A NEW PERSPECTIVE ON SOCIAL MEDIA USE, LONELINESS, AND CYBERBULLYING

by

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Abstract

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The rates of social media use, cyberbullying, and loneliness are interrelated and simultaneously on the rise. Applying Jensen-Campbell's Stress Model of Peer Victimization (Knack, Jensen-Campbell, & Baum, 2011) and the Evolutionary Theory of Loneliness (Cacioppo & Cacioppo, 2018) it is proposed that the negative health effects of social media may be attributed in part to chronic loneliness and cyberbullying. When lonely people recognize a lack of beneficial relationships (i.e., salutary relationship postulate) it may cause their behaviors to become more self-focused (i.e., self-preservation postulate) and they may use social media to fulfill the social disconnect by engaging in cyberbullying perpetration (i.e., selfishness and spiteful behavior). At the same time, lonely individuals in a cyber context may become vulnerable targets due to a lack of supportive connections, potentially increasing their risk of being cyber victims. Specifically, it is expected that there would be a stronger predictive relationship between cyber-perpetration and loneliness for image-based or selfish apps (Instagram) than for word-based apps (Twitter). Also, it was estimated that for lonely individuals increased social media use would predict cyber victimization relative to perpetration resulting in the prediction of poorer physical and mental health outcomes. Finally, it was expected that perceptions of social support would buffer the unique effects of loneliness on poorer physical and mental health outcomes. To test the hypothesized relationships, 393 college students from a Southern University completed online questionnaires. Overall, loneliness predicted greater levels of perpetration deception, total victimization, and public humiliation, malice, and deception victimization, as well as several health outcomes including physical symptoms, depression, perceived stress, state anxiety, and trait anxiety. Also, perpetration predicted physical symptoms, depression, trait and state anxiety, whereas victimization behavior predicted perceived stress and malice victimization predicted state anxiety. However, as not anticipated, time spent on Instagram or Twitter did not moderate the relationships between loneliness and cyberbullying behaviors, or physical and mental health outcomes. Finally, contrary to what was hypothesized, cyberbullying behaviors and social support did not mediate the relationship between loneliness and physical and mental health outcomes, including obesity, physical symptoms, depression, perceived stress, state anxiety, or trait anxiety. The results obtained from the current study support the importance of monitoring students for signs of loneliness, as well as educating college students about digital citizenship to prevent and decrease cyberbullying behaviors to improve an individual's physical and mental health.

Table of Contents

List of Tables

List of Figures

A New Perspective on Social Media Use, Loneliness, and Cyberbullying

"Millennials expect to create a better future, using the collaborative power of digital technology"

- Mal Fletcher

Chapter 1

Overview

It is no secret that young adults today cultivate social connections through use of social media applications, such as Instagram and Twitter. According to a recent survey of young adults in the U.S. ages 18-24, 75% reported that they used Instagram, and 44% reported that they used Twitter. Moreover, 42% of these individuals reported checking Instagram multiple times a day, while 25% admitted that they checked their Twitter account multiple times a day (Pew Research Center, 2019). Although devices/online connections provide knowledge, social connections, and entertainment at our fingertips, there is accumulating evidence regarding potential adverse effects, including cyberbullying and increases in loneliness (Varghese & Pistole, 2017; Smith & Anderson, 2019). However, truly little research has examined the co-occurrence of these adverse outcomes, how one may predict the other, or how their relationship varies by type of online activity. Based on the Evolutionary Theory of Loneliness (Cacioppo & Cacioppo, 2018), and The Stress Model of Peer Victimization (Knack, Jensen-Campbell, & Baum, 2011), it was expected that the relationships between the two will be stronger for image-based or selfish apps (Instagram) than for primarily text-based apps (Twitter). Additionally, it was expected that perceptions of social support would explain the unique effects of social media use and loneliness on poorer physical and mental health outcomes (see Figure 2). The insights gained from this study will allow healthcare providers and other professionals to tailor effective interventions to combat cyberbullying and loneliness, such as the invention of software that detects mean messages on social media (i.e., ReThink), or applications that use “friend-sourcing” so that others can monitor negative text messages, and emails an individual might be tempted to send (i.e., Squad-Box).

Loneliness

Prevalence rates of loneliness have been higher than ever before with nearly 50% of U.S. adult respondents reporting sometimes or always feeling alone or left out, and 43% of Americans responded that they sometimes or always feel that their relationships are not meaningful (Cigna U.S. Loneliness Index, 2019). Due to the increased rates of loneliness, researchers have begun to investigate why this is the case. This has resulted in many researchers putting blame on the increased use of social media. For example, as of the year 2018, it was estimated that there were 3.196 billion social media users (Nazir, 2018). Additionally, according to a recent study conducted by Cigna (2019), Generation Z (adults ages 18-22) is the loneliest generation yet. Due to these findings and others, the current study proposed that increased time spent on social media apps, like Instagram and Twitter, may be used as a platform for cyberbullying, as well as may directly relate to levels of loneliness and thus predict health related outcomes. The effects of social media on levels of loneliness are important to understand because chronic loneliness has been associated with a plethora of physical and mental health consequences including increased stress, risk for cardiovascular disease and stroke, drug and alcohol abuse, antisocial behavior, and depression/suicide (Hammig, 2019). Additionally, loneliness was associated with an increased likelihood of all-cause-mortality; by 29% (Holt-Lunstad, et al., 2015).

Next, it is important to understand how the construct of loneliness is defined. Loneliness has been defined as a negative emotional state that occurs when there is “a discrepancy between…the desired and achieved patterns of social interaction” (Peplau & Perlman, 1982).

Also, it is important to note that loneliness is distinct from being alone in two ways. First, those who are lonely do not consider the experience of being alone a positive one. For non-lonely individuals “alone time” can be refreshing, such as taking a relaxing bubble bath or spending the evening watching a movie by oneself. However, this is not the case for those who are lonely; these individuals when physically left alone interpret this as a negative experience (Peplau & Perlman, 1982). Secondly, even in the presence of loved ones, such as friends and family, lonely people still report feeling socially isolated or disconnected. Theories of loneliness have been devised to explain how loneliness has developed and has been associated with health outcomes.

One theory used to study and predict loneliness and its health outcomes has been the Evolutionary Theory of Loneliness (Cacioppo & Cacioppo, 2018). The theory consisted of eight specific pathways through which loneliness contributed to increased rates of mortality. First, chronically lonely people suffered from decreased sleep quality, which could lead to other physiological issues such as a suppressed immune system or an increased inflammatory response. Also, because loneliness was considered a stressor, it could cause both short-term (sympathetic-adrenal- medullary activation) and long-term physiological activation (hypothalamic-pituitary-adrenal-cortical-axis) of various stress response systems. Overtime, such responses could result in increased resistance of one’s vasculature causing a lack of blood to flow through the body. This could result in permanent organ damage (Cacioppo et al., 2017). An increased stress response has also been associated with altering one’s genes (RNA specifically was modified, Cole et al., 2011). Finally, persistent loneliness causes harmful mental effects due to increased symptoms of anxiety and depression (i.e., social isolation).

The Evolutionary Theory of Loneliness (Cacioppo & Cacioppo, 2018) also incorporated postulates that predicted behavioral responses and the presentation of loneliness. The current study focused on three postulates specifically. First, according to the salutary relationship postulate, lonely individuals were motivated to engage in certain behaviors, like using social media, to try and create beneficial social interactions or to connect with others to promote survival. For instance, in the U.S., 7 out of 10 people reported that they used social media to connect with others (Pew Research Center, 2019). Also, one study reported that 90.2% of participants posted a photo on social media applications, including Facebook and Twitter so they could receive "likes" and other comments from their friends and family members, which made them feel socially connected (Wickel, 2015). Additionally, some of the most daily used applications included Instagram (60%), and Twitter (44%). While, social media may be advantageous through increasing one's odds of creating beneficial relationships and thus potentially leading to procreation as suggested by the salutary relationship postulate, increased media use is not without negative including for some individual's chronic loneliness. The consequential order of social media use and loneliness cannot be determined; which came first increased social media use resulting in feeling lonely, or feelings of loneliness which then led to increased social media use? Research has shown that social media was associated with greater loneliness (Ali, 2018). A recent survey reported that 71% of heavy social media users reported feeling lonely compared to 51% of those who rated their social media use as light (Cigna's U.S. Loneliness Index, 2019). Collectively, the research supported this postulate concluding that beneficial relationships were essential for increasing survival and may have been gained using social media; however, in excess social media use may have negated beneficial relationships and instead increase feelings of loneliness. Not only are salutary relationships important to have, but a lack of such relationships may lead to increased selfish or spiteful behavior.

Secondly, the self-preservation postulate stated that, when an individual understands that they lack beneficial social interactions, they have an increased chance of engaging in social behaviors categorized as selfish or spiteful. In the case of lonely individuals who might use social media to fulfill the lack of salutary relationships, it was reasoned that one form of selfish or spiteful behavior might be cyberbullying perpetration. One study found that posting "selfies" was associated with increased selfishness and narcissism (Wickel, 2015). Also, Alloway et al., (2014) found that the photo feature on Facebook was linked to narcissism, and Moon et al., (2016) found that individuals higher in narcissism posted more selfies, spent more time on Instagram, updated their profile picture more, and rated their profiles as being very attractive. Based on the findings reviewed above, and considering the Evolutionary Theory of Loneliness, it was reasoned that lonely people would use more social media apps; specifically, Instagram and Twitter, as a means to acquire more support, but would experience more cyberbullying. It could also be reasoned that individuals who lack friendships, simultaneously lack social protection thus making themselves a more vulnerable target to be victimized. For example, in a study investigating loneliness and social media usage, it was found that loneliness significantly predicted cyber victimization (Sahin, 2012). Because of this, it was also hypothesized that individuals who used social media apps that increased narcissistic tendencies, like Instagram would engage in more self-preservation behaviors (i.e., selfishness or spitefulness). Therefore, it was estimated that lonely people who used Instagram more would also report increased cyberbullying perpetration behaviors.

The third postulate this study examined was the cumulative deleterious effects postulate. It posited that when an individual does not feel protected, such as lacking beneficial relationships, the brain begins to adjust neuronally, hormonally, and cellularly. In the short-term such changes are beneficial because they alert us to the need to seek out beneficial relationships. However, overtime as this need is unfulfilled chronic loneliness develops, which leads to increased activation of the hypothalamic- pituitary-adrenal-cortical axis. Similar physiological health changes have also been associated with cyberbullying perpetration and victimization (Albdour et al., 2019).

As outlined in the Evolutionary Theory of Loneliness (Cacioppo & Cacioppo, 2018), and Jensen-Campbell's Stress Model of Peer Victimization (Knack, Jensen-Campbell, & Baum, 2011) loneliness and cybervictimization and perpetration further result in harmful consequences, such as increased inflammation, cortisol, and cellular aging, ultimately affecting one's health and well-being across the lifespan. For example, lonely individuals had elevated cortisol levels related to the fact that they perceived daily stressors to be more severe than other nonlonely participants even though the stressors measured were the same (Cacioppo et al., 2000). Additionally, physical consequences have also been associated with cybervictimization and perpetration. In a survey of 7,430 gay or bisexual males in Canada those who had experienced cyber victimization within the past year had statistically significant predictions of both increased levels of physical, and verbal violence, as well as having no social support. Also, 3,143 participants reported taking opioid pain medications to deal with the pain of being victimized (Lam, Ferlatte, & Salway, 2019). In another study, 150 Arab American participants were asked about cyberbullying behaviors; 34% of respondents said they had been victimized within the past year, and 27% reported they had been perpetrators. The most common cyberbullying platforms were texting, Instagram, and Facebook. Finally, cyberbully perpetration significantly predicted physical complaints (p =.001), while cyberbully victimization predicted psychological stress (p =.01; Albdour et al., 2019). Due to the variables reviewed above that have been associated with loneliness and cyberbullying behaviors, outcome measures for both mental (i.e., depression, perceived stress, state/ trait anxiety) and physical health (i.e., obesity and physical symptoms), were tested in the current study. Not only was it important to investigate the relationship between levels of loneliness and cyberbullying, but it was also crucial to examine other variables that impacted the association between loneliness and health outcomes such as cyberbullying behaviors (see Figure 1).

Cyberbullying

The prevalence rates of cyberbullying are on the rise. In a recent study, 17.4% of students said they were a target of cyberbullying in 2019, compared to 16.5% in 2016 (Cyberbullying Research Center, 2019). Additionally, 34% of college students surveyed reported experiencing cyberbullying in their lifetime; and 17% said that it had happened in the last 30 days (Galoustian, 2017; Patchin et al., 2020). Also, upon examining 159 studies it was calculated that victimization prevalence rates within the last year ranged from 1.0% to 61.1%, whereas perpetration rates during the same time period ranged from 3.0% to 39.0%. Lifetime victimization rates ranged from 4.9% to 65.0% whereas lifetime perpetration rates varied between 1.2% and 44.1% (Brochado, Soares, & Fraga, 2017). It was also reported that for adults in the U.S., 20% of the participants admitted that the majority of the cybervictimization they had experienced in their lifetime had occurred in adulthood. Of these respondents, 73% reported that the perpetrator was a colleague or co-worker. Also, 24% indicated that they had been bully perpetrators in their lifetime, and 13.2% reported that the majority of the times that they had been bully perpetrators it was as adults (Kowalski,Toth, & Morgan, 2017). The most-reported cyberbullying behaviors included spreading rumors (60%), posting mean comments (58%), and/or threatening to hurt someone (54%; Florida Atlantic University Cyberbullying Research Center, 2017). Other types of cyberbullying included flaming, online harassment, cyberstalking, denigration, masquerading, trickery/outing, exclusion, trolling, sexting, sockpuppeting, doxing, and catfishing (Willard, 2007; stopbullying.gov, 2018; Nuccitelli, 2020). Girls were more likely to have been victimized online, whereas boys were more likely to have bullied others online. Additionally, increased time spent online equated to an increased risk of being victimized, and those who were traditionally bullied also had increased prevalence rates of being victimized (Kowalski, Limber, & McCord, 2019). For Example, it was reported that most cyberbullying for younger adolescents occurred on Instagram (42%), Facebook (37%), Snapchat (31%), WhatsApp (12%), YouTube (10%), and Twitter (9%; Ditch Lab, 2017).

To investigate cyberbullying outcomes, it was first important to comprehend how cyberbullying has previously been defined. There has been no agreed upon definition of this construct due to several issues, including how to measure the repetition of a cyberbullying act and how to capture the intent/perceptions of an act. In the cyber world, an action can be conducted once by a bully, but with the click of a button, multiple users can see a behavior repeatedly and can even share or post comments adding to a perpetrator's initial act. For example, a person may post an embarrassing photo of their classmate, but this photo may be reposted or further mean comments may appear by other viewers. This begs the question as to how many times a cyber perpetrator must commit an act for it to be considered cyberbullying. Also, it has been nearly impossible to get at the intent behind a behavior. A bully might intend to evoke harm to the victim; however, if a victim did not interpret the behavior as harmful, was it still considered a cyberbullying incident? Based on the findings of a meta-analysis that considered multiple factors including repetition and intent of behaviors, the current study used the following definition of cyberbullying: "cyberbullying is intentional and repeated harm inflicted on others through the use of electronic devices " (Peter & Petermann, 2018; Cyberbullying Research Center, 2016). Therefore, if an act is repeated, including a person posting an embarrassing photo of their classmate only one time, but that photo is then reposted or further mean comments appear by other viewers, this would be considered cyberbullying. Also, intentional harm for a cyberbullying act means that the mere perception of an act, even if accidental, as being cyberbullying does not count, only intentional cyberbullying behavior is legitimate.

Not only have there been questions raised concerning how to define cyberbullying, but researchers have also identified several issues regarding the measurement of cyberbullying, including using poor psychometrically validated scales, participants responding in a socially desirable way, using small sample sizes, or only using one item to measure behaviors of cyberbullying. For instance, one study found that prevalence rates differed depending on whether one-item or multiple-items measured cyberbullying behaviors (Pieschl et al., 2013). When assessed with multi-item instruments, it was about twice as high as when assessed with a one-item instrument. Boateng et al., (2018) also pointed out that using a one-item instrument caused a study to lack reliability. Rather, it was best practice to use multiple items that previously were psychometrically tested. To address these issues, the current study used the Cyberbullying Experience Survey (Doane et al., 2013). This survey had several strengths, such as being psychometrically sound, including having good internal consistency and convergent validity, accounting for social desirability, considering internet use, and being developed using a college student sample (Doane et al., 2016; Doane, Pearson, & Kelley, 2013). Also, this scale measured the two main roles involved with cyberbullying: perpetration and victimization. Additionally, the Cyberbullying Experience Survey asked about cyberbullying behaviors that occurred in the past month, which provided more accurate prevalence rates for cyberbullying outcomes as compared with a scale that used an unspecified timeline. Finally, one thing that is unique about the Cyberbullying Experience Survey is that it accounts for different types of perpetration and victimization behaviors. More specifically, these behaviors include public humiliation, malice, unwanted contact, and deception. Public humiliation behaviors measure events that have occurred in a public space such as distributing electronic information while pretending to be someone else, posting an embarrassing picture publicly, logging into or having someone else log into another individuals online account pretending to be them. Malice behaviors concern name calling, such as calling someone or having someone call you a mean name online using curse words, being teased or teasing another person, or being made fun of online. Unwanted contact was associated with unwanted sexual behaviors. For example, some behaviors measured included sending or receiving a nude or pornographic picture that you did not want from someone electronically, sending or receiving an unwanted sexual message from someone electronically, or sending or receiving a pornographic picture that was not wanted. Finally, examples of deception behaviors included pretending to be another person while talking to someone electronically, lying or having someone else lie about you to someone electronically, or sharing personal information with someone you did not realize was who you thought it was.

Next, researchers have defined cyberbullying roles in several different ways. Generally, there are three main people involved in cyberbullying including the perpetrator or the person who is committing the act of cyberbullying, the victim or person who is the target being bullied, and the bystanders or those who witness perpetration and/or victimization. Furthermore, Dilmac (2009) classified those involved in cyberbullying into four categories- a). Non-bully-victims - witnesses of cyberbullying, b). Pure-victims-those who experience being cyber-bullied, c). Purebullies-those who cyberbully others, and d). Bully-victims- those who have experienced both perpetration and victimization. Also, a new category of bystanders has been generated termed "upstanders" or individuals who witness bullying and do something about it such as telling the appropriate authority figure (bullybust.org). While there are several roles that have been identified, researchers have focused on two roles including cybervictimization, and cyber-perpetration. For instance, 15% of students reported online victimization (National Center for Educational Statistics, 2017), and in another survey 62% of respondents stated that online harassment was a major problem. Also, four out of ten people reported that they had experienced being victimized online including offensive name calling, purposeful embarrassment, and other forms of harassment (Duggan, 2017). Additionally, Dilmac (2009) found that 55.3% of college students had experienced at least one instance of cybervictimization, while 22.5% of participants admitted to being cyber-perpetrators. Livazovic & Ham, (2019) also reported that more males were cyberbully- perpetrators compared with females, and victims reported being emotionally distressed including feeling helpless, sorrowful, and angry. Other factors that were correlated with cyberbully perpetration were having a less educated mother, not being academically successful, decreased quality of family and peer relationships, and reduced overall school attainment (Livazovic & Ham, 2019; Kowalski et al., 2019). Because most research has focused on these two specific roles of cyberbullying behavior, the current study also focused on these two behaviors.

Furthermore, there have been several theoretical approaches to understanding cyberbullying and its consequences. Such theories include the Theory of Reasoned Action (Doane, Pearson, & Kelly, 2014), the Theory of Planned Behavior (Heriman & Walrave, 2012), the General Aggression Model (Kowalski et al., 2014; Savage & Tokunaga, 2017), the General

Strain Theory (Patchin & Hinduja, 2011), I-Cubed Theory (Finkel, 2014), and Problem Behavior Theory (Kırcaburun et al., 2019). The most comprehensive theory of cyberbullying has been the Bartlett & Gentile Cyberbullying Model (2012), leading to its wide adoption (Ansary, 2020; Barlett, Chamberlin, & Witkower, 2017; Barlett et al., 2019; Barlett, & Kowalewski, 2019). One reason this model has been widely adopted and applied to cyberbullying research is because of its four postulates that explain how traditional bullying and cyberbullying are different. Postulate one states that cyberbullying behaviors emerge as the result of several successful learning trials (i.e., acts of perpetration). Also, contained within postulate one are five assumptions regarding perpetrators including the following, 1. Perpetrators are less known to their victims due to anonymity, 2. Physical-size differences cannot be observed between a cyberbully and their victim therefore size is not relevant, 3. Physical damage cannot be seen such as scarring, but there are still negative consequences resulting in harm, 4. Perpetrators do not see the harmful effects of their actions on their victims, 5. It is hard to identify perpetrators by authority figures and parents resulting in no punishment associated with their actions. Moreover, according to the second postulate, perpetration behavior becomes automated as it is repeated leading to a positive attitude, as well as becoming integrated into an individual's personality (postulate three). Therefore, perpetration behavior continues in a cyclic manner because it is understood that this process of perpetration occurs in small increments, as opposed to traditional bullying (postulate four). However, this model has a few limitations, including no biological components and a lack of statistical rigor. For example, Barlett (2017, pg. 273) stated that the Bartlett & Gentile Cyberbullying Model " does not yet posit moderated mediation relationships". Also, Kowalski et al., (2014) suggested that more research was needed to explain the biological, psychological, and social aspects of cyberbullying behaviors. In applying a more holistic approach to the study of cyberbullying, the Jensen-Campbell Stress Model of Peer Victimization (Knack, Jensen-Campbell, & Baum, 2011) was used in the current study.

According to the Jensen-Campbell Stress Model of Peer Victimization (Knack, Jensen-Campbell, & Baum, 2011) when an individual is victimized, they experience activation of the sympathetic nervous system (i.e., the fight or flight response). Over time, as a victim continues to experience being bullied this response becomes chronic, thus resulting in dysregulation of the Hypothalamic-Pituitary-Adrenal-Cortical axis. These physiological changes result in physical harm as evidenced by increased inflammation, cortisol levels, and cellular aging. For example, social victimization was associated with shorter telomeres and poorer health outcomes (Guarneri-White et al., 2018). It was also found that better physical health predicted decreased scores of cyber-perpetrations (Rodelli et al., 2018). These results suggested that healthy lifestyle factors reduced the chance(s) that individuals would be more vulnerable to stress that resulted in cyberbullying. Note this study used BMI as a measure of physical health, therefore the current study also used the measure of BMI as one manner to assess one's physical health.

It was also found that victimized students reported physical symptoms associated with cyberbullying (Vaillancourt Faris, & Mishna, 2017). Specifically, victims had twice the likelihood of reporting that they experienced headaches and stomach aches (Gini & Pozzoli, 2013). Additionally, it was reported that those who experienced peer victimization had increased levels of stress, higher cortisol levels, and worse health outcomes (Knack, Jensen-Campbell, & Baum, 2011). In a longitudinal study both social and physical victimization were related to increased frequency and severity of health problems (Iyer-Eimerbrink and Jensen-Campbell, 2019). Because physical symptoms have been found to be related to cyberbullying the current study also examined this variable.

Moreover, not only has cyberbullying been associated with poorer physical health, but it has also been related to worse mental health. For instance, results from one study found that for college females, increased cyberbullying perpetration was associated with increased depression (Selkie et a1., 2015). Another study reported that depression directly predicted problematic social media use, and indirectly predicted cyberbullying perpetration (Kircaburum et al., 2019). The association between cyberbullying and suicide has been labeled as " bullycide" (Wallace, 2011). Because depression has been found to be related to cyberbullying, this measure was also considered in the current study. Additionally, perceived stress has been found to be related to cyberbullying and increased cortisol levels (Gonzalez-Calvete et al., 2017; Gonzalez-Calvete et al, 2018). Specifically, cyber-victims had the highest reports of perceived stress. Also, cyberbullying has been associated with anxiety. It has been suggested that the physical effects of being victimized cause more chronic damage because cyberbullying can occur 24/7 and has been found to induce more anxiety than traditional bullying (Campbell et al., 2012). Kowalski et al., (2019) also reported that cyber victimization was related to both greater scores of anxiety and increased social media usage. Therefore, the current study examined both state and trait anxiety. To review, many physical and mental health outcomes have been associated with cyberbullying including obesity, physical symptoms, depression, perceived stress, and anxiety. Therefore, these variables were also investigated in the current study. Additionally, indirect effects of variables were also examined including social support, and cyberbullying behaviors.

Social Support

Because prevalence rates of loneliness and cyberbullying have been on the rise simultaneously, it was important that the current study also investigated how other variables, such as social support, may have explained the relationship between levels of loneliness and predicted health outcomes, while at the same time the use of social media, either Instagram or Twitter use, may also be influencing this relationship (see Figure 2). Positive social support is important to have because it helps to buffer against harmful physical and mental effects associated with a lack of support. For example, in depressed participants, those who had decreased scores of perceived social support also had worse health outcomes including more physical symptoms, longer recovery, and decreased social functioning (Wang et al., 2018). Also, it was found that for adults living in a nursing home those who had the highest reported levels of loneliness also had the lowest levels of social support (Eskimez et al., 2019). As participants levels of social support increased, their levels of loneliness also decreased. Concerning cyberbullying, social support is also an important variable to consider. For example, 14% of students who were bullied admitted that it had negatively impacted their relationships with friends, and family (National Center for Education Statistics, 2017). Additionally, researchers (Srabstein & Piazza, 2008) pointed out that, “cyberbullies are people who need social support". Pabian (2019) found that for participants who had experienced cybervictimization they reported the highest levels of depressive symptoms and anxiety, as well as had the lowest levels of well-being and family support. These results highlight how social support and health outcomes go hand-in-hand. One way that people may gain more social support is using social media. Wong, Amon, & Keep (2019) surveyed 313 college aged participants and found that an increased desire to belong statistically and positively predicted increased Instagram use, total perceived social support, and, more specific, perceived social support from friends, family, and significant others. This study showed that social media applications like Instagram can in fact be used to gain social support. Also, Wynn et al., (2017) found that Twitter posts concerning the hashtag “depression” were associated with anxiety and negative emotions providing evidence that social media may not be a consistent means to gain positive social support. As evidenced in this study, it was important to mention that social support could be positive (e.g., Tweeting a friendly message of condolences to a friend) or negative (e.g., unwanted attention such as posting a message asking about the status of a friend's illness after being told not to do so). Due to these findings, it was essential that the current study captured the effect social support had in explaining the relationships between the interaction of social media use and loneliness on predicting mental and physical health outcomes (see Figure 2).

