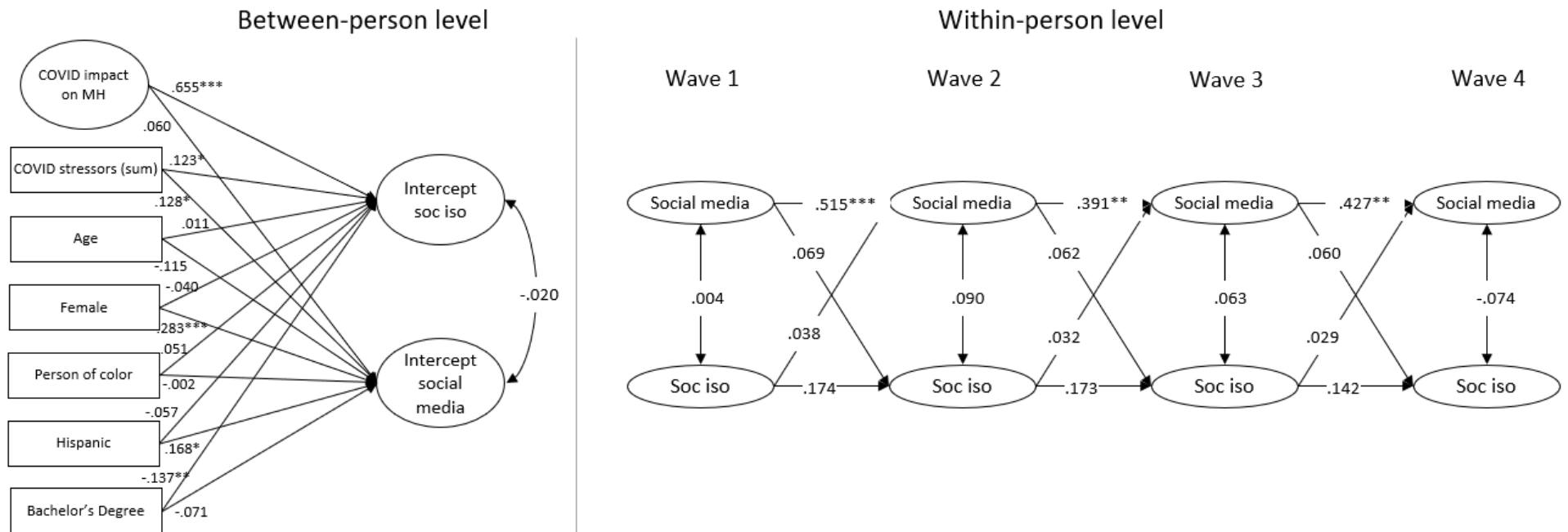
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 9. Results of social isolation—screen time RI-CLPM



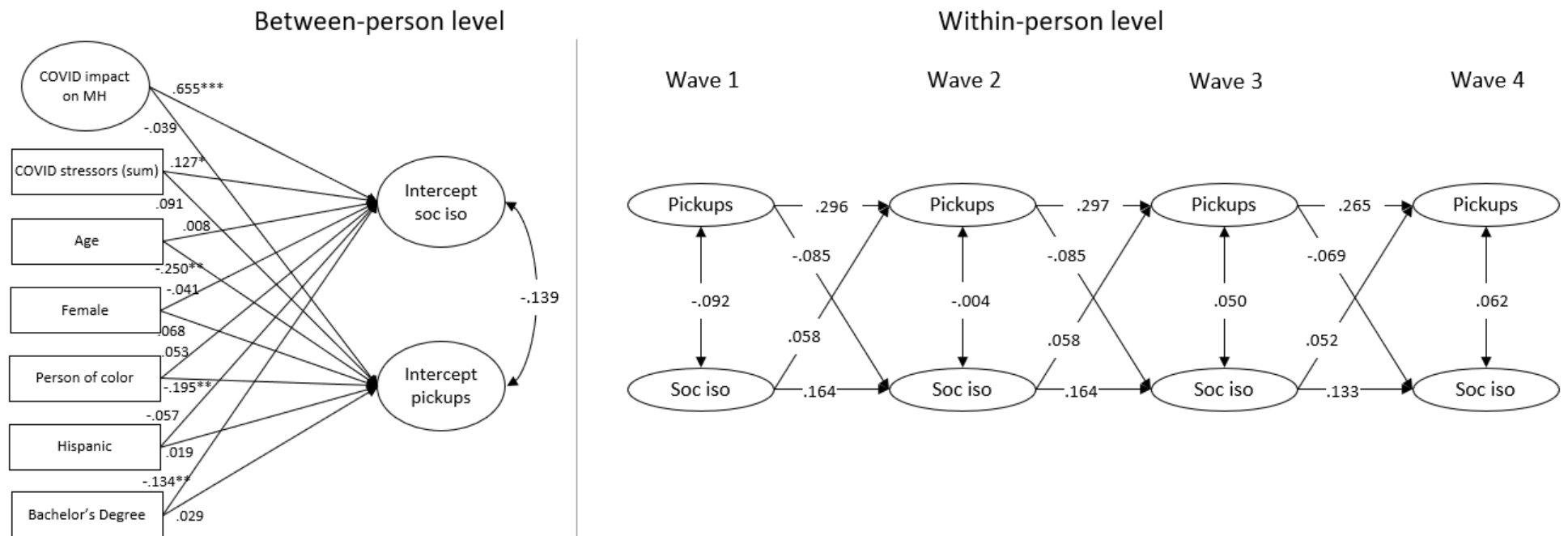
Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 10. Results of social isolation—social media RI-CLPM



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

Figure 11. Results of social isolation—pickups RI-CLPM



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

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