Finally, while the literature surrounding loneliness and cyberbullying is limited, the literature concerning loneliness, social media use, and cyberbullying is nearly nonexistent. This presented a significant gap in the literature. For instance, Bartlett et al., (2018) stated that "the Barlett & Gentile Cyberbullying Model does not theorize social media exposure into its theorizing, but if future work can replicate these findings while including other more established theory-driven cyberbullying predictors, then the theory can be modified to include social media exposure." The results obtained from the current study attempted to fill this gap in the literature by identifying, additional "theory-driven cyberbullying predictors" including social media use, and other possible variables like social support that might explain the effects of loneliness in predicting health outcomes (see Figures 1 & 2). Also, it was suggested by a 2018 National Panel Survey of Demographic, Structural, Cognitive, and Behavioral Characteristics that more research should examine, "statistical models to understand what individual factors are most strongly related to loneliness, including daily behaviors like using text-based versus image-based social media applications, along with demographic factors like gender, race and income. Such data will provide actionable insights for cultivating programs to enhance social well-being and connectivity" (Bruce et al., 2019). Therefore, the current study investigated this exact research suggestion. In order to best interpret and apply the results obtained from this study to answer this research suggestion, it was imperative that some of the variables be controlled. Meaning that, research has shown the variables of sex, age, and socioeconomic status have impacted levels of loneliness, cyberbullying behaviors, and social media use.

Covariates

Sex

In a recent meta-analysis, it was found that between males and females there were no statistically significant differences concerning levels of loneliness across the lifespan (Mund et al., 2020). However, in a classic study, while researchers found no sex differences in UCLA loneliness scores, they did report that for males they reacted to loneliness more negatively (i.e., reported lower scores of self-esteem, anxiety, life satisfaction, happiness, depression, and risk taking behaviors) compared to females (Maes et al., 2019; Schultz & Moore, 1986). It was hypothesized that males attributed feelings of loneliness to personal failure rather than other uncontrollable sources. With regards to cyberbullying, sex differences have existed in both the perpetrator and victim roles. In a meta-analysis regarding sex differences, researchers found that more males compared to females were involved in cyberbullying perpetration (Sun, Fan, & Du, 2016). Additionally, one study found that high school males were more likely to be bullied and to bully others in-person, whereas females were more likely to be victimized and bully others via texting (Abeele & Cock, 2013). Also, another study suggested that males were more likely to engage in cyberbullying perpetration compared to females if they had previously been bullied online (Zsila et al., 2019). In examining differences between males and females using a college sample, it was reported that males had more incidents of cyberbullying, victimization, perpetration, and bystander intervention compared to females (Sun, Fan, & Du, 2016). Also, one study found that female undergraduate students had increased odds of being victimized about topics of sexual activity like nude pictures, while men were more likely to be victimized about topics concerning their skills/talents, as well as their sexual orientation (Brody & Vangelist, 2017). Finally, it has been found that the use of social media applications also differed based on sex. For example, Instagram use remained considerably higher among women (43%) than men (31%), but Twitter use remained higher for men (24%) than women (21%; Pew Research Center, 2019). Due to these differences observed in the literature, it was only appropriate that the current study also control for sex differences between participants.

Age

Next, age has been associated with differences in levels of loneliness, social media use, and cyberbullying. For example, Kowalski et al., (2019) reported that elementary school students engaged in cyberbullying via online gaming, while adolescents and adults used social media applications. Additionally, psychologists have found other factors that influence the prevalence rates of cyberbullying as it pertains to age such as an individual’s workplace environment, intimate relationships, previous experience of being bullied, family relationships, personality traits, preference for the type of technology used most often, etc. (Giumetti & Kowalski, 2019; Kowalski, Limber, & McCord, 2019; Kowalski & Toth, 2018; Kowalski, Toth, Morgan, 2018; Whittaker & Kowalski, 2015). For example, it was found that the type of technology used for perpetration reflected that which was most common with an age group (Kowalski, Limber, & McCord, 2019). For adolescents cyberbullying occurred most often on social media, whereas and for those 18 and older cyberbullying perpetration occurred more on mass multiplayer online games. Another study also found that for children who had been victimized, it predicted patterns of loneliness and social satisfaction into early and late adolescence, and that the more time college students spent on social media, the more likely they were to experience cyberbullying (Kochenderfer-Ladd & Wardop, 2001; Serkan, Hasan-Erguzen, & Atilla, 2011). Finally, as it pertains to age, since the current sample consisted of all young college students it was expected that they had more stable physical and mental health compared to a younger sample of pubescent adolescents, or elementary children. For example, it has been found that for younger children cybervictimization was associated with weight-bias, as well as social and emotional development (DePaolis & Williford, 2019; Lee, Jeong, & Roh, 2018). Younger children have less developed brains leading to a decrease in coping skills, as well as experience physical (e.g., growth spurts, neuronal pruning, etc.), and mental changes (e.g., hormonal and emotional changes) at a much more rapid rate than a mature young adult so they are physically and mentally more impacted by victimization. Based on such findings, it has become important that researchers examine young adults' behavior separately from children or adolescents, which is why the current study investigated participants aged 17-25.

Socioeconomic Status

Socioeconomic status was also an important covariate. Regarding loneliness, one study found that those who lived in lower income/ deprived neighborhoods had higher odds of loneliness (Algren et al., 2020). When social isolation, loneliness; and low socioeconomic status were combined they collectively predicted increased health-risk behaviors. Additionally, researchers reported that increased income was associated with decreased levels of loneliness, while lower-socioeconomic status correlated to increased levels of loneliness (Kiralp, & Serin, 2017; Luhmann & Hawkley, 2016). Also, this variable has been linked to cyberbullying. For instance, adolescent respondents from lower-income families were more likely than those from higher-income families to encounter certain forms of online bullying. For example, 24% of teens whose household income were less than $30,000 a year reported being the target of physical threats online, compared with 12% whose annual household income was $75,000 or more (Pew Research Center, 2018). Additionally, socioeconomic differences have been found in social media use. According to a recent survey individuals whose yearly income was less than $30,000, spent less time on both Instagram (35%) and Twitter (20%) compared to those individuals who reported a yearly income of more than $75,000 who spent more time on both Instagram (42%) and Twitter (31%). Because these differences were observed in the literature, it was only appropriate that the current study also controlled for socioeconomic status. Upon examination of the variable yearly family income it was extremely skewed, therefore it was determined that this was not an accurate reflection of socioeconomic status of the current study sample. Also, there was limited variability in education level and occupation because most of the study participants were freshmen college students who worked part-time jobs. However, it was reported that in previous studies difficulty paying bills was used to measure socioeconomic status. More specific, for adults, difficulty paying monthly bills was associated with increased levels of depression and anxiety (Marshell et al., 2020; Simić-Vukomanović et al., 2016). Therefore, it was found that difficulty paying monthly bills, coded as 1= yes, and no = 0, was the most accurate reflection of the current study samples socioeconomic status. To reiterate, if these variables were not controlled in the current study then it would be nearly impossible to know if any statistical differences found in health outcomes were due to the variables of interest in the study (i.e., loneliness, type of social media used, cyberbullying, social support), or due to other variables including sex, age, and or socioeconomic status.

Study Rationale/ Hypotheses

The goal of the current study was to examine the relationships between measures of loneliness, social media use, and cyberbullying behaviors to predict mental and physical health outcomes. First, because there is a lack of literature that has been published examining the relationship between loneliness and cyberbullying behaviors, the current study wanted to investigate this positive relationship. Also, The Evolutionary Theory of Loneliness posits that chronic loneliness can compromise one's health (i.e., cumulative deleterious effects postulate) due to a lack of beneficial relationships (i.e., salutary relationship postulate) which in turn can lead to spiteful behaviors (i.e., self-preservation postulate). More specific, based on these models it was believed that loneliness levels would increase due to image-based (i.e., Instagram) verses text-based (i.e., Twitter) social media application usage. Also, according to Jensen-Campbell's Stress Model of Peer Victimization, cyberbullying could result in physiological harm. This same type of relationship was expected to be found with cyberbullying behaviors such that increased use of an image-based social media application (i.e., Instagram) would be related to both cyberbullying perpetration (i.e., selfish/spiteful behavior), and victimization (i.e., lack protective social connections) and thus would predict poorer physical and mental health outcomes (see Figure 1). To test these relationships, 393 undergraduate students from the University of Texas at Arlington ages 17-25 completed several questionnaires for course credit. The purpose of this study was to get a better understanding of young adults' behaviors by considering the Evolutionary Theory of Loneliness's related postulates, and Jensen Campbell's Stress Model of Peer Victimization. Furthermore, the intent of reporting such outcomes is to improve interventions used to combat loneliness, and cyberbullying behaviors, which will ultimately improve an individual's mental and physical health. Based on the literature and rationales presented above, the following are outlined as the current study's hypotheses.

***Hypothesis 1*:** It was estimated that there would be a positive relationship between loneliness and cyberbullying behaviors.

***Hypothesis 2*:** In testing the self-preservation postulate, it was hypothesized that the relationship between loneliness and cyberbullying behaviors would be moderated by the type of application used including Twitter or Instagram (i.e., the relationship between loneliness and cyberbullying would be stronger when people have high use of Instagram versus Twitter).

***Hypothesis 3a*:** Based on the cumulative deleterious effects postulate, it was estimated that levels of loneliness would directly predict health outcomes. Specifically, increased levels of loneliness would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety).

Hypothesis 3b: Similarly, based on Jensen-Campbell's Stress Model of Peer Victimization, it was estimated that levels of cyberbullying would directly predict health outcomes. Specifically, increased levels of both cyberbullying perpetration and victimization would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety).

Hypothesis 4: Based on the salutary-relationship postulate and the Jensen-Campbell Stress Model of Peer Victimization, it was estimated that cyberbullying would explain the relationship between loneliness and health outcomes, while at the same time use of social media applications would also help explain the effects of loneliness in predicting health outcomes (see Figure 1).

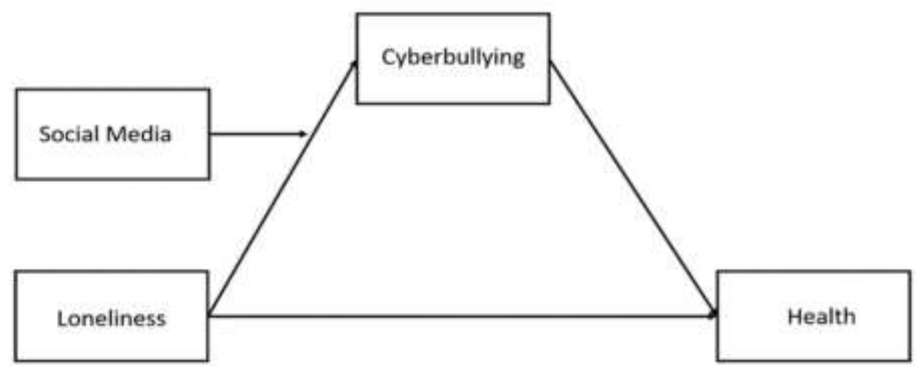

Figure 1. This models demonstrates the relationships that were tested in hypothesis 4 including that the relationship between loneliness and health outcomes would be moderated by cyberbullying behaviors, while at the same time use of social media, either Instagram or Twitter, would influence the relationship between loneliness and cyberbullying, thus acting as a mechanism through which loneliness may have indirect effects on health outcomes.

Hypothesis 5: Finally, also based on the salutary-relationship postulate and the Jensen-Campbell Stress Model of Peer Victimization, it was estimated that social support would account for the relationship between loneliness and health outcomes, while at the same time use of social media applications, either Twitter or Instagram, would also moderate the effects of loneliness in predicting health outcomes (see Figure 2).

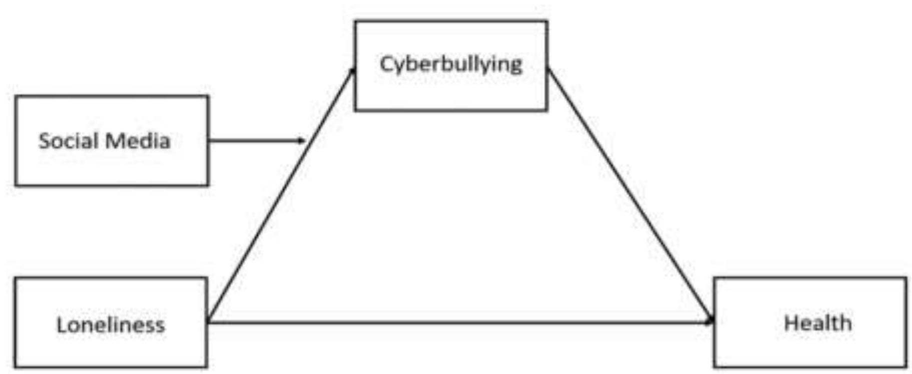

Figure 2. This models demonstrates the relationships that were tested in hypothesis 4 including that the relationship between loneliness and health outcomes would be moderated by social support, while at the same time use of social media, either Instagram or Twitter, would influence the relationship between loneliness and social support, thus acting as a mechanism through which loneliness may have indirect effects on health outcomes.

Chapter 2

Methods

Participants

Undergraduate students (*N* = 393) were recruited from a southwestern university as part of a larger study investigating how young adults use their smartphones and how that use relates to mental health (see Table 1 for descriptive characteristics). Students were recruited from the University's psychology subject pool from September 2017 to April 2018 and were considered eligible if they were able to speak, read, and write in English, were an Apple or Android smartphone user, and were between 17-25 years old. Participation was completely voluntary, and students were given course credit as compensation for their time.

Table 1. ***Study Participant Demographic Information***

Race/Ethnicity	**Total**
Non-Hispanic White	108
Hispanic White	108
Non-Hispanic Black or African American	43
Hispanic Black or African American	2
Non-Hispanic American Indian or Alaska Native	2
Hispanic American Indian or Alaska Native	15
Non-Hispanic Asian	97
Non-Hispanic Hawaiian or Pacific Islander	1
Non-Hispanic Other	2
Non-Hispanic Other	24

Average Age	19.13

Sex	***N***
Males	92
Females	301

Undergraduate Level	***N***
Freshman	230
Sophomore	102
Junior	37
Senior	24

Difficulty Paying Monthly Bills	***N***
Yes	137
No	252

Measures

In the current study, an online questionnaire was used to measure self-reported smartphone use, physical health symptoms, body-mass-index (BMI), loneliness, cyberbullying behaviors, depression, perceived stress, state and trait anxiety, perceived social support, and various demographic characteristics. Note, composite variables were created for all the variables used in the current study by summing the items that corresponded to each scale resulting in a continuous variable(s).

Smartphone Use

The Smartphone Intensity Scale was derived from the Ellison Facebook Intensity Scale (Ellison, Steinfield, & Lampe, 2007), and was used to measure self-reported smartphone use. The Smartphone Intensity Scale was modified from Facebook Intensity Scale by extending the questions to include other applications and to get a sense of general smartphone use (Newell, & Liegey-Dougall, under review). The original Facebook Intensity Scale measured self-reported Facebook activity and the extent to which Facebook was perceived to be a part of an individual's day-to-day activities. Other popular social media platforms, commonly used applications, and disconnected activities were also added to the Smartphone Intensity Scale. Participants estimated the amount of time they spent on each application and activity with the choices "0 – I do not use this application", "1 – Less than 30 minutes", "2 – 30-60 minutes", "3 – 1-2 hours", "4 – 2-3 hours", "5 – 3-4 hours", "6 – 4-5 hours", and "7 – more than 5 hours" to estimate their use. The scale was scored in the same way as Steinfield, Ellison, and Lampe (2008) in which the answers were recoded to reflect the midpoint for each category (i.e., "3 – 1-2 hours" was coded as 90 minutes). This study evaluated the total use of Instagram, and Twitter. Also note, that while previous research has shown that the most prominent social media applications adults used were

YouTube and Facebook, these variables could not be used for the current study because this sample spent less time on Facebook (*M* = 46.79, *SD* =69.16) than Instagram (*M* =91.76 , *SD* =89.50), *t*(392) -9.45, *p* = .001, therefore, Facebook was not considered an appropriate social media platform. In contrast, participants reported spending an equal amount of time on Twitter as on Instagram (*M* =100.61 , *SD* = 114.80), *t(392)*1.37, *p* =.17. Additionally, because Twitter is based on hashtags, and allows you to interact via texting from your phone this makes it a platform that is more text-based, compared to Instagram which is set-up to focus on photos (Pittman & Reich, 2016).

Loneliness

Loneliness was measured using the revised UCLA Loneliness Scale (Russell, 1996). The 20-item scale measured an individual's subjective feelings of loneliness and social isolation on a four-point Likert scale from "1-Never" to "4- Often". To score this instrument, items were summed together generating a score ranging from 0 to 80, with a higher score representing increased feelings of reported loneliness. Cronbach's α was 0.90 for this study.

Cyberbullying

Cyberbullying was measured using the Cyberbullying Experience Survey (Doane et al., 2013). The 41-item scale measured both cybervictimization (first 21 items) and perpetration behaviors (remaining 20 items). This scale also assessed four types of incidents of cyberbullying including, malice, public humiliation, unwanted contact, and deception. Participants reported their answers using a six-point Likert scale from "1 = Never to 6 = Every Day/Almost Every Day". To score both instruments, items were summed together generating a score ranging from 0 to 126 for cybervictimization, and a score ranging from 0 to 120 for cyberbullying perpetration. For both scales a higher score represented increased incidence of cyberbullying behaviors.

Cronbach's α was .88 for cybervictimization, and 0.83 for cyberbullying perpetration for this study.

Body-Mass-Index

Body Mass Index was measured using the Center for Disease Control Formula: 703 x weight (lbs.) / [height (in)]^2. The formula serves as a measure of physical health as it is used to indicate obesity.

Chips

Physical symptoms were measured using the Cohen-Hoberman Inventory of Physical Symptoms (Cohen & Hoberman, 1983). This instrument is a 39-item scale asking participants about the perceived burden of physical symptoms they have felt in the last two weeks using a five-point Likert scale from "0 = Not Bothered" to "5 = Extremely Bothered". A total score of physical symptoms was created by summing across all items. Note the current study modified the original scale from 33 questions to 39 questions to include physical symptoms that would be specific to mobile phone use (e.g. hearing and vision problems etc.). Cronbach's α was 0.93 for this study.

Depression

Symptoms of depression were measured using the Center for Epidemiologic Studies Depression Scale-Revised (CESD-R; Eaton et al., 2004). This scale consisted of 20-items that closely reflect the criteria used to diagnose depression. Participants had to choose between five response options pertaining to how many days in the last month they might have been bothered by symptoms of depression ranging from "Not at All or Less than 1 Day to Nearly Every Day for 2 Weeks". To score this instrument, items were summed together generating a score ranging from 0 to 60, with a higher score representing increased feelings of reported depression. Cronbach's α was 0.93 for this study.

Perceived Stress

The current study measured stress using the Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983). The PSS is a self-report scale that consists of 10-items that measure the degree to which situations in one's life are appraised as stressful. Participants must respond on a scale from "0-Never" to "4-Very often". To score this instrument, items were summed together generating a score ranging from 0 to 40, with a higher score representing increased feelings of reported perceived stress. Cronbach's α was 0.87 for this study.

State and Trait Anxiety

Anxiety was measured using the State-Trait Anxiety Inventory (STAI; Spielberger et al., 1983). The STAI consists of 40-items, with the first 20- items measuring state anxiety, while the remaining 20-items accounted for trait anxiety. Overall, anxiety was scored on a four-point Likert scale from "1 - Almost Never" to "4 - Almost Always". To score this instrument, items were summed together generating a score ranging from 0 to 80. Higher scores on the STAI indicated higher anxiety. Cronbach's α was 0.86 for state anxiety, and 0.93 for trait anxiety for this study.

Social Support

Social support was measured using the Interpersonal Support Evaluation List (ISEL; Cohen et al.,1983). The 12-item scale measured an individual's subjective feelings of social support on a four-point Likert scale from "1-Definitely True" to "4-Definitely False". To score this instrument, items were summed together generating a score ranging from 0 to 48, with a higher score representing increased feelings of reported social support. Cronbach's α was 0.85 for this study.

Procedure

The current study was conducted completely online through Qualtrics. Once in Qualtrics, participants were given a detailed description of the study and were provided the informed consent document. No deception was used for this study, and participants were told the purpose was to understand how young adults used their smartphone and social media, and how that use related to habits, mood, feelings, relationships, and health. After participants provided consent and verified their eligibility, they completed the Smartphone Intensity Scale. Next participants answered questions that assessed physical health, loneliness, depression, perceived stress, and anxiety. Additionally, participants completed three attention check questions that were scattered throughout the survey. The attention check questions asked participants to respond a certain way to assure they were paying attention and reading the questions. Overall, the survey took approximately one hour to complete, and once completed participants were thanked for their time and credit was automatically awarded to their subject pool account.

Power Analysis

Before any of the hypotheses were tested, power analyses were conducted to ensure the proposed analyses would be adequately powered for each hypothesis, as stated below. Meaning there would be decreased likelihood that the null hypothesis would be mistakenly rejected, and that a robust effect indeed would be detected. The estimated effect sizes were based off previous findings in the literature for the proposed hypotheses below (Ali, 2018; Amon, & Keep, 2019; Barlett, Chamberlin, & Witkower, 2017; Barlett, & Kowalewski, 2019).

Hypothesis 1: A power analysis for a linear regression, fixed model was conducted in G-Power to determine a sufficient sample size using an alpha of .05, a power of 0.80, a medium effect size ($f^2 = .15$), and one predictor (i.e., loneliness), plus three covariates (i.e., sex, age, socioeconomic status). Based on these standards, an adequate sample size would be 55 participants. The current study had 393 participants, so it was concluded that this hypothesis's analysis had sufficient power to be conducted.

Hypothesis 2: A power analysis for a linear multiple regression, fixed model was conducted in G-Power to determine a sufficient sample size using an alpha of .05, a power of 0.80, a medium effect size ($f^2 = .15$), and five predictors (i.e., loneliness, Twitter Time, Instagram Time, loneliness x Twitter Time; loneliness x Instagram Time), plus three covariates (i.e., sex, age, socioeconomic status). Based on these standards, an adequate sample size would be 92 participants. The current study had 393 participants, so it was concluded that this hypothesis's analysis had sufficient power to be tested.

Hypothesis 3***:*** A power analysis for a linear regression, fixed model was conducted in G-Power to determine a sufficient sample size using an alpha of .05, a power of 0.80, a medium effect size ($f^2 = .15$), and three predictors (i.e., loneliness, cybervictimization, cyberbullying perpetration), plus three covariates (i.e., sex, age, socioeconomic status). Based on these standards, an adequate sample size would be 77 participants. The current study had 393 participants, so it was concluded that this hypothesis's analysis had sufficient power to be tested.

Hypothesis 4: A power analysis for a linear regression, fixed model was conducted in G-Power to determine a sufficient sample size using an alpha of .05, a power of 0.80, a medium effect size ($f^2 = .15$), and nine predictors (i.e., loneliness, Twitter Time, Instagram Time, cybervictimization, cyberbullying-perpetration, 2-way interactions = loneliness x Instagram

Time; loneliness x Twitter Time; Instagram Time x Twitter Time; 3-way interactions = loneliness x Instagram Time x Twitter Time, plus three covariates (i.e., sex, age, socioeconomic status). Based on these standards, an adequate sample size would be 114 participants. The current study had 393 participants, so it was concluded that Hypothesis Four analyses had sufficient power to be conducted.

Hypothesis 5: A power analysis for a linear regression, fixed model was conducted in G-Power to determine a sufficient sample size using an alpha of .05, a power of 0.80, a medium effect size ($f^2 = .15$), and eight predictors (i.e., loneliness, Twitter Time, Instagram Time, social support, 2-way interactions = loneliness x Twitter Time; loneliness x Instagram Time; Twitter Time x Instagram Time; 3-way interactions = loneliness x Twitter Time x Instagram Time), plus three covariates (i.e., sex, age, socioeconomic status). Based on these standards, an adequate sample size would be 109 participants, therefore Hypothesis Five analyses had sufficient power since there were a total of 393 participants.

Data Analysis

Hypothesis 1: To test hypothesis one that there would be a positive relationship between loneliness and cyberbullying behaviors of both total victimization and perpetration, as well as the subtypes of each of these cyberbullying behaviors a linear regression was used. At the same time, the moderating effect of sex was also tested. First, three covariates were entered into step one including sex, age, and socioeconomic status. Then, for the second step the variable of loneliness was entered, and the third step included the interaction term of loneliness and sex.

Hypothesis 2: Next, hypothesis two tested if different types of social media use; specifically, Instagram or Twitter, moderated the relationship between reported levels of loneliness and predicted cyberbullying, including victimization and perpetration, as well as the subtypes of each of these cyberbullying behaviors a moderated linear hierarchical regression was used. Three covariates including participant's sex, age, and socioeconomic status were entered in the first step of this model. Step two included the variables loneliness, Instagram time, and Twitter Time so that the direct effects of these variables could be examined in predicting cyberbullying behaviors. Finally, the third step included the interaction terms of loneliness and Instagram Time, as well as Loneliness and Twitter Time to examine the indirect effects of these variables in predicting the outcome measures of cybervictimization and perpetration.

Hypothesis 3: In order to test both the cumulous deleterious effects postulate (i.e., hypothesis one-a), and the Jensen- Campbell Stress Model of Peer Victimization (i.e., hypothesis two-b), stated in hypothesis three, to see if loneliness, cybervictimization, and cyberbullying perpetration directly predict various physical and mental health outcomes a linear hierarchical regression was run. The first step for each model included three covariates: participants sex, age, and socioeconomic status. Step two included the variables loneliness, cybervictimization, and cyberbullying perpetration, as well as all the subtypes of cyberbullying behaviors. The outcome variables for all the models tested included obesity, physical symptoms, perceived stress, depression, and state, as well as trait anxiety scores. Note each outcome variable was tested independently.

Hypothesis 4: To test the fourth hypothesis that cyberbullying would explain the relationship between loneliness and health outcomes, while at the same time use of a social media application, either Instagram or Twitter, would also moderate the indirect effects of loneliness in predicting health outcomes a linear hierarchical regression was used (see Figure 1). Step one included sex, age, and socioeconomic status as covariates, while step two tested the direct effects of the following variables: Loneliness, Instagram Time, Twitter Time, Cybervictimization, Cyberbullying Perpetration, as well as included all of the subscales for both forms of cyberbullying. Step three examined the indirect effects or two-way interactions of Loneliness, Twitter Time, and Instagram Time. The final step tested the three-way interactions between Loneliness, Twitter Time, and Instagram Time. Also, because this model involved moderated mediation, it was appropriate to use the macro PROCESS Model 7. This modeling tool was used to confirm the direct and indirect effects of the two-way, and three-way interactions including examining moderated mediation. The output provided a precise measure of the points in which the variable interaction had a significant effect on the predicted outcome measure. It is also important to understand that the outcome variables including obesity, physical symptoms, perceived stress, depression, and state, as well as trait anxiety scores, were tested in separate models.

Hypothesis 5: To test hypothesis five that social support would explain the relationship between loneliness and health outcomes, while at the same time use of a social media application, either Instagram or Twitter, would also influence and help explain this relationship, a linear hierarchical regression was used (see Figure 2). Step one included sex, age, and socioeconomic status as covariates, while step two tested the direct effects of the following variables: Loneliness, Instagram Time, Twitter Time, and Social Support. Step three examined the indirect effects or two-way interactions of Loneliness, Twitter Time, and Instagram Time. Next, the final step tested three-way interactions between Loneliness, Twitter Time, and Instagram Time. Because this model involved moderated mediation, it was appropriate to use the macro PROCESS Model 7. This modeling tool was used to confirm the direct and indirect effects of the two-way, and three-way interactions including examining moderated mediation.

The output provided a precise measure of the points in which the variable interaction had a significant effect on the predicted outcome measures. Finally, the outcome variables including obesity, physical symptoms, perceived stress, depression, and state, as well as trait anxiety scores, were tested in separate models

Chapter 3

Results

Data Screening

Before data were analyzed, they were examined for an inappropriate amount of missing data and patterns, outliers, and skewness. While completing the survey, participants had to answer three attention check questions (i.e., if you are reading this please select answer choice number three). A filter was then created to exclude any participant that did not answer any of the attention check question(s) correctly. Ultimately, the data were filtered down from 507 participants to 393. This screening process also eliminated several outliers. In total, there were 22 missing participant cases, but the pattern of missing data were missing at random. Additionally, all assumptions were examined and data were corrected to meet the required assumptions including linear relationship(s) (i.e., a correlation matrix was conducted-see Table 2, and P-P plots were examined), normality (i.e., data were transformed, and centered due to this assumption being violated, however after transformations were applied, data were then again examined using box-and-whisker plots/histograms, as well as scores for mean, median, mode, skewness, and kurtosis were examined. Collectively all the measures examined indicated that the transformations had corrected the data to keep the assumption of normality), multicollinearity (i.e., all VIF scores were between 1-10), homoscedasticity (i.e., residual plots were examined for a random pattern), and finally the assumption of independence was assumed.

As mentioned above, in examining the variables of interest for the current study, several of them were positively skewed (i.e., Twitter Time, Instagram Time, Cybervictimization, Cyberbullying Perpetration, Illness Symptoms (i.e., physical symptoms), State Anxiety, and Depression). To correct this, various transformations were applied to the data. For example, a square-root transformation was applied to the variables of Twitter Time, Instagram Time, State anxiety, and Depression. A logarithmic transformation was applied to the variables of Illness Symptoms, Cyberbullying Perpetration, Cybervictimization, and all the subscales used (i.e., public humiliation, malice, unwanted contact, deception for both perpetration and cybervictimization) and no transformations were required for Perceived Stress, Loneliness, Social Support or measures of Trait anxiety.

Table 2. ***Zero Order Correlation Matrix for All the Variables In The Current Study***

Zero-Order Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Age	1																						
2. Sex	-0.02	1																					
3. SES (Difficulty Paying Bills)	-0.04	0.04	1																				
4. Cyberbullying Total Perpetration	0.06	-0.22**	-0.04	1																			
5. Cyberbullying Total Victimization	-0.05	-0.14**	0.03	0.65**	1																		
6. Cyberbullying Perpetration Humiliation	-0.02	-0.03	-0.03	0.63**	0.45**	1																	
7. Cyberbullying Perpetration Malice	0.04	-0.22**	-0.01	0.95**	0.62**	0.49**	1																
8. Cyberbullying Perpetration Unwanted Contact	.11*	-0.17**	0.04	0.46**	0.26**	0.31**	0.26**	1															
9. Cyberbullying Perpetration Decpetion	0.01	-0.07	-0.05	0.47**	0.45**	0.25**	0.31**	0.29**	1														
10. Cyberbullying Victimization Humiliation	-0.06	-0.1	0.05	0.05**	0.76**	0.46**	0.44**	0.20**	0.35**	1													
11. Cyberbullying Victimization Malice	0.05	-0.17**	0.03	0.67**	0.09**	0.39**	0.69**	0.21**	0.37**	.61**	1												
12. Cyberbullying Victimization Unwanted Contact	-0.02	0.06	0.01	0.36**	0.76**	0.32**	0.31**	0.16**	0.32**	.43**	0.50**	1											
13. Cyberbullying Victimization Decption	0.02	-0.16**	0.02	0.41**	0.69**	0.26**	0.35**	0.28**	0.43**	.52**	0.47**	0.47**	1										
14. Instagram Time	-0.02	0.13**	-0.02	-0.12*	-0.04	-0.02	-0.08	-0.05	-0.09	-0.03	-0.06	0.06	-0.08	1									
15. Twitter Time	-0.22**	0.02	-0.01	0.06	0.09	0.15**	0.07	-0.02	0.01	0.05	0.08	0.16**	-0.05	0.22**	1								
16. BMI	0.001	0.1	0.07	0.03	0.01	0.04	0.02	0.06	-0.04	-0.04	0.02	0.004	-0.02	0.01	-0.01	1							
17. Physical Symptoms (Chips)	0.02	0.22**	0.09	0.19**	0.21**	0.19**	0.17**	0.1	0.11*	0.20**	0.20**	0.17**	0.15**	-0.03	-0.04	0.14**	1						
18. Social Support (ISEL)	-0.02	0.09	-0.11*	-0.06	-0.12*	-0.08	-0.02	-0.11*	0.17**	.11*	-0.13	-0.02	-0.13**	-0.02	0.03	-0.04	-0.14**	1					
19.Percieved Stress (PSS)	0.02	0.18**	0.19**	0.12*	0.21**	0.09	0.11*	0.05	0.07	.16**	0.19**	0.18**	0.18**	0.02	0.01	0.09	0.46**	-0.23**	1				
20. Depression (CESD)	0.07	0.12*	0.1*	0.16**	0.17**	0.14**	0.14**	0.1	0.11*	.14**	0.17**	0.16**	0.16**	-0.08	0.02	0.10*	0.56**	-0.29**	0.65**	1			
21. Trait Anxiety (STAI-T)	0.07	0.12*	0.17**	0.16**	0.15**	0.13**	0.15**	0.12*	.12*	0.09	0.17**	0.12*	0.12*	-0.07	-0.03	0.10	0.45**	-0.38**	0.73**	0.70**	1		
22. State Anxiety (STAI-S)	0.08	0.04	0.14**	0.17**	0.19**	0.15**	0.16**	0.17**	0.09	0.15**	0.22**	[illegible]	0.14**	-0.03	0.02	0.06	0.39**	-0.29**	0.59**	0.58**	0.71**	1	
23. Loneliness	0.06	0.03	0.08	0.08	0.15**	0.08	0.04	0.04	0.14**	0.10*	0.13*	0.11*	0.14**	-0.04	-0.13**	0.04	0.29**	-0.67**	0.41**	0.47**	0.54**	0.38**	1

**p < .05. ,*

***p <.01.*

Findings

***Hypothesis 1*:**

It was estimated that there would be a positive relationship between loneliness and cyberbullying behaviors. Overall, this hypothesis was partially supported because levels of loneliness predicted some forms of both perpetration and victimization outcomes (refer to Table 3-4). As expected, more loneliness uniquely predicted increased perpetration deception behavior. However contrary to what was predicted, loneliness was not a predictor of other forms of perpetration behavior, including total cyberbullying perpetration, and the subtypes of public humiliation, malice, and unwanted contact. Also, it appeared that being male as compared to female was instrumental in predicting overall cyberbullying perpetration behaviors. Specifically, being male predicted total perpetration scores and the subtypes of cyberbullying perpetration behaviors, including malice and unwanted contact. However, sex did not predict public humiliation or deception perpetration behaviors. Also, sex did not moderate the effects of loneliness in directly predicting perpetration behaviors. Age was also positively associated with perpetration of unwanted contact behavior but was not associated with any other forms of perpetration behaviors including total perpetration, public humiliation, malice, or unwanted contact, and difficulty paying bills was not a predictor of any perpetration behavior.

Also as expected, greater loneliness directly predicted more types of victimization behaviors. There was a positive relationship between scores of loneliness and total victimization, while accounting for the negative relationship between sex and total victimization. Also, as expected, there was a positive association between loneliness and several subtypes of victimization behaviors, including public humiliation, malice, unwanted contact victimization, and deception. Finally, being male predicted more victimization, specifically malice and deception behaviors. However, sex did not predict unwanted contact or public humiliation victimization behaviors, nor did sex moderate the effects of loneliness. Additionally, age and difficulty paying bills were not significant predictors of victimization behavioral outcomes.

Table 3. ***Direct Effects of Loneliness Predicting Outcome Measures of Cyberbullying Perpetration Behaviors Reflecting Hypothesis 1***

Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
Total Cyberbullying Perpetration							
Step 1 $\Delta F(3, 371) = 6.49$, $p < .000$, $\Delta R^2 = .05$							
Age	0.003	0.003	1.02	.31	[-0.003, 0.01]	.05	.05
Difficulty Paying Bills	-0.01	0.01	-0.55	.58	[-0.03, 0.01]	-.03	-.03
Sex	-0.05	0.01	-4.18	<.001**	[-0.07, -0.03]	-.21	-.21
Step 2 $\Delta F(1, 370) = 2.22$, $p = .14$, $\Delta R^2 = .006$							
Age	0.003	0.003	0.92	.36	[-0.003, 0.01]	.05	.05
Difficulty Paying Bills	-0.01	0.01	-0.69	.49	[-0.03, 0.01]	-.04	-.04
Sex	-0.05	0.01	-4.19	<.001**	[-0.07, -0.03]	-.21	-.21
Loneliness	0.001	<0.001	1.49	.14	[0.000, 0.002]	.08	.08
Step 3 $\Delta F(1, 369) = .07$, $p = .79$, $\Delta R^2 = .000$							
Age	0.003	0.003	0.93	.35	[-0.003, 0.01]	.05	.05
Difficulty Paying Bills	-0.01	0.01	-0.68	.50	[-0.03, 0.01]	-.04	-.03
Sex	-0.05	0.01	-4.18	<.001**	[-0.07, -0.02]	-.21	-0.21
Loneliness	0.001	0.001	0.92	.36	[-0.001, 0.003]	.05	.05
Loneliness X sex	<0.001	0.001	-0.26	.79	[-0.003, 0.002]	-.01	-.01
Perpetration - Public Humiliation							
Step 1 $\Delta F(3, 383) = 0.30$, $p = .83$, $\Delta R^2 = .002$							
Age	-0.002	0.004	-0.47	.64	[-0.01, 0.01]	-.02	-.02
Difficulty Paying Bills	-0.01	0.01	-0.67	.51	[-0.03, 0.02]	-.03	-.03
Sex	-0.01	0.01	-0.48	.63	[-0.03, 0.02]	-.02	-.02

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Step 2 $\Delta F(1, 382) = 2.93$, $p = .09$, $\Delta R^2 = .008$							
Age	-0.002	0.004	-0.58	.56	[-0.01, 0.01]	-.03	-.03
Difficulty Paying Bills	-0.01	0.01	-0.80	.42	[-0.03, 0.01]	-.04	-.04
Sex	-0.01	0.01	-0.53	.60	[-0.03, 0.02]	-.03	-.03
Loneliness	0.001	0.001	1.71	.09	[0.000, 0.002]	.09	.09
Step 3 $\Delta F(1, 381) = 0.03$, $p = .85$, $\Delta R^2 < .001$							
Age	-0.002	0.004	-0.57	.57	[-0.01, 0.01]	-.03	-.03
Difficulty Paying Bills	-0.01	0.01	-0.79	.43	[-0.03, 0.01]	-.04	-.04
Sex	-0.01	0.01	-0.54	.59	[-0.03, 0.02]	-.03	-.03
Loneliness	0.001	0.001	0.98	.33	[-0.001, 0.003]	.05	.05
Loneliness X sex	<0.001	0.001	-0.19	.85	[-0.003, 0.002]	-.01	-.01
Perpetration - Malice							
Step 1 $\Delta F(3, 382) = 6.50$, $p < .001$, $\Delta R^2 = .05$							
Age	0.004	0.01	0.71	.48	[-0.01, 0.02]	.04	.04
Difficulty Paying Bills	-0.002	0.02	-0.09	.93	[-0.04, 0.03]	-.01	-.01
Sex	-0.09	0.02	-4.33	<.001**	[-0.13, -0.05]	-.22	-.22
Step 2 $\Delta F(1, 381) = 0.90$, $p = .35$, $\Delta R^2 = .002$							
Age	0.004	0.01	0.64	.52	[-0.01, 0.02]	.03	.03
Difficulty Paying Bills	-0.003	0.02	-0.17	.87	[-0.04, 0.03]	-.01	-.01
Sex	-0.09	0.02	-4.35	<.001**	[-0.13, -0.05]	-.22	-.22
Loneliness	0.001	0.001	0.95	.35	[-0.001, 0.003]	.05	.05
Step 3 $\Delta F(1, 380) = 0.16$, $p = .69$, $\Delta R^2 = .000$							
Age	0.004	0.01	0.67	.51	[-0.01, 0.02]	.03	.03
Difficulty Paying Bills	-0.003	0.02	-0.16	.88	[-0.04, 0.03]	-.01	-.01
Sex	-0.09	0.02	-4.36	<.001**	[-0.13, -0.05]	-.22	-.22
Loneliness	0.002	0.002	0.80	.42	[-0.002, 0.01]	.04	.04

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Loneliness X sex	-0.001	0.002	-0.40	.69	[-0.01, 0.003]	-.02	-.02
Perpetration - Unwanted Contact							
Step 1 $\Delta F(3, 384) = 5.39$, $p < .05$, $\Delta R^2 = .04$							
Age	0.003	0.002	2.15	.03*	[0.000, 0.01]	.11	.11
Difficulty Paying Bills	0.01	0.01	0.97	.33	[-0.01, 0.02]	.05	.05
Sex	-0.02	0.01	-3.28	.001**	[-0.03, -0.01]	-.16	-.16
Step 2 $\Delta F(1, 383) = 0.40$, $p = .53$, $\Delta R^2 = .001$							
Age	0.003	0.002	2.10	.04*	[0.000, 0.01]	.11	.11
Difficulty Paying Bills	0.01	0.01	0.92	.36	[-0.01, 0.02]	.05	.05
Sex	-0.02	0.01	-3.29	.001**	[-0.03, -0.01]	-.17	-.16
Loneliness	<0.001	<0.001	0.63	.53	[0.000, 0.001]	.03	.03
Step 3 $\Delta F(1, 382) = 0.95$, $p = .33$, $\Delta R^2 = .002$							
Age	0.003	0.002	2.17	.03*	[0.000, 0.01]	.11	.11
Difficulty Paying Bills	0.01	0.01	0.95	.34	[-0.01, 0.02]	.05	.05
Sex	-0.02	0.01	-3.32	.001**	[-0.03, -0.01]	-.17	-.17
Loneliness	0.001	0.001	1.16	.25	[0.000, 0.002]	.06	.06
Loneliness X sex	-0.001	0.001	-0.98	.33	[-0.002, 0.001]	-.05	-.05
Perpetration - Deception							
Step 1 $\Delta F(3, 379) = 0.99$, $p = .40$, $\Delta R^2 = .008$							
Age	<0.001	0.003	0.11	.91	[-0.01, 0.01]	.01	.01
Difficulty Paying Bills	-0.01	0.01	-1.01	.31	[-0.03, 0.01]	-.05	-.05
Sex	-0.01	0.01	-1.33	.18	[-0.04, 0.01]	-.07	-.07
Step 2 $\Delta F(1, 378) = 7.87$, $p < .05$, $\Delta R^2 = .02$							
Age	<0.001	0.003	-0.08	.93	[-0.01, 0.01]	-.004	-.004
Difficulty Paying Bills	-0.01	0.01	-1.26	.21	[-0.03, 0.01]	-.07	-.06
Sex	-0.01	0.01	-1.35	.18	[-0.04, 0.01]	-.07	-.07

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Loneliness	0.001	<0.001	2.81	.01*	[0.000, 0.002]	.14	.14
Step 3 $\Delta F(1, 377) = 0.29$, p = 59, $\Delta R^2 = .001$							
Age	0.000	0.003	-0.05	.96	[-0.01, 0.01]	-.003	-.003
Difficulty Paying Bills	-0.01	0.01	-1.24	.22	[-0.03, 0.01]	-.06	-.06
Sex	-0.01	0.01	-1.35	.18	[-0.04, 0.01]	-.07	-.07
Loneliness	0.002	0.001	1.80	.07	[0.000, 0.004]	.09	.09
Loneliness X sex	-0.001	0.001	-0.54	.59	[-0.003, 0.002]	-.03	-.03

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness in predicting various types of cyberbullying perpetration behaviors reflecting Hypothesis 1.

**p*<.05, two-tailed
***p*<.01, two-tailed

Table 4. ***Direct Effects of Loneliness Predicting Outcome Measures of Cybervictimization Behaviors Reflecting Hypothesis 1***

	Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
	Total Cybervictimization							
Step 1	$\Delta F(3, 373) = 2.70$, $p = .046$, $\Delta R^2 = .021$							
	Age	-0.004	0.004	-1.03	.30	[-0.01, 0.004]	-.05	-.05
	Difficulty Paying Bills	0.01	0.01	0.66	.51	[-0.02, 0.03]	.03	.03
	Sex	-0.04	0.01	-2.60	.01*	[-0.06, -0.01]	-.13	-.13
Step 2	$\Delta F(1, 372) = 8.68$, $p < .003$, $\Delta R^2 = .021$							
	Age	-0.01	0.004	-1.22	.22	[-0.01, 0.003]	-.06	-.06
	Difficulty Paying Bills	0.01	0.01	0.45	.66	[-0.02, 0.03]	.02	.02
	Sex	-0.04	0.01	-2.65	.01*	[-0.06, -0.01]	-.14	-.13
	Loneliness	0.002	0.001	2.95	.003*	[0.001, 0.003]	.15	.15
Step 3	$\Delta F(1, 371) = 0.79$, $p = .38$, $\Delta R^2 = .002$							
	Age	-0.004	0.004	-1.17	.24	[-0.01, 0.003]	-.06	-.06
	Difficulty Paying Bills	0.01	0.01	0.45	.65	[-0.02, 0.03]	.02	.02
	Sex	-0.04	0.01	-2.66	.01*	[-0.06, -0.01]	-.14	-.13
	Loneliness	0.003	0.001	2.20	.03*	[0.000, 0.01]	.11	.11
	Loneliness X sex	-0.001	0.001	-0.89	.38	[-0.004, 0.001]	-.05	-.05
	Victimization - Public Humiliation							
Step 1	$\Delta F(3, 378) = 1.97$, $p = .12$, $\Delta R^2 = .02$							
	Age	-0.003	0.002	-1.30	.19	[-0.01, 0.002]	-.07	-.07
	Difficulty Paying Bills	0.01	0.01	0.91	.36	[-0.01, 0.02]	.05	.05
	Sex	-0.02	0.01	-1.88	.06	[-0.03, 0.001]	-.10	-.10
Step 2	$\Delta F(1, 377) = 4.21$, $p = 04$, $\Delta R^2 = .01$							

	Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Age	-0.004	0.002	-1.42	.16	[-0.01, 0.001]	-.07	-.07
	Difficulty Paying Bills	0.01	0.01	0.74	.46	[-0.01, 0.02]	.04	.04
	Sex	-0.02	0.01	-1.91	.06	[-0.03, 0.000]	-.10	-.10
	Loneliness	0.001	<0.001	2.05	.04*	[0.000, 0.002]	.11	.10
Step 3	$\Delta F(1, 376) = 1.59$, $p = .21$, $\Delta R^2 = .004$							
	Age	-0.003	0.002	-1.35	.18	[-0.01, 0.002]	-.07	-.07
	Difficulty Paying Bills	0.01	0.01	0.76	.45	[-0.01, 0.02]	.04	.04
	Sex	-0.02	0.01	-1.93	.05	[-0.03, 0.000]	-.10	-.10
	Loneliness	0.002	0.001	2.09	.04*	[0.000, 0.003]	.11	.11
	Loneliness X sex	-0.001	0.001	-1.26	.21	[-0.003, .0001]	-.06	-.06
	Victimization - Malice							
Step 1	$\Delta F(3, 382) = 4.39$, $p = .005$, $\Delta R^2 = .03$							
	Age	-0.01	0.01	-1.06	.29	[-0.02, 0.01]	-.05	-.05
	Difficulty Paying Bills	0.01	0.02	0.75	.45	[-0.02, 0.05]	.04	.04
	Sex	-0.07	0.02	-3.43	.001**	[-0.12, -0.03]	-.17	-.17
Step 2	$\Delta F(1, 381) = 7.73$, $p = .01$, $\Delta R^2 = .02$							
	Age	-0.01	0.01	-1.26	.21	[-0.02, 0.004]	-.06	-.06
	Difficulty Paying Bills	0.01	0.02	0.53	.60	[-0.03, 0.05]	.03	.03
	Sex	-0.07	0.02	-3.51	<.001**	[-0.12, -0.03]	-.18	-.18
	Loneliness	0.003	0.001	2.78	.01*	[0.001, 0.004]	.14	.14
Step 3	$\Delta F(1, 380) = 0.70$, $p = .41$, $\Delta R^2 = .002$							
	Age	-0.01	0.01	-1.20	.23	[-0.02, 0.01]	-.06	-.06
	Difficulty Paying Bills	0.01	0.02	0.55	.58	[-0.03, 0.05]	.03	.03
	Sex	-0.08	0.02	-3.54	<.001**	[-0.12, -0.03]	-.18	-.18
	Loneliness	0.004	0.002	2.07	.04*	[0.000, 0.01]	.11	.10
	Loneliness X sex	-0.002	0.002	-0.83	.40	[-0.01, 0.002]	-.04	-.04

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Victimization - Unwanted Contact								
Step 1	$\Delta F(3, 383) = 0.52, p = .67, \Delta R^2 = .004$							
	Age	-0.003	0.01	-0.46	.64	[-0.01, 0.01]	-.02	-.02
	Difficulty Paying Bills	0.001	0.02	0.05	.96	[-0.03, 0.04]	.002	.002
	Sex	0.02	0.02	1.14	.25	[-0.02, 0.06]	.06	.06
Step 2	$\Delta F(1, 382) = 4.63, p = .03, \Delta R^2 = .01$							
	Age	-0.003	0.01	-0.61	.54	[-0.01, 0.01]	-.03	-.03
	Difficulty Paying Bills	-0.002	0.02	-0.12	.91	[-0.04, 0.03]	-.01	-.01
	Sex	0.02	0.02	1.10	.27	[-0.02, 0.06]	.06	.06
	Loneliness	0.002	0.001	2.15	.03*	[0.000, 0.004]	.11	.11
Step 3	$\Delta F(1, 381) = 0.32, p = .57, \Delta R^2 = .001$							
	Age	-0.004	0.01	-0.65	.52	[-0.01, 0.01]	-.03	-.03
	Difficulty Paying Bills	-0.002	0.02	-0.13	.89	[-0.04, 0.03]	-.01	-.01
	Sex	0.02	0.02	1.12	.26	[-0.02, 0.06]	.06	.06
	Loneliness	0.001	0.002	0.55	.59	[-0.003, 0.004]	.03	.03
	Loneliness X sex	0.001	0.002	0.56	.57	[-0.003, 0.01]	.03	.03
Victimization - Deception								
Step 1	$\Delta F(3, 382) = 3.38, p = .02, \Delta R^2 = .03$							
	Age	0.001	0.01	0.22	.82	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	0.01	0.02	0.56	.58	[-0.02, 0.04]	.03	.03
	Sex	-0.05	0.02	-3.15	.002**	[-0.09, -0.02]	-.16	-.16
Step 2	$\Delta F(1, 381) = 8.09, p = .01, \Delta R^2 = .02$							
	Age	<0.001	0.01	0.04	.97	[-0.01, 0.01]	.002	.002
	Difficulty Paying Bills	0.01	0.02	0.33	.74	[-0.02, 0.03]	.02	.02
	Sex	-0.05	0.02	-3.24	.001**	[-0.09, -0.02]	-.16	-.16
	Loneliness	0.002	0.001	2.84	.01*	[0.001, 0.003]	.14	.14

	Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
Step 3	$\Delta F(1, 380) = 3.42$, $p = .07$, $\Delta R2 = .01$							
	Age	0.001	0.01	0.16	.87	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	0.01	0.02	0.39	.70	[-0.02, 0.03]	.02	.02
	Sex	-0.06	0.02	-3.31	.001**	[-0.09, -0.02]	-.17	-.16
	Loneliness	0.004	0.001	2.99	.003**	[0.002, 0.01]	.15	.15
	Loneliness X sex	-0.003	0.002	-1.85	.07	[-0.01, 0.000]	-.09	-.09

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness in predicting various types of cybervictimization behaviors reflecting Hypothesis 1.

*p<.05, two-tailed
**p<.01, two-tailed

Hypothesis 2:

In testing the self-preservation postulate, it was hypothesized that the relationship between loneliness and cyberbullying behaviors would be moderated by the type of application used, specifically, Twitter or Instagram (i.e., the relationship between loneliness and cyberbullying would be stronger when people have high use of Instagram versus Twitter). Overall, as not anticipated, this hypothesis was not supported. However, there were several direct effects that predicted cyberbullying behaviors (refer to Table 5-6). Pertaining to cyberbullying perpetration outcomes, contrary to what was expected such that there would be a positive relationship between loneliness and all the subtypes, as well as total perpetration behavior, increased levels of loneliness only predicted increased perpetration public humiliation and deception behaviors but was not a predictor for other types of perpetration outcomes, including total perpetration, malice, and unwanted contact. Also, males, as opposed to females, had increased predicted behaviors of total cyberbullying perpetration, malice, and unwanted contact. However, sex did not predict the subtypes of perpetration behaviors of public humiliation or deception. Age was also positively associated with perpetration of unwanted contact but was not related to all other types of perpetration outcomes (i.e., total perpetration, public humiliation, malice, and deception). As not expected, more time reported on Twitter directly predicted increased measures of total cyberbullying perpetration, as well as increased behaviors of public humiliation perpetration. However, contrary to what was hypothesized, time spent on Twitter did not predict the perpetration subtypes of malice, unwanted contact, or deception behaviors. On the other hand, more time spent on Instagram was associated with decreased predicted scores for total cyberbullying perpetration and did not predict any other subtypes of perpetration (i.e., public humiliation, malice, unwanted contact, and deception). Contrary to expectations, time spent on Instagram and Twitter did not moderate the relationship between loneliness and perpetration behaviors. Also, difficulty paying the bills was not associated with any perpetration outcomes.

Regarding cybervictimization, as expected, greater levels of loneliness directly predicted increased total cybervictimization, public humiliation victimization, malice, unwanted contact, and deception behaviors. It also appeared that being male compared to female had greater influence in predicting higher measures of total cybervictimization, malice, and deception behaviors. Sex was not related to public humiliation or unwanted contact victimization. Also, neither age nor difficulty paying the bills predicted any behaviors related to cybervictimization. Next, as expected, more time reported on Twitter directly predicted increased measures of total cybervictimization, as well as increased behaviors of malice and unwanted contact. In opposition to what was hypothesized, time spent on Twitter did not predict the perpetration subtypes of public humiliation or deception behaviors. Finally, also as not anticipated, time spent on Instagram was not associated with any cybervictimization behaviors. Also, no statistically significant interactions between Instagram and loneliness, or Twitter and loneliness emerged to predict cyberbullying or victimization outcomes (i.e., total perpetration and victimization, as well as all the subtypes).

Table 5. ***Direct Effects of Loneliness and Social Media Predicting Outcome Measures of Cyberbullying Perpetration Reflecting Hypothesis 2***

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Total Cyberbullying Perpetration							
Step 1 $\Delta F(3, 371) = 6.49$, $p < .001$, $\Delta R^2 = .05$							
Age	0.003	0.003	1.02	.31	[-0.003, 0.01]	.05	.05
Difficulty Paying Bills	-0.01	0.01	-0.55	.58	[-0.02, 0.01]	-.03	-.03
Sex	-0.05	0.01	-4.18	<.001**	[-0.07, -0.02]	-.21	-.21
Step 2 $\Delta F(3, 368) = 3.41$, $p = .02$, $\Delta R^2 = .03$							
Age	0.004	0.003	1.35	.18	[-0.002, 0.01]	.07	.07
Difficulty Paying Bills	-0.01	0.01	-0.73	.47	[-0.03, 0.01]	-.04	-.04
Sex	-0.04	0.01	-3.91	<.001**	[-0.07, -0.02]	-.20	-.20
Instagram Time	-0.01	0.01	-2.22	.03*	[-0.02, -0.001]	-.11	-.11
Twitter Time	0.01	0.01	2.17	.03*	[0.001, 0.02]	.11	.11
Loneliness	0.01	0.01	1.67	.09	[-0.001, 0.02]	.09	.08
Step 3 $\Delta F(2, 366) = 0.10$, $p = .91$, $\Delta R^2 < .001$							
Age	0.004	0.003	1.33	.18	[-0.002, 0.01]	.07	.07
Difficulty Paying Bills	-0.01	0.01	-0.72	.47	[-0.03, 0.01]	-.04	-.04
Sex	-0.04	0.01	-3.89	<.001**	[-0.07, -0.02]	-.20	-.20
Instagram Time	-0.01	0.01	-2.20	.03*	[-0.02, -0.001]	-.11	-.11
Twitter Time	0.01	0.01	2.18	.03*	[0.001, 0.02]	.11	.11
Loneliness	0.01	0.01	1.70	.09	[-0.001, 0.02]	.09	.09
Instagram Time X Loneliness	0.001	0.01	0.16	.88	[-0.01, 0.01]	.01	.01
Twitter Time X Loneliness	0.002	0.01	0.36	.72	[-0.01, 0.01]	.02	.02
Perpetration - Public Humiliation							
Step 1 $\Delta F(3, 383) = 0.30$, $p = .83$, $\Delta R^2 = .002$							

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Age	-0.002	0.004	-0.47	.64	[-0.01, 0.01]	-.02	-.02
	Difficulty Paying Bills	-0.01	0.01	-0.67	.50	[-0.03, 0.01]	-.03	-.03
	Sex	-0.01	0.01	-0.48	.63	[-0.03, 0.02]	-.02	-.02
Step 2	$\Delta F(3, 380) = 4.94, p = .002, \Delta R^2 = .04$							
	Age	0.001	0.004	0.18	.86	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	-0.01	0.01	-0.78	.44	[-0.03, 0.01]	-.04	-.04
	Sex	-0.01	0.01	-0.51	.61	[-0.03, 0.02]	-.03	-.03
	Instagram Time	-0.01	0.01	-0.96	.34	[-0.02, 0.01]	-.05	-.05
	Twitter Time	0.02	0.01	3.43	.001**	[0.01, 0.03]	.17	.17
	Loneliness	0.01	0.01	2.12	.03*	[0.001, 0.02]	.11	.11
Step 3	$\Delta F(2, 378) = 1.41, p = .25, \Delta R^2 = .01$							
	Age	<0.001	0.004	0.07	.94	[-0.01, 0.01]	.004	.004
	Difficulty Paying Bills	-0.01	0.01	-0.76	.44	[-0.03, 0.01]	-.04	-.04
	Sex	-0.01	0.01	-0.41	.68	[-0.03, 0.02]	-.02	-.02
	Instagram Time	-0.01	0.01	-0.98	.33	[-0.02, 0.01]	-.05	-.05
	Twitter Time	0.02	0.01	3.51	<.001**	[0.01, 0.03]	.18	.18
	Loneliness	0.01	0.01	2.26	.02*	[0.002, 0.02]	.12	.11
	Instagram Time X Loneliness	0.01	0.01	1.48	.14	[-0.003, 0.02]	.08	.07
	Twitter Time X Loneliness	0.002	0.01	0.39	.70	[-0.01, 0.01]	.02	.02
Perpetration - Malice								
Step 1	$\Delta F(3, 382) = 6.50, p < .001, \Delta R^2 = .05$							
	Age	0.004	0.01	0.71	.48	[-0.01, 0.02]	.04	.04
	Difficulty Paying Bills	-0.002	0.02	-0.09	.93	[-0.04, 0.03]	-.01	-.01
	Sex	-0.09	0.02	-4.33	<.001**	[-0.13, -0.05]	-.22	-.22
Step 2	$\Delta F(3, 379) = 2.30, p = .08, \Delta R^2 = .02$							
	Age	0.01	0.01	1.10	.27	[-0.01, 0.02]	.06	.05

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Difficulty Paying Bills	-0.003	0.02	-0.18	.86	[-0.04, 0.03]	-.01	-.01
	Sex	-0.09	0.02	-4.19	<.001**	[-0.13, -0.05]	-.21	-.21
	Instagram Time	-0.01	0.01	-1.49	.14	[-0.03, 0.004]	-.08	-.07
	Twitter Time	0.02	0.01	2.23	.03*	[0.002, 0.04]	.11	.11
	Loneliness	0.01	0.01	1.16	.25	[-0.01, 0.03]	.06	.06
Step 3	$\Delta F(2, 377) = 0.13$, $p = .88$, $\Delta R^2 = .001$							
	Age	0.01	0.01	1.11	.27	[-0.01, 0.02]	.06	.06
	Difficulty Paying Bills	-0.003	0.02	-0.18	.85	[-0.04, 0.03]	-.01	-.01
	Sex	-0.09	0.02	-4.19	<.001**	[-0.13, -0.05]	-.21	-.21
	Instagram Time	-0.01	0.01	-1.46	.14	[-0.03, 0.01]	-.08	-.07
	Twitter Time	0.02	0.01	2.23	.03*	[0.002, 0.04]	.11	.11
	Loneliness	0.01	0.01	1.16	.25	[-0.01, 0.03]	.06	.06
	Instagram Time X Loneliness	-0.003	0.01	-0.31	.75	[-0.02, 0.01]	-.02	-.02
	Twitter Time X Loneliness	0.004	0.01	0.47	.64	[-0.01, 0.02]	.02	.02
Perpetration - Unwanted Contact								
Step 1	$\Delta F(3, 384) = 5.39$, $p = .001$, $\Delta R^2 = .04$							
	Age	0.003	0.002	2.15	.03*	[0.000, 0.01]	.11	.11
	Difficulty Paying Bills	0.01	0.01	0.97	.33	[-0.01, 0.01]	.05	.05
	Sex	-0.02	0.01	-3.28	.001**	[-0.03, -0.01]	-.16	-.16
Step 2	$\Delta F(3, 381) = 0.27$, $p = .85$, $\Delta R^2 = .002$							
	Age	0.004	0.002	2.13	.03*	[0.000, 0.01]	.11	.11
	Difficulty Paying Bills	0.01	0.01	0.91	.37	[-0.01, 0.01]	.05	.05
	Sex	-0.02	0.01	-3.18	.002**	[-0.03, -0.01]	-.16	-.16
	Instagram Time	-0.001	0.002	-0.59	.55	[-0.01, 0.003]	-.03	-.03
	Twitter Time	0.001	0.003	0.39	.70	[-0.004, 0.01]	.02	.02
	Loneliness	0.002	0.002	0.65	.52	[-0.003, 0.01]	.03	.03

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Step 3	$\Delta F(2, 379) = 1.10, p = .34, \Delta R^2 = .01$							
	Age	0.004	0.002	2.16	.03*	[0.000, 0.01]	.11	.11
	Difficulty Paying Bills	0.01	0.01	0.93	.36	[-0.01, 0.01]	.05	.05
	Sex	-0.02	0.01	-3.20	.001**	[-0.03, -0.01]	-.16	-.16
	Instagram Time	-0.002	0.002	-0.62	.53	[-0.01, 0.003]	-.03	-.03
	Twitter Time	0.001	0.003	0.32	.75	[-0.004, 0.01]	.02	.02
	Loneliness	0.001	0.002	0.53	.60	[-0.003, 0.01]	.03	.03
	Instagram Time X Loneliness	-0.001	0.002	-0.28	.78	[-0.01, 0.004]	-.01	-.01
	Twitter Time X Loneliness	-0.003	0.003	-1.33	.18	[-0.01, 0.002]	-.07	-.07
Perpetration - Deception								
Step 1	$\Delta F(3, 379) = 0.99, p = .40, \Delta R^2 = .01$							
	Age	<0.001	0.003	0.11	.91	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	-0.01	0.01	-1.01	.31	[-0.03, 0.01]	-.05	-.05
	Sex	-0.01	0.01	-1.33	.18	[-0.04, 0.01]	-.07	-.07
Step 2	$\Delta F(3, 376) = 3.95, p = .01, \Delta R^2 = .03$							
	Age	<0.001	0.003	0.14	.89	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	-0.01	0.01	-1.29	.20	[-0.03, 0.01]	-.07	-.07
	Sex	-0.01	0.01	-1.12	.27	[-0.03, 0.01]	-.06	-.06
	Instagram Time	-0.01	0.01	-1.84	.07	[-0.02, 0.001]	-.09	-.09
	Twitter Time	0.01	0.01	1.15	.25	[-0.004, 0.01]	.06	.06
	Loneliness	0.01	0.01	2.85	.01*	[0.004, 0.02]	.15	.14
Step 3	$\Delta F(2, 374) = 0.10, p = .90, \Delta R^2 = .001$							
	Age	<0.001	0.003	0.11	.91	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	-0.01	0.01	-1.29	.20	[-0.03, 0.01]	-.07	-.07
	Sex	-0.01	0.01	-1.07	.28	[-0.03, 0.01]	-.06	-.05
	Instagram Time	-0.01	0.01	-1.85	.07	[-0.02, 0.001]	-.10	-.09

Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
Twitter Time	0.01	0.01	1.16	.25	[-0.004, 0.01]	.06	.06
Loneliness	0.01	0.01	2.87	.004	[0.004, 0.02]	.15	.15
Instagram Time X Loneliness	0.002	0.01	0.43	.67	[-0.01, 0.01]	.02	.02
Twitter Time X Loneliness	<0.001	0.01	0.03	.98	[-0.01, 0.01]	.002	.001

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness and time spent on the social media applications Twitter and Instagram predicting various types of cyberbullying perpetration behaviors reflecting Hypothesis 2.

**p*<.05, two-tailed
***p*<.01, two-tailed

Table 6. ***Direct Effects of Loneliness and Social Media Predicting Outcome Measures of Cybervictimization Reflecting Hypothesis 2***

Outcome Variable:		***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
Total Cybervictimization								
Step 1	$\Delta F(3, 373) = 2.70$, $p = .046$, $\Delta R^2 = .02$							
	Age	-0.004	0.004	-1.03	.30	[-0.01, 0.004]	-.05	-.05
	Difficulty Paying Bills	0.01	0.01	0.66	.51	[-0.02, 0.03]	.03	.03
	Sex	-0.04	0.01	-2.60	.01*	[-0.06, -0.01]	-.13	-.13
Step 2	$\Delta F(3, 370) = 4.43$, $p = .004$, $\Delta R^2 = .03$							
	Age	-0.003	0.004	-0.74	.46	[-0.01, 0.01]	-.04	-.04
	Difficulty Paying Bills	0.01	0.01	0.46	.65	[-0.02, 0.03]	.02	.02
	Sex	-0.03	0.01	-2.57	.01*	[-0.06, -0.01]	-.13	-.13
	Instagram Time	-0.004	0.01	-0.75	.46	[-0.02, 0.01]	-.04	-.04
	Twitter Time	0.01	0.01	2.11	.04*	[0.001, 0.02]	.11	.11
	Loneliness	0.02	0.01	3.16	.002**	[0.01, 0.03]	.16	.16
Step 3	$\Delta F(2, 386) = 0.08$, $p = .92$, $\Delta R^2 = <.001$							
	Age	-0.003	0.004	-0.74	.46	[-0.01, 0.01]	-.04	-.04
	Difficulty Paying Bills	0.01	0.01	0.45	.65	[-0.02, 0.03]	.02	.02
	Sex	-0.03	0.01	-2.57	.01*	[-0.06, -0.01]	-.13	-.13
	Instagram Time	-0.004	0.01	-0.73	.47	[-0.02, 0.01]	-.04	-.04
	Twitter Time	0.01	0.01	2.12	.03*	[0.001, 0.02]	.11	.11
	Loneliness	0.02	0.01	3.16	.002**	[0.01, 0.03]	.16	.16
	Instagram Time X Loneliness	-0.001	0.01	-0.11	.91	[-0.01, 0.01]	-.01	-.01
	Twitter Time X Loneliness	0.002	0.01	0.40	.69	[-0.01, 0.01]	.02	.02
Victimization - Public Humiliation								
Step 1	$\Delta F(3, 378) = 1.97$, $p = .12$, $\Delta R^2 = .02$							

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Age	-0.003	0.002	-1.30	.19	[-0.01, 0.002]	-.07	-.07
	Difficulty Paying Bills	0.01	0.01	0.91	.36	[-0.01, 0.02]	.05	.05
	Sex	-0.02	0.01	-1.88	.06	[-0.03, 0.001]	-.10	-.10
Step 2	$\Delta F(3, 375) = 1.90$, $p = .13$, $\Delta R^2 = .02$							
	Age	-0.003	0.003	-1.13	.26	[-0.01, 0.002]	-.06	-.06
	Difficulty Paying Bills	0.01	0.01	0.74	.46	[-0.01, 0.02]	.04	.04
	Sex	-0.02	0.01	-1.85	.07	[-0.03, 0.001]	-.10	-.09
	Instagram Time	-0.002	0.004	-0.48	.63	[-0.01, 0.01]	-.02	-.02
	Twitter Time	0.01	0.004	1.20	.23	[-0.003, 0.01]	.06	.06
	Loneliness	0.01	0.004	2.16	.03*	[0.001, 0.02]	.11	.11
Step 3	$\Delta F(2, 373) = 0.44$, $p = .64$, $\Delta R^2 = .002$							
	Age	-0.003	0.003	-1.18	.24	[-0.01, 0.002]	-.06	-.06
	Difficulty Paying Bills	0.01	0.01	0.74	.46	[-0.01, 0.02]	.04	.04
	Sex	-0.02	0.01	-1.80	.07	[-0.03, 0.001]	-.09	-.09
	Instagram Time	-0.002	0.004	-0.47	.64	[-0.01, 0.01]	-.02	-.02
	Twitter Time	0.01	0.004	1.24	.22	[-0.003, 0.01]	.06	.06
	Loneliness	0.01	0.004	2.22	.03*	[0.001, 0.02]	.11	.11
	Instagram Time X Loneliness	0.002	0.004	0.58	.56	[-0.01, 0.01]	.03	.03
	Twitter Time X Loneliness	0.002	0.004	0.57	.57	[-0.01, 0.01]	.03	.03
Victimization - Malice								
Step 1	$\Delta F(3, 382) = 4.39$, $p = .005$, $\Delta R^2 = .03$							
	Age	-0.01	0.01	-1.06	.29	[-0,02, 0.01]	-.05	-.05
	Difficulty Paying Bills	0.01	0.02	0.75	.45	[-0.02, 0.05]	.04	.04
	Sex	-0.07	0.02	-3.43	.001**	[-0.12, -0.03]	-.17	-.17
Step 2	$\Delta F(3, 379) = 4.28$, $p = .005$, $\Delta R^2 = .03$							
	Age	-0.01	0.01	-0.76	.45	[-0.02, 0.01]	-.04	-.04

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Difficulty Paying Bills	0.01	0.02	0.53	.60	[-0.03, 0.05]	.03	.03
	Sex	-0.07	0.02	-3.41	.001**	[-0.11, -0.03]	-.17	-.17
	Instagram Time	-0.01	0.01	-1.10	.27	[-0.03, 0.01]	-.06	-.05
	Twitter Time	0.02	0.01	2.16	.03*	[0.002, 0.04]	.11	.11
	Loneliness	0.03	0.01	2.99	.003**	[0.01, 0.04]	.15	.15
Step 3	$\Delta F(2, 377) = 0.57$, $p = .57$, $\Delta R^2 = .003$							
	Age	-0.004	0.01	-0.68	.50	[-0.02, 0.01]	-.04	-.03
	Difficulty Paying Bills	0.01	0.02	0.52	.60	[-0.03, 0.05]	.03	.03
	Sex	-0.07	0.02	-3.47	.001**	[-0.12, -0.03]	-.18	-.17
	Instagram Time	-0.01	0.01	-1.06	.29	[-0.03, 0.01]	-.05	-.05
	Twitter Time	0.02	0.01	2.12	.03*	[0.002, 0.04]	.11	.11
	Loneliness	0.03	0.01	2.91	.004**	[0.01, 0.04]	.15	.14
	Instagram Time X Loneliness	-0.01	0.01	-1.06	.29	[-0.03, 0.01]	-.05	-.05
	Twitter Time X Loneliness	0.002	0.01	0.21	.83	[-0.02, 0.02]	.01	.01
Victimization - Unwanted Contact								
Step 1	$\Delta F(3, 383) = 0.52$, $p = .67$, $\Delta R^2 = .004$							
	Age	-0.003	0.01	-0.46	.64	[-0.01, 0.01]	-.02	-.02
	Difficulty Paying Bills	0.001	0.02	0.05	.96	[-0.03, 0.04]	.002	.002
	Sex	0.02	0.02	1.14	.25	[-0.02, 0.06]	.06	.06
Step 2	$\Delta F(3, 380)= 5.60$, $p = .001$, $\Delta R^2 = .04$							
	Age	0.001	0.01	0.12	.90	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	-0.001	0.02	-0.07	.95	[-0.04, 0.03]	-.003	-.003
	Sex	0.02	0.02	0.98	.33	[-0.02, 0.06]	.05	.05
	Instagram Time	0.004	0.01	0.42	.67	[-0.01, 0.02]	.02	.02
	Twitter Time	0.03	0.01	3.25	.001**	[0.01, 0.05]	.16	.16

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Loneliness	0.02	0.01	2.59	.01*	[0.01, 0.04]	.13	.13
Step 3	$\Delta F(2, 378) = 0.18$, $p = .84$, $\Delta R^2 = .001$							
	Age	0.001	0.01	0.14	.89	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	-0.001	0.02	-0.07	.94	[-0.04, 0.03]	-.004	-.004
	Sex	0.02	0.02	0.95	.34	[-0.02, 0.06]	.05	.05
	Instagram Time	0.004	0.01	0.44	.66	[-0.01, 0.02]	.02	.02
	Twitter Time	0.03	0.01	3.26	.001**	[0.01, 0.05]	.17	.16
	Loneliness	0.02	0.01	2.59	.01*	[0.01, 0.04]	.13	.13
	Instagram Time X Loneliness	-0.003	0.01	-0.31	.76	[-0.02, 0.01]	-.02	-.02
	Twitter Time X Loneliness	0.01	0.01	0.57	.57	[-0.01, 0.02]	.03	.03
Victimization - Deception								
Step 1	$\Delta F(3, 382) = 3.38$, $p = .02$, $\Delta R^2 = .03$							
	Age	0.001	0.005	0.22	.82	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	0.01	0.01	0.56	.58	[-0.02, 0.04]	.03	.03
	Sex	-0.05	0.02	-3.15	.002**	[-0.09, -0.02]	-.16	-.16
Step 2	$\Delta F(3, 379) = 3.06$, $p = .03$, $\Delta R^2 = .02$							
	Age	<0.001	0.01	-0.08	.94	[-0.01, 0.01]	-.004	-.004
	Difficulty Paying Bills	0.01	0.01	0.31	.76	[-0.02, 0.03]	.02	.02
	Sex	-0.05	0.02	-3.09	.002**	[-0.08, -0.02]	-.16	-.15
	Instagram Time	-0.01	0.01	-0.82	.41	[-0.02, 0.01]	-.04	-.04
	Twitter Time	-0.003	0.01	-0.46	.64	[-0.02, 0.01]	-.02	-.02
	Loneliness	0.02	0.01	2.73	.01*	[0.01, 0.03]	.14	.14
Step 3	$\Delta F(2, 377) = 0.88$, $p = .42$, $\Delta R^2 = .004$							
	Age	-0.001	0.01	-0.16	.87	[-0.01, 0.01]	-.01	-.01
	Difficulty Paying Bills	0.01	0.01	0.31	.76	[-0.02, 0.03]	.02	.02
	Sex	-0.05	0.02	-2.99	.003**	[-0.08, -0.02]	-.15	-.15

Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
Instagram Time	-0.01	0.01	-0.85	.40	[-0.02, 0.01]	-.04	-.04
Twitter Time	-0.003	0.01	-0.42	.68	[-0.02, 0.01]	-.02	-.02
Loneliness	0.02	0.01	2.83	.01*	[0.01, 0.03]	.14	.14
Instagram Time X Loneliness	0.01	0.01	1.22	.22	[-0.01, 0.02]	.06	.06
Twitter Time X Loneliness	0.001	0.01	0.19	.85	[-0.01, 0.02]	.01	.01

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness and time spent on the social media applications Twitter and Instagram predicting various types of cybervictimization behaviors reflecting Hypothesis 2

*p<.05, two-tailed

**p<.01, two-tailed

Hypothesis 3a:

Based on the cumulative deleterious effects postulate, it was estimated that levels of loneliness would directly predict health outcomes. Specifically, increased levels of loneliness would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety). Overall, this hypothesis was supported, (refer to Table 7). More precise, as it relates to the cumulative deleterious effects postulate, there was a direct effect for the variable of loneliness. As expected, increased levels of loneliness predicted increased scores of physical symptoms, depression, perceived stress, state anxiety, and trait anxiety, but was not related to obesity. Also, being female was associated with greater reports of physical symptoms, depression, perceived stress, and trait anxiety. Sex was not related to outcome measures of obesity or state anxiety. Finally, difficulty paying one’s monthly bills positively predicted increased scores of perceived stress, state anxiety, and trait anxiety, but there was no association between this covariate and the outcome measures of obesity, physical symptoms, or depression. Age also was not associated with any of the outcome variables tested.

Table 7. ***Direct Effects of Loneliness Predicting Outcome Measures of Mental and Physical Health Reflecting Hypothesis 3a***

Outcome Variable:	***B***	***SE***	***t***	***p***	***95%CI's***	***partial coefficients***	***part coefficients***
BMI							
Step 1 $\Delta F(3, 369) = 1.92$, $p = .13$, $\Delta R^2 = .02$							
Age	<0.001	0.003	0.08	.93	[-0.01, 0.01]	.004	.004
Difficulty Paying Bills	0.01	0.01	1.37	.17	[-0.01, 0.03]	.07	.07
Sex	0.02	0.01	1.90	.06	[-0.01, 0.04]	.10	.10
Step 2 $\Delta F(1, 368) = 0.29$, $p = .59$, $\Delta R^2 = .001$							
Age	<0.001	0.003	0.05	.96	[-0.01, 0.01]	.002	.002
Difficulty Paying Bills	0.01	0.01	1.32	.19	[-0.01, 0.03]	.07	.07
Sex	0.02	0.01	1.89	.06	[-0.001, 0.04]	.10	.10
Loneliness	<0.001	<0.001	0.54	.59	[-0.001, 0.001]	.03	.03
Physical Symptoms							
Step 1 $\Delta F(3, 384) = 8.20$, $p < .001$, $\Delta R^2 = .06$							
Age	0.04	0.07	0.53	.60	[-0.10, 0.17]	.03	.03
Difficulty Paying Bills	0.31	0.22	1.44	.15	[-0.11, 0.74]	.07	.07
Sex	1.14	0.25	4.66	<.001**	[0.66, 1.62]	.23	.23
Step 2 $\Delta F(1, 383) = 34.65$, $p < .001$, $\Delta R^2 = .08$							
Age	0.01	0.07	0.17	.87	[-0.12, 0.14]	.01	.01
Difficulty Paying Bills	0.21	0.21	1.01	.31	[-0.20, 0.62]	.05	.05
Sex	1.11	0.24	4.73	<.001**	[0.65, 1.57]	.23	.22
Loneliness	0.06	0.01	5.89	<.001**	[0.04, 0.08]	.29	.28
Depression							
Step 1 $\Delta F(3, 384) = 3.91$, $p = .009$, $\Delta R^2 = .03$							
Age	0.10	0.06	1.69	.09	[-0.02, 0.21]	.09	.09
Difficulty Paying Bills	0.33	0.18	1.86	.06	[-0.02, 0.68]	.09	.09

Outcome Variable:		*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
	Sex	0.46	0.20	2.31	.02*	[0.07, 0.85]	.12	.12
Step 2	$\Delta F(1, 383) = 103.69$, $p < .001$, $\Delta R^2 = .21$							
	Age	0.06	0.05	1.24	.22	[-0.04, 0.16]	.06	.06
	Difficulty Paying Bills	0.20	0.16	1.25	.21	[-0.11, 0.51]	.06	.06
	Sex	0.42	0.18	2.38	.02*	[0.07, 0.76]	.12	.11
	Loneliness	0.08	0.01	10.18	<.001**	[0.06, 0.09]	.46	.46
Perceived Stress								
Step 1	$\Delta F(3, 304) = 6.08$, $p < .001$, $\Delta R^2 = .06$							
	Age	0.03	0.20	0.15	.88	[-0.37, 0.43]	.01	.01
	Difficulty Paying Bills	1.86	0.64	2.92	.004**	[0.61, 3.10]	.17	.16
	Sex	2.17	0.75	2.91	.004**	[0.70, 3.64]	.16	.16
Step 2	$\Delta F(1, 303) = 36.86$, $p < .001$, $\Delta R^2 = .10$							
	Age	-0.05	0.19	-0.25	.81	[-0.43, 0.33]	-.01	-.01
	Difficulty Paying Bills	1.63	0.60	2.70	.01*	[0.44, 2.81]	.15	.14
	Sex	2.14	0.71	3.03	.003**	[0.75, 3.53]	.17	.16
	Loneliness	0.18	0.03	6.07	<.001**	[0.12, 0.24]	.33	.32
State-Anxiety								
Step 1	$\Delta F(3, 383) = 3.92$, $p = .01$, $\Delta R^2 = .03$							
	Age	0.56	0.31	1.77	.08	[-0.06, 1.17]	.09	.09
	Difficulty Paying Bills	2.84	0.98	2.90	.004**	[0.92, 4.77]	.15	.15
	Sex	0.71	1.10	0.64	.52	[-1.46, 2.88]	.03	.03
Step 2	$\Delta F(1, 382) = 64.56$, $p < .001$, $\Delta R^2 = .14$							
	Age	0.40	0.29	1.39	.17	[-0.17, 0.97]	.07	.06
	Difficulty Paying Bills	2.24	0.91	2.47	.01*	[0.46, 4.03]	.13	.12
	Sex	0.55	1.02	0.54	.59	[-1.46, 2.56]	.03	.03

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Loneliness	0.36	0.04	8.03	<.001**	[0.27, 0.44]	.38	.37
Trait-Anxiety							
Step 1 $\Delta F(3, 383) = 6.11$, $p < .001$, $\Delta R^2 = .05$							
Age	0.56	0.35	1.60	.11	[-0.13, 1.24]	.08	.08
Difficulty Paying Bills	3.57	1.09	3.28	.001**	[1.43, 5.70]	.17	.16
Sex	2.71	1.23	2.21	.03*	[0.30, 5.12]	.11	.11
Step 2 $\Delta F(1, 382) = 155.80$, $p < .001$, $\Delta R^2 = .28$							
Age	0.32	0.29	1.08	.28	[-0.26, 0.90]	.06	.05
Difficulty Paying Bills	2.63	0.92	2.85	0.01*	[0.82, 4.44]	.14	.12
Sex	2.46	1.03	2.37	.02*	[0.42, 4.49]	.12	.10
Loneliness	0.56	0.05	12.48	<.001**	[0.47, 0.65]	.54	.53

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness in predicting various types of physical and mental health outcomes reflecting Hypothesis 3a.

**p*<.05, two-tailed
***p*<.01, two-tailed

Hypothesis 3b:

Based on Jensen-Campbell's Stress Model of Peer Victimization, it was estimated that levels of cyberbullying would directly predict health outcomes. Specifically, increased levels of both cyberbullying perpetration and victimization would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety). Overall, this hypothesis was partially supported, (refer to Table 8) because cyberbullying perpetration and victimization behaviors directly predicted only some of the physical and mental health outcomes. Pertaining to perpetration as a predictor, as expected, there was a positive association between total perpetration and increased reports of physical symptoms as well as trait anxiety. Additionally, increased scores of unwanted contact perpetration were associated with greater reports of state anxiety. However, contrary to what was expected, total perpetration and its subtypes were not related to any other mental or physical health measures including obesity, depression, and perceived stress.

Next, as hypothesized by Jensen-Campbell's Stress Model of Peer Victimization, increased total victimization predicted greater reports of physical symptoms and greater perceived stress. Furthermore, higher scores on the subtype of unwanted contact predicted increased perceived stress, and higher scores on the malice subtype predicted greater state anxiety. Contrary to what was expected, victimization behavior (both total and the subtypes) did not predict any other outcome measures tested including obesity, depression, or trait anxiety.

It is also important to highlight that several direct effects emerged for other predictor variables in addition to perpetration and victimization. Like Hypothesis 3a, it appeared that being female compared to male had a greater influence on predicting worse physical (i.e., physical symptoms) and mental health (i.e., depression, perceived stress, trait anxiety) outcomes. Next, difficulty paying one's monthly bills directly predicted increased levels of perceived stress, as well as increased scores for both state and trait anxiety, but did not predict outcome measures of obesity, physical symptoms, or depression. Also, age did not predict the outcome measures tested including obesity, physical symptoms, depression, perceived stress, or state and trait anxiety.

Table 8. ***Direct Effects of Cyberbullying Behaviors Predicting Outcome Measures of Physical and Mental Health Reflecting Hypothesis 3b***

Outcome Variable:		***B***	***SE***	***t***	***p***	***95%CI's***	***partial coefficients***	***part coefficients***
BMI (Cyberbullying Subtypes)								
Step 1	$\Delta F(3, 351) = 2.40$, $p = .07$, $\Delta R^2 = 0.02$							
	Age	0.001	0.003	0.25	.80	[-0.01, 0.01]	.01	.01
	Difficulty Paying Bills	0.02	0.01	1.71	.09	[-0.003, 0.04]	.09	.09
	Sex	0.02	0.01	1.95	.05	[0.000, 0.04]	.10	.10
Step 2	$\Delta F(8, 343) = 0.68$, $p = .71$, $\Delta R^2 = 0.02$							
	Age	< 0.001	0.003	-0.002	1.00	[-0.01, 0.01]	< .001	< .001
	Difficulty Paying Bills	0.02	0.01	1.65	.10	[-0.003, 0.04]	.09	.09
	Sex	0.03	0.01	2.18	.03	[0.003, 0.05]	.12	.12
	Perpetration-Public Humiliation	0.04	0.06	0.71	.48	[-0.07, 0.15]	.04	.04
	Perpetration-Malice	0.02	0.04	0.43	.67	[-0.06, 0.10]	.02	.02
	Perpetration- Unwanted Contact	0.12	0.11	1.12	.26	[-0.09, 0.33]	.06	.06
	Perpetration- Deception	-0.05	0.06	-0.74	.46	[-0.17, 0.08]	-.04	-.04
	Victimization-Public Humiliation	-0.12	0.09	-1.28	.20	[-0.30, 0.06]	-.07	-.07
	Victimization-Malice	0.04	0.04	0.84	.40	[-0.05, 0.13]	.05	.05
	Victimization-Unwanted Contact	-0.01	0.04	-0.36	.72	[-0.09, 0.06]	-.02	-.02
	Victimization- Deception	-0.002	0.05	-0.04	.97	[-0.09, 0.09]	-.002	-.002
BMI (Cyberbullying Total)								
Step 1	$\Delta F(3, 347) = 2.30$, $p = .08$, $\Delta R^2 = 0.02$							
	Age	0.001	0.003	0.27	.79	[-0.01, 0.01]	.02	.01
	Difficulty Paying Bills	0.02	0.01	1.65	.10	[-0.003, 0.04]	.09	.09
	Sex	0.02	0.01	1.92	.06	[-0.001, 0.04]	.10	.10
Step 2	$\Delta F(2, 345) = 0.83$, $p = .44$, $\Delta R^2 = 0.01$							
	Age	< 0.001	0.003	0.12	.91	[-0.01, 0.01]	.01	.01

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Difficulty Paying Bills	0.02	0.01	1.73	.09	[-0.002, 0.04]	.09	.09
Sex	0.03	0.01	2.13	.03	[0.002, 0.05]	.11	.11
Total Cyberbullying Perpetration	0.09	0.07	1.24	.22	[-0.05, 0.22]	.07	.07
Total Cybervictimization	-0.03	0.06	-0.54	.59	[-0.14, 0.08]	-.03	-.03
Physical Symptoms (Cyberbullying Subtypes)							
Step 1 $\Delta F(3, 366) = 7.19$, $p < .001$, $\Delta R^2 = 0.06$							
Age	0.04	0.07	0.61	.54	[-0.10, 0.18]	.03	.03
Difficulty Paying Bills	0.24	0.22	1.08	.28	[-0.20, 0.68]	.06	.06
Sex	1.11	0.25	4.42	< 0.001	[0.62, 1.60]	.23	.22
Step 2 $\Delta F(8, 358) = 3.89$, $p < .001$, $\Delta R^2 = 0.08$							
Age	0.04	0.07	0.51	.61	[-0.10, 0.18]	.03	.03
Difficulty Paying Bills	0.22	0.22	1.03	.31	[-0.21, 0.65]	.05	.05
Sex	1.36	0.26	5.28	< 0.001	[0.85, 1.86]	.27	.26
Perpetration-Public Humiliation	1.38	1.22	1.13	.26	[-1.01, 3.77]	.06	.06
Perpetration-Malice	0.87	0.87	1.00	.32	[-0.84, 2.58]	.05	.05
Perpetration- Unwanted Contact	2.46	2.35	1.05	.30	[-2.17, 7.08]	.06	.05
Perpetration- Deception	-0.05	1.34	-0.04	.97	[-2.69, 2.58]	-.002	-.002
Victimization-Public Humiliation	1.09	1.99	0.55	.59	[-2.83, 5.00]	.03	.03
Victimization-Malice	0.78	0.96	0.82	.42	[-1.10, 2.67]	.04	.04
Victimization-Unwanted Contact	0.18	0.79	0.23	.82	[-1.36, 1.73]	.01	.01
Victimization- Deception	1.19	0.97	1.23	.22	[-0.72, 3.09]	.07	.06
Physical Symptoms (Cyberbullying Total)							
Step 1 $\Delta F(3, 362) = 6.31$, $p < .001$, $\Delta R^2 = 0.05$							

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Age	0.04	0.07	0.54	.59	[-0.10, 0.18]	.03	.03
Difficulty Paying Bills	0.29	0.22	1.29	.20	[-0.15, 0.73]	.07	.07
Sex	1.02	0.25	4.04	< 0.001	[0.52, 1.52]	.21	.21
Step 2 $\Delta F(2, 360) = 13.33$, $p <.001$, $\Delta R^2 = 0.07$							
Age	0.04	0.07	0.52	.60	[-0.10, 0.17]	.03	.03
Difficulty Paying Bills	0.28	0.22	1.31	.19	[-0.14, 0.71]	.07	.07
Sex	1.26	0.25	5.06	< 0.001	[0.77, 1.76]	.26	.25
Total Cyberbullying Perpetration	3.36	1.48	2.27	.02	[0.45, 6.27]	.12	.11
Total Cybervictimization	2.53	1.21	2.08	.04	[0.14, 4.91]	.11	.10
Depression (Cyberbullying Subtypes)							
Step 1 $\Delta F(3, 366) = 3.22$, $p = .02$, $\Delta R^2 = 0.03$							
Age	0.10	0.06	1.68	.09	[-0.02, 0.21]	.09	.09
Difficulty Paying Bills	0.28	0.18	1.55	.12	[-0.08, 0.64]	.08	.08
Sex	0.42	0.20	2.08	.04	[0.02, 0.82]	.11	.11
Step 2 $\Delta F(8, 358) = 2.55$, $p = .01$, $\Delta R^2 = 0.05$							
Age	0.09	0.06	1.62	.11	[-0.02, 0.21]	.09	.08
Difficulty Paying Bills	0.29	0.18	1.59	.11	[-0.07, 0.64]	.08	.08
Sex	0.54	0.21	2.54	.01	[0.12, 0.95]	.13	.13
Perpetration-Public Humiliation	0.54	1.00	0.54	.59	[-1.42, 2.51]	.03	.03
Perpetration-Malice	0.55	0.71	0.77	.44	[-0.85, 1.96]	.04	.04
Perpetration- Unwanted Contact	1.76	1.93	0.91	.36	[-2.04, 5.56]	.05	.05
Perpetration- Deception	1.11	1.10	1.01	.32	[-1.06, 3.27]	.05	.05
Victimization-Public Humiliation	-0.13	1.63	-0.08	.94	[-3.34, 3.09]	-.004	-.004
Victimization-Malice	0.87	0.79	1.11	.27	[-0.68, 2.42]	.06	.06
Victimization-Unwanted Contact	0.70	0.65	1.08	.28	[-0.57, 1.97]	.06	.06

Outcome Variable:		*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Victimization- Deception		-0.43	0.80	-0.54	.59	[-1.99, 1.14]	-.03	-.03
Depression (Cyberbullying Total)								
Step 1	$\Delta F(3, 362) = 3.02$, $p = .03$, $\Delta R^2 = 0.02$							
Age		0.09	0.06	1.63	.11	[-0.02, 0.21]	.09	.08
Difficulty Paying Bills		0.32	0.18	1.76	.08	[-0.04, 0.68]	.09	.09
Sex		0.36	0.20	1.78	.08	[-0.04, 0.77]	.09	.09
Step 2	$\Delta F(2, 360) = 8.41$, $p < .001$, $\Delta R^2 = 0.04$							
Age		0.09	0.06	1.62	.11	[-0.02, 0.21]	.09	.08
Difficulty Paying Bills		0.32	0.18	1.77	.08	[-0.04, 0.67]	.09	.09
Sex		0.52	0.21	2.55	.01	[0.12, 0.93]	.13	.13
Total Cyberbullying Perpetration		2.20	1.22	1.81	.07	[-0.19, 4.59]	.10	.09
Total Cybervictimization		1.64	1.00	1.65	.10	[-0.32, 3.60]	.09	.08
Perceived Stress (Cyberbullying Subtypes)								
Step 1	$\Delta F(3, 293) = 5.13$, $p = .002$, $\Delta R^2 = 0.05$							
Age		-0.003	0.21	-0.02	.99	[-0.42, 0.41]	-.001	-.001
Difficulty Paying Bills		1.68	0.65	2.57	.01	[0.40, 2.97]	.15	.15
Sex		2.13	0.76	2.81	.01	[0.64, 3.62]	.16	.16
Step 2	$\Delta F(8, 285) = 2.26$, $p = .02$, $\Delta R^2 = 0.06$							
Age		0.08	0.21	0.38	.70	[-0.33, 0.49]	.02	.02
Difficulty Paying Bills		1.65	0.65	2.53	.01	[0.36, 2.93]	.15	.14
Sex		2.17	0.79	2.76	.01	[0.62, 3.72]	.16	.15
Perpetration-Public Humiliation		-1.46	3.60	-0.41	.69	[-8.55, 5.63]	-.02	-.02
Perpetration-Malice		-1.08	2.57	-0.42	.67	[-6.14, 3.98]	-.03	-.02

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Perpetration- Unwanted Contact	0.87	7.59	0.11	.91	[-14.07, 15.80]	.01	.01
Perpetration- Deception	-1.26	3.88	-0.32	.75	[-8.89, 6.38]	-.02	-.02
Victimization-Public Humiliation	6.23	6.16	1.01	.31	[-5.89, 18.36]	.06	.06
Victimization-Malice	4.19	2.82	1.49	.14	[-1.36, 9.74]	.09	.08
Victimization-Unwanted Contact	5.41	2.33	2.33	.02	[0.83, 9.99]	.14	.13
Victimization- Deception	-5.15	2.80	-1.84	.07	[-10.67, 0.36]	-.11	-.10
Perceived Stress (Cyberbullying Total)							
Step 1 $\Delta F(3, 291) = 5.20$, $p = .002$, $\Delta R^2 = 0.05$							
Age	0.002	0.21	0.01	.99	[-0.41, 0.41]	.001	.001
Difficulty Paying Bills	1.76	0.65	2.69	.01	[0.47, 3.04]	.16	.15
Sex	2.07	0.76	2.73	.01	[0.57, 3.56]	.16	.16
Step 2 $\Delta F(2, 289) = 5.41$, $p = .005$, $\Delta R^2 = 0.03$							
Age	0.06	0.21	0.30	.76	[-0.35, 0.47]	.02	.02
Difficulty Paying Bills	1.70	0.65	2.64	.01	[0.43, 2.97]	.15	.15
Sex	2.37	0.76	3.10	.002	[0.86, 3.87]	.18	.17
Total Cyberbullying Perpetration	-2.09	4.46	-0.47	.64	[-10.86, 6.69]	-.03	-.03
Total Cybervictimization	10.08	3.65	2.77	.01	[2.90, 17.25]	.16	.16
State-Anxiety (Cyberbullying Subtypes)							
Step 1 $\Delta F(3, 365) = 2.96$, $p = .03$, $\Delta R^2 = 0.02$							
Age	0.63	0.32	1.97	.05	[0.000, 1.26]	.10	.10
Difficulty Paying Bills	2.05	1.00	2.04	.04	[0.07, 4.02]	.11	.11
Sex	1.10	1.13	0.98	.33	[-1.12, 3.32]	.05	.05
Step 2 $\Delta F(8, 357) = 3.46$, $p = .001$, $\Delta R^2 = 0.07$							
Age	0.63	0.32	1.98	.05	[0.01, 1.26]	.10	.10
Difficulty Paying Bills	1.87	0.99	1.90	.06	[-0.07, 3.81]	.10	.10

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Sex	1.77	1.17	1.51	.13	[-0.53, 4.07]	.08	.08
Perpetration-Public Humiliation	4.98	5.49	0.91	.37	[-5.81, 15.77]	.05	.05
Perpetration-Malice	-2.38	3.92	-0.61	.55	[-10.09, 5.34]	-.03	-.03
Perpetration- Unwanted Contact	25.65	10.61	2.42	.02	[4.79, 46.51]	.13	.12
Perpetration- Deception	0.61	6.10	0.10	.92	[-11.38, 12.61]	.01	.01
Victimization-Public Humiliation	3.06	8.97	0.34	.73	[-14.57, 20.70]	.02	.02
Victimization-Malice	10.46	4.32	2.42	.02	[1.96, 18.96]	.13	.12
Victimization-Unwanted Contact	2.44	3.57	0.68	.49	[-4.57, 9.45]	.04	.03
Victimization- Deception	-6.68	4.39	-1.52	.13	[-15.31, 1.94]	-.08	-.08
State-Anxiety (Cyberbullying Total)							
Step 1 $\Delta F(3, 361) = 3.00$, $p = .03$, $\Delta R^2 = 0.02$							
Age	0.62	0.32	1.92	.06	[-0.01, 1.25]	.10	.10
Difficulty Paying Bills	2.19	1.01	2.17	.03	[0.21, 4.18]	.11	.11
Sex	0.93	1.14	0.81	.42	[-1.32, 3.17]	.04	.04
Step 2 $\Delta F(2, 359) = 7.63$, $p = .001$, $\Delta R^2 = 0.04$							
Age	0.62	0.32	1.95	.05	[-0.004, 1.25]	.10	.10
Difficulty Paying Bills	2.16	0.99	2.17	.03	[0.21, 4.12]	.11	.11
Sex	1.75	1.15	1.52	.13	[-0.52, 4.01]	.08	.08
Total Cyberbullying Perpetration	9.82	6.78	1.45	.15	[-3.52, 23.16]	.08	.07
Total Cybervictimization	10.24	5.56	1.84	.07	[-0.69, 21.17]	.10	.09
Trait-Anxiety (Cyberbullying Subtypes)							
Step 1 $\Delta F(3, 365) = 5.40$, $p = .001$, $\Delta R^2 = 0.04$							
Age	0.68	0.36	1.90	.06	[-0.02, 1.38]	.10	.10

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Difficulty Paying Bills	3.09	1.12	2.77	.01	[0.90, 5.29]	.14	.14
Sex	2.74	1.26	2.17	.03	[0.26, 5.21	.11	.11
Step 2 $\Delta F(8, 357) = 2.29$, $p = .02$, $\Delta R^2 = 0.05$							
Age	0.63	0.36	1.74	.08	[-0.08, 1.33]	.09	.09
Difficulty Paying Bills	3.13	1.11	2.82	.01	[0.94, 5.32]	.15	.14
Sex	3.51	1.32	2.65	.01	[0.91, 6.10]	.14	.13
Perpetration-Public Humiliation	6.46	6.19	1.04	.30	[-5.72, 18.64]	.06	.05
Perpetration-Malice	1.57	4.43	0.35	.72	[-7.14, 10.28]	.02	.02
Perpetration- Unwanted Contact	17.17	11.98	1.43	.15	[-6.38, 40.72]	.08	.07
Perpetration- Deception	6.41	6.89	0.93	.35	[-7.13, 19.95]	.05	.05
Victimization-Public Humiliation	-7.53	10.12	-0.74	.46	[-27.44, 12.38]	-.04	-.04
Victimization-Malice	7.25	4.88	1.49	.14	[-2.34, 16.84]	.08	.08
Victimization-Unwanted Contact	1.71	4.03	0.43	.67	[-6.20, 9.63]	.02	.02
Victimization- Deception	-2.33	4.95	-0.47	.64	[-12.07, 7.41]	-.03	-.02
Trait-Anxiety (Cyberbullying Total)							
Step 1 $\Delta F(3, 361) = 5.30$, $p = .001$, $\Delta R^2 = 0.04$							
Age	0.69	0.36	1.93	.06	[-0.01, 1.39]	.10	.10
Difficulty Paying Bills	3.25	1.12	2.90	.004	[1.05, 5.45]	.15	.15
Sex	2.37	1.27	1.87	.06	[-0.12, 4.86]	.10	.10
Step 2 $\Delta F(2, 359) = 6.66$, $p = .001$, $\Delta R^2 = 0.03$							
Age	0.65	0.35	1.84	.07	[-0.05, 1.35]	.10	.09
Difficulty Paying Bills	3.29	1.10	2.98	.003	[1.12, 5.46]	.16	.15
Sex	3.33	1.28	2.61	.01	[0.82, 5.85]	.14	.13
Total Cyberbullying Perpetration	15.99	7.54	2.12	.03	[1.18, 30.81]	.11	.11
Total Cybervictimization	5.57	6.17	0.90	.37	[-6.57, 17.71]	.05	.05

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of cyberbullying perpetration behaviors predicting various physical and mental health outcomes reflecting Hypothesis H3b.

*p<.05, two-tailed

**p<.01, two-tailed

Hypothesis 4:

Based on the salutary-relationship postulate and the Jensen-Campbell's Stress Model of Peer Victimization, it was estimated that cyberbullying would explain the relationship between loneliness and health outcomes, while at the same time use of social media applications would help explain the effects of loneliness in predicting health outcomes (see Figure 1). Overall, this hypothesis was not supported. More specific, contrary to expectations there were no significant moderated mediation, moderation, or mediation effects. However, several direct effects emerged that are worth mentioning as it pertains to this hypothesis (refer to Table 9). Also, note that because there were no significant moderated mediation, moderation, or mediation effects that emerged when testing this hypothesis using the macro PROCESS Model 7, the non-significant data results were not reported in the Table 9. As previously expected, and confirmed, greater loneliness predicted increased levels of physical symptoms, depression, perceived stress, state anxiety, and trait anxiety. Contrary to what was anticipated, loneliness did not predict levels of obesity. Also, being female as compared to male predicted overall worse physical and mental health outcomes, specifically higher reports of physical symptoms, depression, perceived stress, and trait anxiety. Overall, sex did not predict levels of obesity or state anxiety. As observed in the previous hypotheses results, difficulty paying one's monthly bills also predicted higher scores of perceived stress as well as trait anxiety. However, this predictor was not associated with the outcome measures of obesity, physical symptoms, or depression. There was also no relationship between age and any of the outcome variables examined. Another direct effect emerged such that more Instagram time predicted lower scores of depression, but contrary to what was expected was not related to any other outcome variables tested. On the other hand, more time spent on Twitter was associated with higher predicted scores of depression. Both

Instagram and Twitter use were not related to any other of the outcomes measured including obesity, physical symptoms, perceived stress, state anxiety, or trait anxiety.

Additionally, as anticipated total cyberbullying perpetration was positively related to physical symptoms, depression, and trait anxiety, but did not predict scores of obesity, perceived stress, or state anxiety. Unwanted contact perpetration was associated with increased scores of state anxiety but was not related to any other outcomes tested. Contrary to expectations, none of the other subtypes of perpetration, including public humiliation, malice, or deception, predicted any of the outcome measures tested (i.e., obesity, physical symptoms, depression, perceived stress, state, and trait-anxiety).

Moreover, greater total victimization and unwanted contact victimization directly predicted increased scores of perceived stress. Also, malice victimization was positively related to greater predicted measures of state anxiety. Contrary to expectations, total victimization did not predict outcomes related to obesity, physical symptoms, depression, state anxiety, and trait anxiety. Other subtypes of victimization, including public humiliation, and deception, were also not associated with any of the outcome variables tested including obesity, physical symptoms, depression, perceived stress, state, and trait anxiety.

Table 9. ***Direct Effects of Loneliness, Time Spent on Social Media Applications, and Cyberbullying Behaviors Predicting Outcome***

Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
BMI (Cyberbullying Subtypes)							
Step 1 $\Delta F(14, 339) = 0.96$, $p = .50$, $\Delta R^2 = 0.04$							
Age	< 0.001	0.003	-0.15	.88	[-0.01, 0.01]	-.01	-.01
Difficulty Paying Bills	0.02	0.01	1.58	.11	[-0.004, 0.04]	.09	.08
Sex	0.03	0.01	2.16	.03*	[0.002, 0.05]	.12	.12
Loneliness	< 0.001	0.001	0.72	.48	[-0.001, 0.001]	.04	.04
Instagram Time	< 0.001	0.01	-0.05	.96	[-0.01, 0.01]	-.003	-.003
Twitter Time	-0.002	0.01	-0.44	.66	[-0.01, 0.01]	-.02	-.02
Perpetration- Public Humiliation	0.04	0.06	0.72	.47	[-0.07, 0.16]	.04	.04
Perpetration- Malice	0.02	0.04	0.48	.63	[-0.06, 0.10]	.03	.03
Perpetration- Unwanted Contact	0.12	0.11	1.11	.27	[-0.09, 0.33]	.06	.06
Perpetration- Deception	-0.05	0.06	-0.78	.43	[-0.17, 0.07]	-.04	-.04
Victimization- Public Humiliation	-0.12	0.09	-1.24	.22	[-0.30, 0.07]	-.07	-.07
Victimization- Malice	0.04	0.05	0.79	.43	[-0.05, 0.12]	.04	.04
Victimization- Unwanted Contact	-0.01	0.04	-0.33	.75	[-0.09, 0.06]	-.02	-.02
Victimization- Deception	-0.01	0.05	-0.14	.89	[-0.10, 0.08]	-.01	-.01
BMI (Cyberbullying Total)							
Step 1 $\Delta F(8, 341) = 1.16$, $p = .32$, $\Delta R^2 = 0.03$							
Age	< 0.001	0.003	-0.03	.97	[-0.01, 0.01]	-.002	-.002
Difficulty Paying Bills	0.02	0.01	1.66	.10	[-0.003, 0.04]	.09	.09
Sex	0.03	0.01	2.13	.03*	[0.002, 0.05]	.12	.11
Loneliness	< 0.001	0.001	0.70	.48	[-0.001, 0.001]	.04	.04
Instagram Time	< 0.001	0.01	-0.08	.94	[-0.01, 0.01]	-.004	-.004
Twitter Time	-0.002	0.01	-0.40	.69	[-0.01, 0.01]	-.02	-.02
Total Cyberbullying Perpetration	0.09	0.07	1.27	.20	[-0.05, 0.23]	.07	.07
Total Cybervictimization	-0.04	0.06	-0.61	.55	[-0.15, 0.08]	-.03	-.03

Outcome Variable:	B	SE	t	p	95% CI's	partial coefficients	part coefficients
Physical Symptoms (Cyberbullying Subtypes)							
Step 1 $\Delta F(14, 354) = 5.99$, $p = < .001$, $\Delta R^2 = 0.19$							
Age	0.002	0.07	0.03	.98	[-0.14, 0.14]	.001	.001
Difficulty Paying Bills	0.13	0.21	0.63	.53	[-0.28, 0.55]	.03	.03
Sex	1.37	0.25	5.47	< .001**	[0.88, 1.86]	.28	.26
Loneliness	0.05	0.01	4.98	< .001**	[0.03, 0.07]	.26	.24
Instagram Time	-0.05	0.10	-0.44	.66	[-0.25, 0.16]	-.02	-.02
Twitter Time	-0.05	0.11	-0.47	.64	[-0.26, 0.16]	-.03	-.02
Perpetration- Public Humiliation	1.08	1.19	0.90	.37	[-1.27, 3.42]	.05	.04
Perpetration- Malice	1.22	0.85	1.44	.15	[-0.44, 2.89]	.08	.07
Perpetration- Unwanted Contact	2.58	2.28	1.13	.26	[-1.90, 7.07]	.06	.05
Perpetration- Deception	-0.63	1.31	-0.48	.63	[-3.20, 1.94]	-.03	-.02
Victimization- Public Humiliation	1.38	1.93	0.72	.47	[-2.41, 5.18]	.04	.03
Victimization- Malice	0.36	0.93	0.39	.70	[-1.47, 2.20]	.02	.02
Victimization- Unwanted Contact	0.24	0.78	0.31	.75	[-1.28, 1.77]	.02	.02
Victimization- Deception	0.85	0.95	0.90	.37	[-1.02, 2.72]	.05	.04
Physical Symptoms (Cyberbullying Total)							
Step 1 $\Delta F(8, 356) = 9.56$, $p = < .001$, $\Delta R^2 = 0.18$							
Age	-0.003	0.07	-0.04	.97	[-0.14, 0.13]	-.002	-.002
Difficulty Paying Bills	0.19	0.21	0.92	.36	[-0.22, 0.61]	.05	.04
Sex	1.29	0.24	5.30	< .001**	[0.81, 1.77]	.27	.26
Loneliness	0.05	0.01	4.92	< .001**	[0.03, 0.07]	.25	.24
Instagram Time	-0.05	0.10	-0.43	.67	[-0.25, 0.16]	-.02	-.02

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Twitter Time	-0.08	0.11	-0.77	.44	[-0.29, 0.13]	-.04	-.04
Total Cyberbullying Perpetration	3.56	1.45	2.46	.01*	[0.72, 6.40]	.13	.12
Total Cybervictimization	1.79	1.19	1.51	.13	[-0.54, 4.13]	.08	.07
Depression (Cyberbullying Subtypes)							
Step 1 $\Delta F(14, 354) = 9.15$, $p = < .001$, $\Delta R^2 = 0.27$							
Age	0.08	0.05	1.44	.15	[-0.03, 0.18]	.08	.07
Difficulty Paying Bills	0.17	0.16	1.04	.30	[-0.15, 0.49]	.06	.05
Sex	0.59	0.19	3.08	.002**	[0.21, 0.96]	.16	.14
Loneliness	0.08	0.01	9.25	< .001**	[0.06, 0.09]	.44	.42
Instagram Time	-0.17	0.08	-2.18	.03*	[-0.33, -0.02]	-.12	-.10
Twitter Time	0.16	0.08	1.98	.05*	[0.001, 0.33]	.11	.09
Perpetration- Public Humiliation	-0.20	0.91	-0.22	.83	[-1.98, 1.59]	-.01	-.01
Perpetration- Malice	1.01	0.64	1.57	.12	[-0.26, 2.27]	.08	.07
Perpetration- Unwanted Contact	2.07	1.73	1.19	.23	[-1.34, 5.48]	.06	.05
Perpetration- Deception	0.15	0.99	0.15	.88	[-1.81, 2.10]	.01	.01
Victimization- Public Humiliation	0.40	1.47	0.27	.79	[-2.49, 3.28]	.01	.01
Victimization- Malice	0.30	0.71	0.42	.68	[-1.10, 1.69]	.02	.02
Victimization- Unwanted Contact	0.54	0.59	0.92	.36	[-0.62, 1.70]	.05	.04
Victimization- Deception	-0.61	0.72	-0.85	.40	[-2.03, 0.81]	-.05	-.04
Depression (Cyberbullying Total)							
Step 1 $\Delta F(8, 356) = 15.13$, $p = < .001$, $\Delta R^2 = 0.25$							
Age	0.08	0.05	1.46	.15	[-0.03, 0.18]	.08	.07
Difficulty Paying Bills	0.21	0.16	1.28	.20	[-0.11, 0.52]	.07	.06

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Sex	0.56	0.19	3.03	.003**	[0.20, 0.93]	.16	.14
Loneliness	0.07	0.01	9.15	< .001**	[0.06, 0.09]	.44	.42
Instagram Time	-0.17	0.08	-2.11	.04*	[-0.32, -0.01]	-.11	-.10
Twitter Time	0.16	0.08	2.00	.05*	[0.002, 0.32]	.11	.09
Total Cyberbullying Perpetration	2.20	1.10	2.00	.05*	[0.04, 4.37]	.11	.09
Total Cybervictimization	0.58	0.91	0.64	.52	[-1.20, 2.36]	.03	.03
Perceived Stress (Cyberbullying Subtypes)							
Step 1 $\Delta F(14, 282) = 5.07$, $p = < .001$, $\Delta R^2 = 0.20$							
Age	0.04	0.20	0.19	.85	[-0.36, 0.44]	.01	.01
Difficulty Paying Bills	1.45	0.62	2.34	.02*	[0.23, 2.67]	.14	.13
Sex	2.28	0.75	3.03	.003**	[0.80, 3.76]	.18	.16
Loneliness	0.18	0.03	5.76	< .001**	[0.12, 0.24]	.33	.31
Instagram Time	-0.11	0.30	-0.36	.72	[-0.71, 0.49]	-.02	-.02
Twitter Time	0.29	0.32	0.88	.38	[-0.35, 0.92]	.05	.05
Perpetration- Public Humiliation	-3.11	3.45	-0.90	.37	[-9.91, 3.68]	-.05	-.05
Perpetration- Malice	0.07	2.45	0.03	.98	[-4.76, 4.90]	.002	.002
Perpetration- Unwanted Contact	3.21	7.25	0.44	.66	[-11.07, 17.48]	.03	.02
Perpetration- Deception	-3.72	3.72	-1.00	.32	[-11.04, 3.60]	-.06	-.05
Victimization- Public Humiliation	8.36	5.87	1.42	.16	[-3.20, 19.91]	.08	.08
Victimization- Malice	2.74	2.70	1.02	.31	[-2.57, 8.05]	.06	.05
Victimization- Unwanted Contact	4.71	2.26	2.09	.04*	[0.27, 9.16]	.12	.11
Victimization- Deception	-4.97	2.69	-1.84	.07	[-10.27, 0.34]	-.11	-.10
Perceived Stress (Cyberbullying Total)							

Outcome Variable:	*B*	*SE*	*t*	*p*	*95%CI's*	*partial coefficients*	*part coefficients*
Step 1 $\Delta F(8, 286) = 7.80$, $p = < .001$, $\Delta R^2 = .18$							
Age	0.03	0.20	0.14	.89	[-0.37, 0.43]	.01	.01
Difficulty Paying Bills	1.58	0.62	2.57	.01*	[0.37, 2.79]	.15	.14
Sex	2.34	0.73	3.19	.002**	[0.90, 3.78]	.19	.17
Loneliness	0.18	0.03	5.70	< .001**	[0.12, 0.24]	.32	.31
Instagram Time	-0.04	0.30	-0.13	.89	[-0.64, 0.56]	-.01	-.01
Twitter Time	0.38	0.31	1.21	.23	[-0.24, 1.00]	.07	.07
Total Cyberbullying Perpetration	-1.71	4.26	-0.40	.69	[-10.09, 6.68]	-.02	-.02
Total Cybervictimization	7.94	3.49	2.27	.02*	[1.07, 14.82]	.13	.12
State Anxiety (Cyberbullying Subtypes)							
Step 1 $\Delta F(14, 353) = 6.82$, $p = < .001$, $\Delta R^2 = 0.21$							
Age	0.53	0.31	1.74	.08	[-0.07, 1.13]	.09	.08
Difficulty Paying Bills	1.39	0.93	1.50	.14	[-0.44, 3.21]	.08	.07
Sex	1.89	1.10	1.71	.09	[-0.28, 4.05]	.09	.08
Loneliness	0.34	0.05	7.27	< .001**	[0.25, 0.43]	.36	.34
Instagram Time	-0.21	0.46	-0.46	.65	[-1.11, 0.69]	-.02	-.02
Twitter Time	0.57	0.47	1.21	.23	[-0.36, 1.50]	.06	.06
Perpetration- Public Humiliation	2.00	5.20	0.39	.70	[-8.22, 12.22]	.02	.02
Perpetration- Malice	-0.12	3.69	-0.03	.98	[-7.38, 7.15]	-.002	-.001
Perpetration- Unwanted Contact	27.22	9.95	2.74	.01*	[7.65, 46.80]	.14	.13
Perpetration- Deception	-3.47	5.75	-0.60	.55	[-14.78, 7.85]	-.03	-.03
Victimization- Public Humiliation	5.13	8.41	0.61	.54	[-11.42, 21.67]	.03	.03
Victimization- Malice	8.13	4.07	2.00	.05*	[0.13, 16.13]	.11	.09
Victimization- Unwanted Contact	1.29	3.40	0.38	.71	[-5.40, 7.98]	.02	.02
Victimization- Deception	-7.27	4.16	-1.75	.08	[-15.46, 0.92]	-.09	-.08

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
State Anxiety (Cyberbullying Total)							
Step 1 $\Delta F(8, 355) = 9.85$, $p = < .001$, $\Delta R^2 = .18$							
Age	0.54	0.31	1.76	.08	[-0.06, 1.14]	.09	.08
Difficulty Paying Bills	1.72	0.94	1.83	.07	[-0.13, 3.56]	.10	.09
Sex	1.78	1.09	1.64	.10	[-0.36, 3.92]	.09	.08
Loneliness	0.33	0.05	7.10	< .001**	[0.24, 0.43]	.35	.34
Instagram Time	-0.18	0.46	-0.39	.70	[-1.09, 0.73]	-.02	-.02
Twitter Time	0.63	0.47	1.34	.18	[-0.29, 1.55]	.07	.06
Total Cyberbullying Perpetration	10.79	6.43	1.68	.09	[-1.85, 23.43]	.09	.08
Total Cybervictimization	5.25	5.28	0.99	.32	[-5.13, 15.63]	.05	.05
Trait Anxiety (Cyberbullying Subtypes)							
Step 1 $\Delta F(14, 353) = 13.11$, $p = < .001$, $\Delta R^2 = 0.34$							
Age	0.38	0.31	1.22	.22	[-0.23, 1.00]	.07	.05
Difficulty Paying Bills	2.28	0.96	2.39	.02*	[0.40, 4.16]	.13	.10
Sex	3.77	1.13	3.32	.001**	[1.54, 6.00]	.17	.14
Loneliness	0.55	0.05	11.50	< .001**	[0.46, 0.64]	.52	.50
Instagram Time	-0.66	0.47	-1.41	.16	[-1.59, 0.26]	-.08	-.06
Twitter Time	0.31	0.49	0.64	.52	[-0.64, 1.27]	.03	.03
Perpetration- Public Humiliation	2.30	5.35	0.43	.67	[-8.22, 12.82]	.02	.02
Perpetration- Malice	5.18	3.80	1.36	.17	[-2.30, 12.66]	.07	.06
Perpetration- Unwanted Contact	19.14	10.25	1.87	.06	[-1.01, 39.29]	.10	.08
Perpetration- Deception	-0.26	5.92	-0.05	.96	[-11.91, 11.38]	-.002	-.002
Victimization- Public Humiliation	-4.10	8.66	-0.47	.64	[-21.13, 12.93]	-.03	-.02
Victimization- Malice	3.19	4.19	0.76	.45	[-5.05, 11.42]	.04	.03

Outcome Variable:	*B*	*SE*	*t*	*p*	*95% CI's*	*partial coefficients*	*part coefficients*
Victimization- Unwanted Contact	1.00	3.50	0.29	.78	[-5.89, 7.89]	.02	.01
Victimization- Deception	-4.42	4.29	-1.03	.30	[-12.85, 4.01]	-.06	-.04
Trait Anxiety (Cyberbullying Total)							
Step 1 $\Delta F(8, 355) = 21.80$, $p = < .001$, $\Delta R^2 = 0.33$							
Age	0.41	0.31	1.33	.18	[-0.20, 1.03]	.07	.06
Difficulty Paying Bills	2.47	0.95	2.60	.01*	[0.60, 4.34]	.14	.11
Sex	3.57	1.10	3.24	.001**	[1.41, 5.74]	.17	.14
Loneliness	0.54	0.05	11.42	< .001**	[0.45, 0.64]	.52	.50
Instagram Time	-0.64	0.47	-1.37	.17	[-1.56, 0.28]	-.07	-.06
Twitter Time	0.32	0.47	0.66	.51	[-0.62, 1.25]	.04	.03
Total Cyberbullying Perpetration	17.43	6.51	2.68	.01*	[4.63, 30.22]	.14	.12
Total Cybervictimization	-2.28	5.34	-0.43	.67	[-12.79, 8.22]	-.02	-.02

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness, time spent on twitter/ Instagram, and cyberbullying behaviors in predicting various physical and mental health outcome measures reflecting Hypothesis 4.

*p<.05, two-tailed

**p<.01, two-tailed

Hypothesis 5:

Finally, also based on the salutary-relationship postulate and the Jensen-Campbell Stress Model of Peer Victimization, it was estimated that social support would account for the relationship between loneliness and health outcomes, while at the same time use of social media applications, either Twitter or Instagram, would also moderate the effects of loneliness in predicting health outcomes (see Figure 2). Overall, this hypothesis was not supported. More specific, contrary to expectations there were no significant moderated mediation, moderation, or mediation effects. However, several direct effects were observed that replicate findings from previous hypotheses (refer to Table 10). Also, note that because there were no significant moderated-mediation, moderated, or mediated effects that emerged when testing this hypothesis using the macro PROCESS Model 7, the non-significant data results were not reported in Table 10. For instance, increased levels of loneliness predicted increased scores of physical symptoms, depression, perceived stress, state anxiety, and trait anxiety. Contrary to expectations, loneliness did not predict levels of obesity. There was also a positive direct effect observed between sex and the outcome variables of physical symptoms, depression, perceived stress, and trait anxiety, but was not related to predicted scores of obesity or state anxiety. Specifically, it appeared that being female, as opposed to male, had greater influence in predicting worse physical and mental health outcomes. Difficulty paying bills was also positively associated with perceived stress, state anxiety, and trait anxiety. However, this variable did not predict outcome measures of physical symptoms, obesity, or depression. Also, age nor social support were associated with any of the physical or mental health outcomes tested. Finally, as it pertains to social media use, increased time spent on Instagram was associated with lower levels of depression but was not associated with any other outcome variables tested including physical symptoms, obesity, perceived stress, state anxiety, or trait anxiety. Also, more time spent on Twitter was related to higher levels of predicted depression and state anxiety, but contrary to what was anticipated it was not associated with any of the other outcome variables measured.

Table 10. ***Direct Effects of Loneliness, Time Spent on Social Media Applications, and Social Support Predicting Outcome Measures of Physical and Mental Health Reflecting Hypothesis 5***

Outcome Variable:	***B***	***SE***	***t***	***p***	***95% CI's***	***partial coefficients***	***part coefficients***
BMI							
Step 1 $\Delta F(7, 365) = 0.94, p = .47, \Delta R^2 = 0.02$							
Age	< 0.001	0.003	-0.002	1.00	[-0.01, 0.01]	< .001	< 0001
Difficulty Paying Bills	0.01	0.01	1.24	.22	[-0.01, 0.03]	.07	.06
Sex	0.02	0.01	1.95	.05*	[0.000, 0.04]	.10	.10
Loneliness	< 0.001	0.001	-0.13	.90	[-0.001, 0.001]	-.01	-.01
Instagram Time	< 0.001	0.01	0.09	.93	[-0.01, 0.01]	.01	.01
Twitter Time	-0.002	0.01	-0.34	.74	[-0.01, 0.01]	-.02	-.02
Social Support	-0.001	0.002	-0.73	.47	[-0.01, 0.002]	-.04	-.04
Physical Symptoms							
Step 1 $\Delta F(7, 380) = 9.01, p = < .001, \Delta R^2 = 0.14$							
Age	0.01	0.07	0.21	.83	[-0.12, 0.15]	.01	.01
Difficulty Paying Bills	0.23	0.21	1.07	.29	[-0.19, 0.64]	.06	.05
Sex	1.10	0.24	4.58	< .001**	[0.63, 1.57]	.23	.22
Loneliness	0.07	0.01	4.99	< .001**	[0.04, 0.10]	.25	.24
Instagram Time	-0.09	0.10	-0.82	.41	[-0.29, 0.12]	-.04	-.04
Twitter Time	0.04	0.11	0.38	.70	[-0.17, 0.25]	.02	.02
Social Support	0.04	0.04	1.05	.30	[-0.03, 0.11]	.05	.05
Depression							
Step 1 $\Delta F(7, 380) = 18.89, p = < .001, \Delta R^2 = 0.26$							
Age	0.09	0.05	1.82	.07	[-0.01, 0.19]	.09	.08
Difficulty Paying Bills	0.20	0.16	1.28	.20	[-0.11, 0.51]	.07	.06
Sex	0.44	0.18	2.50	.01*	[0.10, 0.79]	.13	.11

Outcome Variable:	***B***	***SE***	***t***	***p***	***95%CI's***	***partial coefficients***	***part coefficients***
Loneliness	0.08	0.01	8.06	< .001**	[0.06, 0.11]	.38	.36
Instagram Time	-0.17	0.08	-2.18	.03*	[-0.32, -0.02]	-.11	-.10
Twitter Time	0.23	0.08	2.91	.004*	[0.08, 0.39]	.15	.13
Social Support	0.02	0.03	0.57	.57	[-0.04, 0.07]	.03	.03
Perceived Stress							
Step 1 $\Delta F(7, 300) = 8.77$, $p = < .001$, $\Delta R^2 = 0.17$							
Age	0.01	0.20	0.07	.95	[-0.38, 0.40]	.004	.004
Difficulty Paying Bills	1.71	0.60	2.83	.01*	[0.52, 2.90]	.16	.15
Sex	2.04	0.72	2.84	.01*	[0.63, 3.45]	.16	.15
Loneliness	0.23	0.04	5.40	< .001**	[0.14, 0.31]	.30	.28
Instagram Time	-0.12	0.30	-0.40	.69	[-0.71, 0.47]	-.02	-.02
Twitter Time	0.50	0.31	1.61	.11	[-0.11, 1.11]	.09	.09
Social Support	0.14	0.11	1.27	.20	[-0.07, 0.35]	.07	.07
State Anxiety							
Step 1 $\Delta F(7, 379) = 11.95$, $p = < .001$, $\Delta R^2 = 0.18$							
Age	0.54	0.30	1.81	.07	[-0.05, 1.12]	.09	.08
Difficulty Paying Bills	2.19	0.91	2.41	.02*	[0.41, 3.98]	.12	.11
Sex	0.72	1.04	0.69	.49	[-1.33, 2.76]	.04	.03
Loneliness	0.33	0.06	5.44	< .001**	[0.21, 0.45]	.27	.25
Instagram Time	-0.30	0.45	-0.67	.50	[-1.19, 0.59]	-.03	-.03
Twitter Time	0.91	0.46	1.97	.05*	[0.002, 1.81]	.10	.09
Social Support	-0.14	0.16	-0.87	.39	[-0.46, 0.18]	-.04	-.04
Trait Anxiety							
Step 1 $\Delta F(7, 379) = 26.69$, $p = < .001$, $\Delta R^2 = 0.33$							

Outcome Variable:	***B***	***SE***	***t***	***p***	***95%CI's***	***partial coefficients***	***part coefficients***
Age	0.41	0.30	1.36	.18	[-0.18, 1.00]	.07	.06
Difficulty Paying Bills	2.55	0.92	2.77	.01*	[0.74, 4.36]	.14	.12
Sex	2.77	1.05	2.63	.01*	[0.70, 4.83]	.13	.11
Loneliness	0.53	0.06	8.65	< .001**	[0.41, 0.66]	.41	.36
Instagram Time	-0.78	0.46	-1.71	.09	[-1.68, 0.12]	-.09	-.07
Twitter Time	0.63	0.47	1.36	.18	[-0.28, 1.55]	.07	.06
Social Support	-0.13	0.16	-0.78	.44	[-0.45, 0.19]	-.04	-.03

Note. *B* = unstandardized coefficients, *SE* = standard error, *t* = t-value, *CI* = confidence interval. Depicted are the results of loneliness, time spent on twitter/ Instagram, and cyberbullying behaviors in predicting various physical and mental health outcome measures reflecting Hypothesis 4.

*p<.05, two-tailed

**p<.01, two-tailed

Chapter 4

Discussion

The purpose of the current study was to gain a better understanding as to why there has been a simultaneous surge of chronic loneliness, social media use, and cyberbullying behaviors. To comprehend these relationships, the Evolutionary Theory of Loneliness and Jensen-Campbell's Stress Model of Peer Victimization were used. Overall, several associations between the variables of interest emerged including direct effects of loneliness, social media use, and cyberbullying behaviors to predict physical and mental health outcomes. However, there were also a lot of effects that were not statistically significant, such as time spent on Instagram or Twitter did not moderate the effects of loneliness nor did cyberbullying behaviors, or social support mediate the relationship between loneliness and physical and mental health outcomes tested.

Hypothesis 1

General Hypothesis Overview

It was first hypothesized that there would be a positive relationship between loneliness and cyberbullying behaviors. According to the Evolutionary Theory of Loneliness, chronic loneliness could lead to premature death through different pathways such as increased HPA dysregulation, decreased sleep, increased depressive symptoms, etc. More specific to this theory, over time loneliness could lead to increased spiteful behaviors (self-preservation postulate), and a lack of beneficial relationships that could result in a deficiency of social and physical protection (salutary relationship postulate). It was reasoned then that loneliness would predict cyberbullying behaviors based off these postulates (i.e., spiteful behavior would be manifested through cyberbullying perpetration, and a lack of protective friendships would result in more victimization). Overall, this hypothesis was partially supported because loneliness only directly predicted deception perpetration as opposed to total perpetration, but fully predicted total victimization behavior and its corresponding subtypes as estimated by the Evolutionary Theory of Loneliness. In a recent study, this same positive relationship between loneliness and the tendency to deceive was reported (Demir & Kumcagiz, 2020), suggesting that deception perpetration should be a focus of future research.

Cyberbullying Perpetration

Contrary to expectations, loneliness did not predict total perpetration behavior or the subtypes of public humiliation, malice, and unwanted contact. There has been limited research on these relationships in the literature, so it was unclear whether these effects were present but too small to be detected or were not existent. Also, it was possible that people labeled their actions as other closely related behaviors (e.g., playful teasing, soliciting an undesirable opinion, gossiping, etc.) rather than cyberbullying perpetration or the specific subtypes measured (Lindsey et al., 2016; Martinez-Pecino & Duran, 2019). It has also been pointed out that one flaw of cyberbullying research was that when similar terminology was used, such as cyberbullying and harassment, but operationally defined differently it led to a false belief that cyberbullying behavior was measured when really different phenomena were investigated (e.g., harassment is a type of cyberbullying, but the behavior of perpetration is much larger than just cyber-harassment; Gahagan, Vaterlaus & Frost, 2016). Consequently, researchers may need to refine the understanding of cyberbullying behaviors to include specific types of cyberbullying behaviors (e.g., doxing, flaming, flaring, sockpuppeting, etc.), and examine the applicability of other postulates that constitute the Evolutionary Theory of Loneliness (e.g., Lifespan postulate, Repair-Replace postulate, Selfish-postulate, etc.). Next, it was anticipated that sex would moderate the relationship between loneliness and cyberbullying behaviors. While there were no interaction effects, sex directly predicted both perpetration and victimization outcomes. Males, compared to females, drove the outcomes of total perpetration, malice, and unwanted contact perpetration behaviors, such that males had higher predicted scores of engaging in total perpetration, malice, and unwanted contact perpetration behaviors. These results were in line with previous reports that males had higher rates of both perpetration and victimization behaviors (e.g., Gou, 2016; Sun, Fan, & Du, 2016; Zsila, 2019). Additionally, as not anticipated, sex did not predict public humiliation or deception perpetration. One alternate explanation for this might have been that because the intent of cyberbullying perpetration was not known from the sample obtained, opposite sexes may have had different perceptions of the cyberbullying behaviors of public humiliation and deception. For instance, someone may have perceived the question, " have you pretended to be someone else while talking to someone electronically" as referring to talking to a cute guy or girl over text or their best friend and not interpret this type of behavior as a form of cyberbullying deception perpetration.

Finally, the last variable that was a significant positive predictor of cyberbullying unwanted contact perpetration behavior was age. Several of the questions on the Cyberbullying Experience Survey regarding unwanted contact asked about sexual activity (i.e., "have you sent a message electronically to a stranger requesting sex" or, "have you ever sent an unwanted pornographic picture to someone electronically"). Since the current sample consisted of those ages 17-25, which typically has been a prevalent dating period, this may have influenced the positive relationship between age and unwanted contact perpetration that emerged. This is consistent with prior findings that age moderated the relationship between sex and perpetration outcomes (Barlett & Coyne, 2014; Kowalski, Limber, & McCord, 2019; Kowalski et al., 2014). More specifically, increased age of males was associated with higher levels of cyberbullying during later adolescence compared to females who had higher rates of perpetration in early adolescence. On the contrary, age was not directly associated with any other forms of cyberbullying perpetration in the current study, which may have been influenced by the sample lacking variability in the age ranges. For instance, Bartlett et al., (2019) found age differences associated with both perpetration and victimization (i.e., cyberbullying increased into young adulthood then decreased), but had a sample of ages ranging from 19-74 years of age. This same explanation (i.e., a lack of variability in the participant's socioeconomic status) could have also explained why difficulty paying one's bills was not related to perpetration behavior.

Cybervictimization

As anticipated, loneliness directly predicted total victimization, humiliation, malice, unwanted contact, and deception victimization. These results complemented those of Varghese (2017), who reported a positive relationship between levels of cybervictimization and increased levels of loneliness. Also, sex directly predicted victimization outcomes. In the current study, males, compared to females, drove the outcomes of total cybervictimization, malice, and deception victimization behaviors. Specifically, males had higher anticipated reports of victimization outcomes. These results were consistent with previous reports that males had higher rates of both perpetration and victimization behaviors (Giumetti & Kowalski, 2019; Kowalski & Toth, 2018; Zhou, Zheng, & Gao, 2019). Finally, age did not predict any of the victimization outcome variables tested. This finding is in opposition to what others have found. For example, Kowalski et al. (2019) found that for younger students cyberbullying occurred more face-to-face, but for adolescents it was more prevalent via social media, and then at age 18 cyberbullying behaviors were more prevalent via online gaming platforms. Also, difficulty paying one's monthly bills was not related to victimization behaviors. As mentioned above, this might have been due to a lack of variability in the participant's socioeconomic status. Note that the direct effects of loneliness, sex, and age were maintained in the subsequent analyses and therefore, to avoid redundancy will not be discussed.

Hypothesis 2

General Hypothesis Overview

Secondly, it was estimated that different types of social media use; specifically, Instagram or Twitter, would moderate the relationship between loneliness and predicted cyberbullying, including victimization and perpetration, as well as the subtypes of each of these cyberbullying behaviors. The direct effects of loneliness, sex, and age found in Hypothesis One were maintained in Hypothesis Two, supporting the robustness of these effects. However, overall, this hypothesis was not supported. As reviewed above, the Evolutionary Theory of Loneliness posited that chronic loneliness can ultimately lead to premature death. More specific, the salutary relationship postulate explained that beneficial social interactions and relationships contribute to our survival. However, over time a lack of such relationships (loneliness) leads to our brains becoming more self-protective increasing selfish or spiteful behaviors unconsciously (self-preservation postulate). Therefore, greater use of Instagram (considered a selfish app due to the overwhelming posting of selfies) was estimated to moderate the relationship between loneliness and cyberbullying outcomes, compared to the non-image-based application Twitter. However, this hypothesis was not supported in the current study but should not be discredited. Rather, future research should examine the moderating effects of other social media applications. Recent policy changes, such as those implemented by Instagram (note these policy changes were first implemented during data collection for the current study (starting September 2017-May 2020), have several features to buffer against the negative effects of loneliness (i.e., kindness camera, positive bulk comment thread feature), therefore fostering a more positive communal environment, whereas Twitter continues to pride itself on allowing people to express their freedom of speech. Therefore, Instagram has been rebranded as a less selfish application than initially hypothesized. Also results obtained in Hypothesis One partially supported the relationship between loneliness and cyberbullying (i.e., deception perpetration, total victimization, public humiliation victimization, malice victimization, and unwanted contact victimization) so the current rationale still holds merit, but should be retested using different applications such as YouTube, Facebook, Twitch, or Tik Tok. For instance, it may have been that in the environment of a competitive game the self- preservation postulate would be more prominent because if you are actively competing against others to win the game then your behavior in trying to win will become more selfish (e.g., cursing at other players who are beating you, trying to kill other players game characters, trying to download game shortcuts or enhancements, etc.).

Cyberbullying Perpetration

Furthermore, as expected, a greater amount of time spent on Twitter directly predicted increased measures of total cyberbullying perpetration and public humiliation perpetration. These results were consistent with what Whittaker & Kowalski (2015) found such that cyberbullying was most prevalent on Twitter and Facebook, as opposed to Instagram. Additionally, Brody & Vangelisti (2017) reported that both public and private comments, status updates, and posts were common ways that perpetration occurred in a young adult sample. Based on these results, it makes sense then that total perpetration and public humiliation were directly related to time spent on Twitter because the more time one spends online the more activity they engage in such as posting private and public comments, updating their status, etc. (Giumetti & Kowalski, 2019; Kowalski, Toth, & Morgan, 2018). On the other hand, more time spent on Instagram was associated with decreased predicted scores for total cyberbullying perpetration but did not predict any other forms of perpetration. In a previous study, Instagram use was associated with an increased desire to belong, and total perceived support (Andalibi, Ozturk, & Forte, 2017; Hwnag, 2018; Wong, Amon, & Keep, 2019). Also, Instagram use was not related to any subtypes of perpetration behaviors. One reason that a significant interaction may have not emerged between social media use including time spent on Instagram or Twitter and levels of loneliness could be because these variables were too strongly related. Therefore, it may have been that social media was a mediator of the effects of loneliness or that loneliness was a mediator of social media. A larger, longitudinal study would need to be conducted to tease these relationships apart.

Cybervictimization

Next, as expected, more time reported on Twitter directly predicted increased measures of total cybervictimization, as well as increased behaviors of malice and unwanted contact. These results supported previous literature. More specifically, Twitter was the most commonly used medium associated with cybervictimization, (Al-Garadi, Varathan, & Ravana, 2016; McHugh, Saperstein, & Gold, 2019; Whittaker & Kowalski, 2015). In opposition to what was hypothesized, time spent on Twitter did not predict public humiliation or deception victimization behaviors. Considering social norms as it related to deception and public humiliation, these behaviors have recently become more normalized, such as daily occurrences of prominent political figures and celebrities (i.e., one celebrity tweeting about how another famous person is stupid). It can be reasoned then, that because these types of cyberbullying behaviors have become normalized (i.e., targets of such post become desensitized), they may no longer be interpreted as victimization, but rather “meaningless noise” (Choo, 2015; Pabian et al., 2016). Finally, as mentioned above, because Instagram can be used to build social connections with others (Pew Research Center, 2019), it could be reasoned that no relationship was observed between Instagram use and victimization outcomes due to this. It might have been that Instagram was used to view other friends and family member's daily stories, whereas Twitter was used to gather information. To know why there was no relationship observed as hypothesized, it would be important to collect data concerning how the current study participants used different platforms more precisely.

Hypothesis 3a

General Hypothesis Overview

Next, based on the cumulative deleterious effects postulate, it was estimated that increased levels of loneliness would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety). The cumulative deleterious effects postulate explained that in the short-term, feelings of loneliness could be beneficial because it acted as an alarm motivating us to reassess our social health. However, in the long-term the consequences of loneliness could cause harm to one's health and well-being. The results obtained supported this postulate and were consistent with previous reports that greater levels of loneliness predicted worse mental and physical health (Cacioppo, & Cacioppo, 2014; Chou et al., 2014; Lee et al., 2019). However, future research should replicate this postulate using a longitudinal study as opposed to the cross-sectional approach used here. An unexpected finding was that loneliness did not predict measures of obesity. One explanation for this may have been that the overall data collected were extremely skewed such that the majority of participants reported lower BMIs. For instance, people may have felt a need to under-report their weight or inflate their height, resulting in an inaccurate BMI calculation. A more accurate measurement of this variable would have been to collect each participant's height and weight in-person compared to asking for it via questionnaire.

Sex

Also, being female was associated with greater reports of physical symptoms, depression, perceived stress, and trait anxiety, which was consistent with the larger literature that has documented females reporting more symptoms than males (e.g., Giumetti & Kowalski, 2019; Guo, 2016; Simić-Vukomanović et al., 2016). Additionally, researchers have documented evolutionary sex-related differences in well-being, including differences in hormones, aggression, social skills, depression, and anxiety (Archer, 2019). However, sex was not related to outcome measures of obesity or state anxiety. As mentioned above, the measurement of obesity was highly skewed so this could explain why no association was present. Regarding no relationship between sex and state anxiety, an alternative explanation might be that other external factors might have influenced participants levels of state anxiety that were not considered in the current study. For example, other variables that have been identified, in addition to sex, that were related to state anxiety include family socioeconomic status, college major, year of study, parental expectations of academic success, sleep, physical activity, and spirituality (Peng, 2015; Simić-Vukomanović et al., 2016; Viner et al., 2019).

Age/Difficulty Paying Monthly Bills

Finally, age was not associated with any of the outcome variables tested. As stated previously, this was likely due to a lack of variability in ages. Also, difficulty paying one's monthly bills positively predicted increased scores of perceived stress, state anxiety, and trait anxiety which complements the results of previous literature (Marshell et al., 2020; Simić-Vukomanović et al., 2016). More specific, it was reported that for adults, difficulty paying monthly bills was associated with increased levels of depression and anxiety. As not anticipated, there was no association between this covariate and the outcome measures of obesity, physical symptoms, or depression. An alternate explanation concerning a lack of association between difficulty paying one's monthly bills and physical symptoms may have been that because the study sample consisted of younger healthy adults (i.e., ages ranging from 17-25), rather than a sample of older adults, there may not have been a lot of variability in different physical symptoms reported (i.e., the highest score possible was 156, and the mean score for the current sample was 29.82). Regarding no relationship between difficulty paying one's monthly bills and depression, it may have been that because a majority of the participants were freshman college students it was estimated that these individuals would have fewer monthly bills, such as a house mortgage, or high medical insurance premiums, compared to an older sample. Note that the direct effects of loneliness, sex, and difficulty paying one's monthly bills were maintained in the subsequent analyses and, therefore, to avoid redundancy will not be discussed in Hypotheses 3b, 4, or 5.

Hypothesis 3b

General Hypothesis Overview

Moreover, based on Jensen-Campbell's Stress Model of Peer Victimization, it was estimated that levels of cyberbullying would directly predict health outcomes. Specifically, increased levels of both cyberbullying perpetration and victimization would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety). Overall, this hypothesis was partially supported given that cyberbullying perpetration, and not victimization, directly predicted only some of the physical and mental health outcomes measured. One alternative explanation for victimization not predicting physical health outcomes may have been that other factors masked any physical symptoms that might have been present in this sample. For example, college students have been known to consume large amounts of caffeine, so if researchers ask if they feel fatigued after they have consumed a Red Bull or a Starbucks expresso, they may have been likely to respond no. Also, it may have been reasoned that other influences (i.e., repetition, intent, power imbalances, direct and indirect bullying, and perception), might have been at play here but were not captured in the current study (Peter & Petermann, 2018). For example, your friend may post a “cute” picture of you both on Instagram, but because you think you do not look “cute” in the picture you interpret the act of your friend posting the picture maliciously as a way to make you look bad on Instagram. In future studies, it would be important to use a hybrid methodological approach (i.e., use questionnaires and conduct interviews with participants) to get a better picture of how these other influences (i.e., repetition, intent, power imbalances, direct and indirect bullying, and perception) might affect college students and cyberbullying behaviors more specifically (e.g., does the number of followers increase or decrease targeted cyberbullying attacks). As evidenced by several prior studies (Arana et al., 2018; Knack, Jensen-Campbell, & Baum, 2011; Knack, Iyer, & Jensen-Campbell, 2012; Iyer-Eimberbrink, & Jensen-Campbell, 2019), the Jensen-Campbell Stress Model of Peer Victimization has had strong support so this theory should still be considered credible and applied to the current study. However, it appears this theory would fit more specific types of cybervictimization behaviors that occur in specific contexts that are more likely to mimic traditional bullying such as receiving physical threats on

Twitter or Instagram. In the future, it would be important to use other cyberbullying theories such as the Barlett Gentile Cyberbullying Model in combination with the Jensen-Campbell Stress Model of Peer Victimization to investigate both perpetration and victimization behaviors in predicting physical and mental health outcomes.

Age

It is important to note that several direct effects were observed that should also be discussed. First, there was a positive association between age and trait anxiety. One explanation for this may have been that as people get older, they tend to encounter more major life stressors, such as having children, caring for aging parents, or increased work stress. However, as not anticipated, there was no relationship between age and any of the other outcome variables examined including obesity, physical symptoms, depression, perceived stress, or state anxiety.

Cyberbullying Perpetration

Additionally, as anticipated total cyberbullying perpetration was positively related to increased levels of physical symptoms and trait anxiety, but did not predict scores of obesity, depression, perceived stress, or state anxiety. These results are in line with current research findings (Camerini et al., 2020; Tosuntas et al., 2018). More specific, anxiety-related aggression mediated the relationship for males between their preference for bedtime and cyberbullying perpetration. Also, anxiety related to personal issues was associated with perpetration. As not anticipated, none of the other subtypes of perpetration including public humiliation, malice, or deception predicted any of the outcome measures tested (i.e., obesity, physical symptoms, depression, perceived stress, state, and trait anxiety). One point to consider is that Jensen-Campbell's Stress Model of Peer Victimization hypothesized a positive relationship between victimization, and not necessarily perpetration behaviors, and decreased physical health. This positive relationship between victimization, as opposed to perpetration, and worse predicted physical and mental health outcomes has also been confirmed by other researchers (Austin, 2018; Whittaker & Kowalski, 2015; Kowalski, Toth, & Morgan, 2017; Yuchang et al., 2017; Zych, Farrington, & Ttofi, 2019). Therefore, it was not really unexpected that a lack of relationship emerged between perpetration behaviors and health outcomes.

Cybervictimization

As expected, total victimization and unwanted contact victimization directly predicted increased scores of physical symptoms and perceived stress. These results supported the findings of broader scholarship including the positive association between victimization and increased scores of physical symptoms and stress (e.g., Albdour et al., 2019; Gonzalez-Cabrera et al., 2017; Whittaker & Kowalski, 2015; Musharraf, & Anis-ul-Haque, 2018; Quintana-Orts, Rey, & Neto, 2020). As not hypothesized, total victimization did not predict outcomes related to obesity, depression, state anxiety, and trait anxiety. The other subtypes of victimization, including public humiliation, unwanted contact, and deception, were also not associated with any of the outcome variables tested, including obesity, physical symptoms, depression, perceived stress, state, and trait anxiety. As a reminder, these same results, and alternative explanations were provided above (i.e., lack of variability, self-selection bias, etc.). One reason that victimization may not have been related to state anxiety may have been because different types of perpetration acts, direct or indirect, were not accounted (i.e.., direct cyberbullying compared to indirect cyberbullying has been considered to have a lesser impact; Sticca & Perren, 2013). For example, if someone texted a mean gif directly to you, it may hurt your feelings, but chances are you will shake it off and ignore or even block the person who sent the gif. However, if a malicious meme was posted on your Instagram wall with a caption that indirectly targeted you, given the public platform you will have the added fear that this content can be reposted or that new comments will further catalyze the initial perpetration act. Because there are substantial differences in direct versus indirect victimization, the experience of state anxiety may have been higher with indirect victimization, but the nuances would not have been captured (Brighi et al., 2012; Hong et al., 2018; Slonjc, Smith, & Frisen, 2017). Finally, there was no association between victimization behaviors and trait anxiety.

Hypothesis 4

General Hypothesis Overview

Fourth, based on the salutary-relationship postulate and Jensen-Campbell's Stress Model of Peer Victimization, it was estimated that cyberbullying would moderate the relationship between loneliness and health outcomes, while at the same time use of social media applications would help explain the effects of loneliness in predicting health outcomes. Overall, this hypothesis was not supported. Specifically, social media use did not mediate the relationship between loneliness and health outcomes. Finally, no moderated-mediated effect emerged between loneliness, social support, and social media use in predicting health outcomes.

Based on the results obtained, the salutary relationship postulate was supported. More specific, according to this postulate establishing beneficial social interactions were important to our health and ultimate survival, therefore loneliness acted as a signal to let us know that our social connections were amiss. In the current study, loneliness was associated with both physical and mental health outcomes, therefore reinforcing the relationship between loneliness and health. However, Jensen-Campbell's Stress Model of Peer Victimization was not supported. Loneliness directly predicted mental health outcomes, but contrary to Jensen-Campbell's Stress Model of Peer Victimization which hypothesized a direct relationship between victimization and poor health outcomes, the current study only found support for the direct relationship between perpetration and health outcomes.

An alternate explanation for this hypothesis not being supported may be that there is a myriad of variables that could influence levels of loneliness, social media use, and cyberbullying behaviors, and the current study may have failed to investigate all such possible predictors that moderate these relationships. For example, in a recent study examining possible social media moderators on cyberbullying outcomes problematic internet use, emotional regulation, and parental control of applications used directly predicted perpetration outcomes. (Yudes, Rey, & Extremera, 2020). Also, other factors pertaining to loneliness and cyberbullying on social media need to be considered such as the venue (e.g., Facebook comments, blog post, etc.), as well as the closeness of someone. For example, online aggressive comments directed towards peers were perceived more negatively compared to mean comments directed at a random person online (Whittaker & Kowalski, 2015). Additionally, Patchin (2020) pointed out that other influences on cyberbullying and social media use may entail how often someone unfriends, unfollows, or mutes others, as well as how credible a post is. For example, if someone fails to unfriend those who often post malicious or fake stories it may be that that individual would be the target of cybervictimization, compared to another person who muted an online perpetrator therefore leaving no opportunity for cyberbullying to occur.

Health Outcomes & Social Media

Although it was hypothesized that social support use would mediate the relationship between loneliness and health outcomes, while at the same time social media would moderate this relationship, this hypothesis was not supported. However, one direct effect that emerged was that more time spent on Instagram predicted lower levels of depression, supporting the results of other researchers (Andalibi, Ozturk, & Forte, 2017), and contrary to what was expected (i.e., that there would be a positive relationship between social media use and loneliness), time spent on Instagram was not related to any other outcome variables tested. More specifically, Andalibi, Ozturk, & Forte (2017) reported that people used Instagram for self-disclosure and storytelling, transforming Instagram into a social support platform ultimately reducing levels of depression supporting the salutary relationship postulate. On the other hand, time spent on Twitter was associated with increased predicted scores of depression, aligning with the findings of the self-preservation postulate, and was also confirmed by previous literature (e.g., Keles, McCrae, & Grealish, 2020; Stephen, 2019; Tsugawa et al., 2015). More specifically, it was found that after two months of observing a user's activities, depression could be detected with 69% accuracy. Both Instagram and Twitter users were not related to any of the other outcomes measured including obesity, physical symptoms, perceived stress, state anxiety, or trait anxiety. The lack of associations may have been due to highly skewed data obtained, as well as the study lacking variability such that the sample consisted of mostly healthy young adults who operate under consistently high levels of stress being in a university environment. Therefore, it is estimated that a majority of participants had high levels of perceived stress and anxiety. Selection bias may have also been another influencing factor because those who were extremely stressed or anxious would most likely not take part in the current study.

Cyberbullying Perpetration

As anticipated, total cyberbullying perpetration was positively related to physical symptoms, depression, and trait anxiety, which is consistent with the results of previous literature (e.g., Albdour et al., 2019; Che, Ho, & Lwin, 2017). More specifically, the later study found that physical complaints predicted perpetration. It has also been suggested that cyberbullying is used as a means to displace physical and psychological pain/frustration (Selkie et al., 2015). Also, cyberbully perpetrators who have increased levels of trait anxiety may not have effective coping strategies to deal with their anxiety, so they bully others instead. However, total cyberbullying perpetration did not predict scores of obesity, perceived stress, or state anxiety. Concerning a lack of association between total perpetration and perceived stress, as well as state anxiety, it may be that in general, participants failed to report an accurate amount of perpetration behavior in which they engaged. Therefore, resulting in no direct relationship between perpetration and the other outcome variables measured, including perceived stress and state anxiety. Rather, as discussed previously, a better way to measure total perpetration behavior may have been to ask participants about their attitudes towards this type of bullying. For example, research has demonstrated a link between pro cyberbullying attitudes and cyberbullying perpetration. Such that, cyberbullying attitudes have predicted the intent, as well as future intent that someone would bully another individual (Heirman & Walrave, 2012; Lazuras et al., 2013).

Next, unwanted contact perpetration was associated with increased scores of state anxiety but was not related to any other outcomes tested. Also as not anticipated, none of the other subtypes of perpetration including public humiliation, malice, or deception predicted any of the outcome measures tested (i.e., obesity, physical symptoms, depression, perceived stress, and trait anxiety). One explanation for the positive relationship between unwanted contact perpetration and state anxiety could be that if you send someone nude or pornographic pictures repeatedly that they did not ask to see, because this type of action could result in potential legal consequence it might generate immense anxiety. Contrary to total perpetration, the subtypes of cyberbullying perpetration examined did not predict levels of depression. One alternate explanation for this may have been that participants did not interpret the questions in light of cyberbullying perpetration. For example, “have you ever asked a stranger electronically about what they are wearing”, or “have you teased someone electronically”? It may be that you bought an item off of Facebook marketplace and in meeting a stranger to buy an item, you had to text them and ask them what they were wearing so you could identify the seller. Or it could be the case that you and your best friend send gif’s back and forth to tease each other, but chances are it is with a playful demeanor and not with the intention of perpetration. Regarding the subtypes of public humiliation, malice, unwanted contact, and deception not being related to physical symptoms, this finding was not unanticipated because victimization, and not necessarily perpetration, have been linked to physical symptoms resulting from cyberbullying (Albdour et al., 2020; Austin, 2018; Lee, Jeong, & Roh, 2018). Finally, none of the subtypes tested were associated with perceived stress or trait anxiety. In light of the results found by Gonzalez-Cabrera et al., (2017) victimization and not perpetration were related to perceived stress, so it is not shocking that total perpetration or the subtypes of perpetration directly predicted levels of perceived stress.

Also, another alternate explanation for this may be that other variables that were not considered in the current study may have had a stronger association with the outcome variables tested as it pertained to cyberbullying perpetration. For example, instead of investigating trait anxiety, a better variable may have been to test different personalities (Kircaburun et al., 2019; Resett, & Gamez-Guadix, 2017; Zhou, Zhang, & Gao, 2019). For instance, it was reported that agreeableness was negatively related to engaging in perpetration, while neuroticism was positively related to bystander behavior (i.e., passively participating in perpetration due to witnessing an act and not intervening).

Cybervictimization

As anticipated, total cybervictimization, as well as the subtype of unwanted contact, were positively related to perceived stress, but did not predict scores of any other outcome variables including obesity, physical symptoms, depression, state, or trait anxiety. These results complement those found by Gonzalez-Cabrera et al., (2017) which revealed that cyber victims scored higher on measures of perceived stress compared to perpetrators or bystanders. Also, malice victimization was positively related to greater predicted measures of state anxiety. An alternative explanation for the lack of associations between total or subtypes of victimization and the outcome measures of obesity, physical symptoms, depression, state anxiety, or trait anxiety, may have been that since the current sample consisted of all young college students it was expected that they have more stable physical and mental health compared to a younger sample of pubescent adolescents, or elementary children. Therefore, leading to a lack of variability for physical and mental health outcomes related to victimization. For example, it was found that for younger children cybervictimization was associated with weight-bias, as well as social and emotional development (DePaolis & Williford, 2019; Lee, Jeong, & Roh, 2018). Younger children have less developed brains leading to a decrease in coping skills, as well as experience physical (e.g., growth spurts, neuronal pruning, etc.), and mental changes (e.g., hormonal and emotional changes) at a much more rapid rate than a mature young adult so they are physically and mentally more impacted by victimization. Also, note that the direct effects of Instagram and Twitter use were maintained in the subsequent analysis and therefore to avoid redundancy will not be discussed in hypothesis five.

Hypothesis 5

General Hypothesis Overview

Finally, also based on the salutary-relationship postulate and the Jensen-Campbell Stress Model of Peer Victimization, it was estimated that social support would account for the relationship between loneliness and health outcomes, while at the same time use of social media applications, either Twitter or Instagram, would also moderate the effects of loneliness in predicting health outcomes. Overall, this hypothesis was not supported.

One alternate explanation for the hypothesis not being supported may be the type of social media that was considered for potential moderating effects (Instagram and Twitter). Other social media applications (e.g., Facebook, Snapchat, YouTube, etc.) or alternative moderating variables (e.g., social media addiction) should be explored in future research. For instance, Wu et al., (2016) reported that internet addiction was negatively related to social support, and positively correlated with levels of depression. Furthermore, they found that depression mediated the relationship between social support and internet addiction. More recently, Lin et al. (2020), found that social support mediated the effects of loneliness and active social networking sites. Therefore, because the current study used college students who reported very high levels of time spent per day on Instagram and Twitter, it may have been that not the type of social media used, but rather the levels of addiction on active social networking sites like Instagram and Twitter would influence the relationship between levels of loneliness and social support.

One explanation for the lack of association between social support and Instagram or Twitter use mediating or moderating loneliness and health outcomes may be explained by the potential variables of interest (i.e., Instagram, Twitter use, loneliness, and social support) lacking much variability in the current sample. Because social support may be either positive or negative if someone is lonely, then according to the Evolutionary Theory of Loneliness, this will cause them to interpret social cues with a more pessimistic lens compared to someone who is not chronically lonely (Cacioppo & Cacioppo, 2018). For example, Wang et al., (2018) found that people with depression perceived decreased levels of social support which in turn was related to decreased social functioning. It was also reported that greater loneliness predicted poorer depression outcomes. Additionally, one alternative explanation for why social support did not mediate the effects of loneliness on physical and mental health outcomes, could be that the current type of support received for a participant was not beneficial, or that an individual's capacity/need for support was influenced heavily by external effects that were not measured in the current study. For instance, Cole et at., (2019) examined the size of one's Twitter network compared to their in-person network and found that those with larger Twitter followings who had smaller in-person networks and who were very active on Twitter gained more positively perceived social support from the use of this application, compared to individuals who received more in-person social support. Also, Wong & Keep (2019), examined social support and time spent on Instagram and found that the amount of time spent on Instagram did not predict levels of perceived support, but rather a greater desire to belong (i.e., frequency of posting, number of likes received, number of posts viewed) positively predicted Instagram use. Also, concerning a lack of association between time spent on Instagram or Twitter interacting with levels of loneliness to predict health outcomes, as stated above in Hypothesis 2, it may have been that these variables were too strongly related. Rather, it may have been that social media was a mediator of the effects of loneliness or that loneliness was a mediator of social media. In order to parse out this relationship a larger, longitudinal study would need to be conducted in future research.

Study Limitations

As addressed throughout the discussion section, and to recap the current study was not without a few limitations. First, the design of the study was cross-sectional meaning that information was gathered from participants at only one time point. To measure the chronic effects of loneliness, social media use, and cyberbullying behaviors a longitudinal approach is needed. However, the current sample was a good starting point to examine chronic emotions pertaining to loneliness, social media use, and cyberbullying behaviors in a college age sample, yielding important implications. Secondly, the current study collected self-reported data, which can lend itself to social desirability (i.e., not reporting accurate weight, height, cyberbullying behaviors, or social media usage), and selection bias (i.e., highly depressed people or those stressed with not enough time to participate would most likely end up not taking part in the study). However, it is important to remember that the measures used did account for social desirability, as well as a three-question attention check was implemented to filter out bad data. Considering that human data are not perfect, such flaws are not good justification to extinguish such research, rather some research concerning the current studies variables of interest are better than no attempt to empirically understand such relationships.

Also, participants were not presented with a definition of cyberbullying perpetration and victimization before responding to questions on the Cyberbullying Experience Survey. This may have unintentionally allowed the opportunity for vast differences in interpreting this construct (Olweus, 2012). In one study this exact effect was measured, and it was found that there was a statistically significant difference between participants given a definition of cyberbullying compared to those not. Specifically, those provided a definition reported more cybervictimization (Ybarra et al., 2012). Additionally, not all forms of social media were considered so it may be that such behaviors occur on newer platforms such as Tik Tok, Qzone, WhatsApp, Pinterest, or Snapchat. Finally, while four subtypes of perpetration and victimization were tested, there are several other subtypes of cyberbullying that were not examined (e.g., cyberstalking, cyber-harassment, doxing, trickery, etc.). Therefore, future research will need to investigate the relationship between different types of cyberbullying and newer social media applications (e.g., loneliness and time spent on WhatsApp may interact to predict doxing cyberbullying).

Another weakness of the current study may have been that for the subtypes of malice, unwanted contact, and deception behaviors, respondents may have classified actions in each of these categories as non-distinctive because all these subtypes of behavior are remarkably similar or follow a sequential order. For example, if an individual has, " tried to get information from someone they talked to electronically that the other person did not want to give them", then chances are they also " lied to someone else about themselves electronically" to get the undisclosed information they initially desired. These subtypes of behavior go hand-in-hand; making it hard to parse-out and thus measure these different types of cyberbullying behaviors. While this was a possible limitation, note that for the current study the assumption of multicollinearity was met.

Additionally, the Evolutionary Theory of Loneliness is not without flaws including the notion that several postulates explain that behaviors related to loneliness are based on unconscious processes. It is not plausible then to empirically test unconscious processes exposing one weakness of this theory (Barrett, Pollet, & Stulp, 2014). Also, because this theory is rooted in the evolutionary psychology perspective other flaws surrounding this type of research include hindsight bias and not accounting for culture, and, as stated above these types of theories cannot be tested, therefore, they are not falsifiable (Confer et al., 2010; Fenici & Garofoli, 2019; Ploeger et al., 2008). Additionally, because questionnaires were used to collect data, specific details concerning intent and perception were not obtained. Therefore, the generalizability of this study's findings should be cautiously interpreted and applied. A more desirable approach would entail using a hybrid study design collecting both qualitative and quantitative data. This would provide both the patterns of behavior and the "why" a behavior was enacted. This type of study design, while more ideal, still has barriers, such as increased time and resources to conduct and analyze collected data.

Also, the current sample was homogenous which may have limited variability in several of the measures examined including age (17-25 years of age), socioeconomic status (most participants were freshman and may have limited monthly bills to pay compared to non-college freshman), sex (90 males vs 300 females), and potentially perceived stress and anxiety scores (i.e., participants with high perceived stress or anxiety scores would most likely not have taken part in the study resulting in a self-selection bias potentially leading to a lack of variability in measures of perceived stress and state/trait anxiety). Examining a larger sample of students, as well as those outside of the university such as community dwelling citizens may help to increase variability. While these were a few limitations of the current study, it was still very insightful and serves as a good foundation to conduct further research upon.

Future Research

Because levels of loneliness, social media use, and cyberbullying are still on the rise more research should investigate why this is the case. One area that needs to be further investigated includes identifying vulnerable individuals. Research has found that those who are racial minorities, identify with the LGBTQ community, as well as individuals with disabilities are amongst those who experience the most victimization (Giumetti & Kowalski 2019; Kowalski & Toth, 2017). The University of Texas Arlington is known for its excellence in racial diversity, facilitating a community for those identifying as LGBTQ, and has a large wheelchair population. Because of this, this institute would be an ideal environment to study such populations concerning cyberbullying and health outcomes. Another population that has largely been understudied as it relates to the moderating effects of loneliness, social media use, and cyberbullying behaviors are those ages 65 and older. Research has shown older adults are among the loneliest individuals (Cigna Loneliness Index, 2019) and many are active on social media (Pew Research, 2019), but little is known about their cyberbullying behaviors. It could be that maturity has a great impact on reducing cyberbullying behaviors, but it could also be that alternative patterns of behaviors have yet to be identified. For example, it may be that older adults who are lonely and use social media in excess are more likely to tweet malicious messages, or harass someone on Facebook, compared to someone else who is not chronically lonely or who spends a lot of time on social media. Also, it is important then to identify generational influences as it relates to the moderating or mediating effects between cyberbullying, loneliness, and social media use to predict health outcomes. For instance, because more schools are successfully implementing interventions aimed that reduce cyberbullying (i.e., curriculum that demonstrates to students the fact that their IP address is linked to a single user including their mobile phone reduces cyberbullying perpetration; Barlett, 2017), it would also be important to implement cyberbullying intervention and prevention programs in areas such as senior living facilities, nursing homes, and assisted-care facilities. Therefore, more research should investigate younger generations compared to older generations as it relates to effective intervention programs.

This then leads to another important point of investigation for future research which includes examining how one's occupation relates to cyberbullying. For example, it may be that celebrities or those with very prestigious occupations are forced to use social media as a means to increase their social influence leading them to intentionally or unintentionally bully others online or become targeted cyber victims (Ouvrein, Vandebosch, & De Becker, 2019). For instance, Ed Sheeran stated that, "I go on it and there's nothing but people saying mean things. One comment can ruin your day. But that's why I've come off it."- referring to Facebook and Twitter. It may also be that celebrities or other individuals with prestigious occupations do not have the time to properly cope with the stress/anxieties resulting from their job which may also lead to increased levels of loneliness and cyberbullying behaviors. Also, it could be that someone else and not the actual high-profile individual is managing their social media accounts so it would be important to examine the role that social media managers play as it pertains to the cyberbullying of celebrities specifically.

Next, while the current study gained insight into cyberbullying perpetration and victimization, future studies should also examine other typologies of cyberbullying such as bully-victims, bystanders, and upstanders (Alqahtani et al., 2018). More specific, research should focus on the influences associated with bully-victims to predict poor physical and mental health consequences. For example, some of the factors that have been associated with bully-victims include having a negative attitude about themselves, being isolated by their peers, and struggling academically (Cook et al., 2010). It has also been suggested that out of all the bully-types that bully-victims suffer the most health consequences such as increased anxiety, depression, suicidal ideation, eating disorders, as well as physical symptoms such as poor appetites, headaches, sleep disturbances, abdominal pain, and fatigue (Sansome & Sansome, 2008). This information is important to understand so that public service campaigns and school intervention programs can focus on promoting successful behavior of preventing cyberbullying and/or teach others how to properly cope emotionally and behaviorally when cyberbullying is involved. For example, if researchers can know what causes someone to stand-up to cyberbullying (i.e., being able to report a malicious post anonymously to a community standards board, not further engaging in perpetration behaviors so that an audience does not provide a platform for a bully to continue to indirectly target someone, etc.), then they can teach effective strategies to others. Not only is it important to examine other profiles of cyberbullying, but other platforms also need to be investigated. For instance, research should focus on newer applications such as Tik Tok or live gaming platforms like Twitch.

Also, Barlett (2017) point out, more research is needed to understand specific principles unique to cyberbullying compared to traditional bullying including intent, perception, repetition, influencing power, and anonymity. For instance, it may be that cyberbullying behaviors that occur on Instagram are influenced by the number of followers one has. In the age of YouTube stars, comprehending the power "influencers" have is key as it may ignite or help extinguish cyberbullying behaviors on a plethora of platforms. Additionally, Bartlett (2017), noted that future research should focus on anonymity. For instance, Facebook users have their name and profile picture associated with their posts and comments, whereas other applications including online gaming systems like Xbox Live allow for more privacy. While people can create fake profiles including their name and profile pictures (i.e., catfishing), it is suspected that "more anonymous-friendly social networking sites are more likely to be used to harm others on". However, limited studies have investigated this hypothesis therefore more research is crucial (Barlett, 2017).

Moreover, future research should continue to investigate the association between loneliness and cybervictimization to test if it is bidirectional. While the current study hypothesized that there would be a positive relationship between loneliness and cybervictimization, based on the salutary relationship postulate explaining that a lack of beneficial connections would result in a lack of social protection, the opposite relationship could also be plausible. It has been found that because people are victimized resulting in self-blame for these acts, this can result in loneliness. For example, it was reported that overt and relational victimization were positively associated with predicted increased scores of loneliness, physical symptoms, fear of negative evaluation, and social avoidance (Boivin, Vitaro, & Gagnon, 1995). Also, loneliness was found to mediate the relationship between a depressed mood associated with withdrawal, and a negative experience with peers to predict increased scores of victimizations. Finally, the bidirectional relationship between loneliness and victimization was investigated by Espinoza, Schacter & Juvonen (2020), finding that school-based victimization and loneliness were related, but contrary to what was expected cybervictimization and loneliness were not related. Based on these findings then it can be argued that victimization and loneliness are bidirectional, and future research should continue to examine this specific relationship.

Other variables that future research should consider include sleeping patterns, levels of physical activity, alcohol and recreational drug use, cultural differences, and or race/ethnicity (Rodelli et al., 2018; Selkie et al., 2015). For example, it was reported that students who used recreational drugs, as well as had high levels of alcohol use had increased odds of engaging in cyberbullying perpetration by as much as five times, compared to those who did not report drug or alcohol use (Choi et al., 2019). Additionally, cultural factors including power-distance, individualism versus collectivism, and masculinity versus femininity influence cyberbullying

(Giumetti & Kowalski, 2019; Hu et al., 2018; Barlett et al., 2014). For instance, there was found to be more perpetration behaviors from supervisors from Turkey and India (higher-power distance countries) compared to Australia (lower-power distance country). Also, U.S. college students (individualist culture) had higher rates of cyberbullying behaviors compared to Japanese college students (collectivist culture), these results were moderated by the levels of self-interdependence (Barlett et al., 2013). When investigating various countries/cultures and cyberbullying prevalence rates (i.e., Central European, Mediterranean, North American, South America and Asian culture), culture alone accounted for 66% of the total variance (Lozano-Blasco, Cortés-Pascual, & Latorre-Martínez, 2020). Furthermore, Joenaro, Flores, & Frias (2018), found that one's race and the quality of interpersonal relationships are important to consider as they relate to cyberbullying behaviors. Specifically, ethnic minorities and those who have fewer interpersonal relationships had an increased risk of being victimized. In the U.S., research has shown that multiracial females have the highest reported levels of being victimized (Cyber Bullying Research Center, 2019). Finally, race and ethnicity have also been found to influence outcomes of loneliness, and social media use. For instance, Wu & Penning (2013) found that when examining levels of loneliness that race/ethnicity influenced loneliness particularly among immigrants. Such that, immigrants had higher levels of loneliness compared to native-born participants. Concerning social media use, ethnic differences have also been observed. For instance, Hispanic (51%) and Black adults (40%) are considerably more likely to use the platform Instagram than White adults (33%; Marketing Charts, 2019). Note that for the current study, race was not controlled for when conducting the study analyses because the variables for race and ethnicity were not assessed adequately for the purposes of suggesting racial or ethnic differences.

Moreover, future research should also examine the different types of social support and their effect either positive or negative in relation to cyberbullying, social media use, and loneliness. Pittmann & Reich (2016) found that the image-based applications were associated with decreased loneliness based on the premise that image-based applications provide more social support. Therefore, future studies should explore different applications such as MarcoPolo, Tik Tok, or Instagram Reels, and other applications as it is suspected that an imaged-based, and even more lifelike video-based application would provide increased levels of perceived social support. For example, it may be that a chronically lonely individual can use Facetime to receive appraisal support from their friend leading to improved well-being. On the other hand, simply Facetiming a friend to try to provide emotional support instead of meeting them in person might be a negative form of support (e.g., it might be interpreted as you did not make time to help your friend instead you called them which was not the type of support they really needed). Additionally, other variables like depression, and social media addiction would also be important to examine. For instance, being addicted to social media was associated with increased rates of cyberbullying and loneliness (Al Qudah et al., 2020).

Finally, as it relates to the theoretical framework of cyberbullying, continuing to test different theories is important. For example some theories to examine might include, Tend and Befriend Theory (e.g., how does the perpetration and victimization behavior of lonely females who lack social support differ than lonely males who lack social support), Theory of Planned Behavior (e.g., how do social norms change cyberbullying behaviors, how does perceived control effect perpetration and victimization behaviors for lonely and non-lonely individuals), and various postulates of the Evolutionary Theory of Loneliness (Ajzen, 1991; Cacioppo & Cacioppo, 2018; Taylor et al, 2000). First, according to the Tend and Befriend Theory (Taylor et al., 2000) in times of stress women will reach out to others for social support compared to men. Therefore, because loneliness and being victimized are both stressors, it would be important to understand their relationship as it pertains to social media use, loneliness, and cyberbullying behaviors. For example, one important research question to investigate would be that if lonely women who are victimized reach out to others and receive positive social support, would that mitigate the health consequences associated with the stressors of loneliness and cybervictimization? It is important to note that the current study did test the effects of sex but did not find that sex moderated the effects of loneliness.

Next, because The Theory of Planned Behavior (Ajzen, 1991) considers attitudes, social norms, and perceived behavioral control it would be an important theoretical framework to apply in investigating the relationships between social media use, loneliness, and cyberbullying outcomes. More specific, when asking participants about their cyberbullying behavior it would be hard for respondents to provide an unbiased answer (i.e., it is not socially desirable to admit to cyberbullying others or being victimized). Rather, attitudes have been found to predict intent of cyber bullying perpetration, as well as an individual’s future intentions of perpetrating someone else (Heirman & Walrave, 2012; Lazuras et al., 2013). Therefore, measuring attitudes about cyberbullying compared to asking about specific behaviors may reduce the effects of social desirability. Also, subjective norms are important to consider when investigating cyberbullying behaviors. For example, Gaffney Farrington, & Ttofi (2019), found that several intervention and prevention programs have been successful in reducing cyberbullying behaviors among high school students. Consequently, it may be that as high school students who have participated in such programs go into college there is a subsequent positive change in cyberbullying norms (i.e., a large decrease in both perpetration and victimization incidents). Therefore, considering subject norms would be important for researchers to understand, especially as it relates to the relationships between social media use, loneliness, and cyberbullying behaviors. Finally, the Theory of Planned Behavior accounts for an individual's perceived control. Specific to cyberbullying this aspect of the model might be related to anonymity. For example, one study found that the more private a person could be online, the more likely they were to bully another individual (e.g., " it is easy to bully someone via the internet or mobile phone"; Pabian & Vanderbosch, 2014). Collectively, applying the Theory of Planned Behavior (Ajzen, 1991) in understanding the attitudes, subjective norms, and perceived behavioral control involved in cyberbullying behaviors would be greatly beneficial to researchers to predict cyberbullying outcomes.

Lastly, it would be important for researchers to continue to expand the Evolutionary Theory of Loneliness by testing other postulates. For example, in testing the moderating effect of loneliness and cyberbullying behaviors, an alternative postulate to have tested would have been the Aversive Signal Postulate. According to this postulate, an aversive stimulus is what triggers loneliness. Using this logic, it would be expected that cyberbullying constitutes an aversive signal thus triggering loneliness. Therefore, investigating the sequence of outcomes would be crucial to understand (i.e., which comes first being lonely or being cyberbullied?). As Marvin Gorden said, "no research is ever quite complete. It is the glory of a good bit of work that it opens the way for something still better, and this repeatedly leads to its own eclipse".

Implications

To recap, the goal of the current study was to gain a better understanding of why a simultaneous surge of chronic loneliness, social media use, and cyberbullying behaviors have occurred. To comprehend these relationships the Evolutionary Theory of Loneliness and Jensen

Campbell's Stress Model of Peer Victimization were used. Overall, several associations between the variables of interest emerged including direct effects of loneliness, social media use, and cyberbullying behaviors to predict physical and mental health outcomes resulting in various study implications.

Hypothesis one

Concerning hypothesis one, it was estimated that there would be a positive relationship between loneliness and cyberbullying behaviors. Overall, this hypothesis was partially supported because loneliness was associated with victimization, and only the subtype of deception perpetration. Based on these results there are three major areas that have the potential for enhancement as it relates to the direct relationships observed including reducing rates of bullycide, understanding how age impacts cyberbullying behaviors, and sex differences. As discussed above in the literature review section, many victims of cyberbullying have taken their own life-hence the term "bullycide". The current study confirmed the positive relationship between loneliness and victimization; therefore, two specific implications should result. First, school staff (i.e., teachers, coaches, principals, school counselors, etc.), and healthcare providers should be on the lookout for students who are showing signs of chronic loneliness such as eating alone, having trouble sleeping, being withdrawn from social activities, not participating in class discussions, or expressing other depressive symptomology (e.g., being lethargic, having mood swings, etc.). Ansary (2020), suggest that these authoritative figures once having identified a lonely student have a responsibility to act. For instance, healthcare workers when conducting yearly physicals should implement specific screening questions related to loneliness and cyberbullying. This would allow not only for a student's physical health to be assessed, but also their mental health which the current study and others have shown can also impact an individual's well-being. Not only do schools and health professionals play a role in reducing bullycide, but federal and state authorities should also continue to implement policies and laws pertaining to cyberbullying. For instance, the state of Texas passed David's Law (September 2017), which allows schools to discipline off-campus incidents (Varghese, 2017). Ansary (2020), also highlights that while all states have laws related to cyberbullying, Hinduja & Patchin (2015) provided six ways that such laws can be improved including the following.

> "(1) have a specific definition of harassment, intimidation, and bullying with explicit mention of various technologies; (2) implement sanctions that increase in severity based on repetition; (3) have clear policies for reporting; (4) offer clear policies on investigating; (5) have explicit mention of activities occurring off-school grounds that constitute cyberbullying; and (6) enact policies and procedures for preventing cyberbullying."

Other implications that are important to discuss as they pertain to the results of hypothesis one, specifically the positive relationship between loneliness and victimization, are that workplaces should also be taking steps towards preventing cyberbullying behaviors. For instance, Muhonen & Jonsson (2016), reported that the social organizational climate of one's place of employment mediated the relationship between cyberbullying and health. While most employers offer training over workplace harassment, more focus and resources should be put into cyberbullying training. It is also important that companies use cyberbullying monitoring tools such as the application SquadBox. This application filters emails and allows other moderators to identify harassing messages. Additionally, all organizations including schools, colleges, or other corporations, need to establish a positive culture of empathetic listening. It is only under the condition that people feel heard that they will report cyberbullying. If no action is taken to stop this behavior, then chances are it will not be reported and will continue to be a serious issue.

Lastly, as it pertains to the findings of hypothesis one and a positive association between sex and cyberbullying behaviors, it was confirmed that for both cyberbullying behaviors of perpetration and victimization, males influenced this positive relationship more compared to females. This confirms the findings of Guo (2016), that males had increased rates of both perpetration and victimization behaviors, therefore Sun, Fan, & Du (2016) suggested that when resources are limited that targeted interventions should be given to males. For instance, material could focus on how males could be more empathetic. Doane, Pearson, & Kelley (2014), found that increased empathy decreased cyberbullying, both perpetration and victimization, behaviors drastically.

Hypothesis Two

Secondly, it was estimated that different types of social media use; specifically, Instagram or Twitter, would moderate the relationship between reported levels of loneliness and predicted cyberbullying, including victimization and perpetration, as well as the subtypes of each of these cyberbullying behaviors. Overall, this hypothesis was not supported. Many direct relationships emerged between loneliness, sex, age, and time spent on Instagram and Twitter to predict cyberbullying behaviors; here the focus will be on the implications that surround the use of social media specifically. The good news is that now more than ever social media giants like Instagram and Twitter are taking notice of the research surrounding cyberbullying and thus enacting policy to prevent this behavior from happening on their platforms. For example, Instagram, also the owner of Facebook, rolled out a new feature to encourage self-love and support from others via their kindness camera effect feature (Boyce, 2018). Once a selfie is taken hearts appear on the screen and you are then prompted to tag someone who is a positive supporter. Also, Instagram is experimenting with removing both the comment and like features. This is twofold, first if no comments are posted then harassment will be avoided, and secondly people will not feel pressured to measure the success of a post by the number of likes they do or do not receive. Additionally, Instagram as of recent, May 2020, added the ability for users to delete negative comments in bulk (Hutchinson, 2020). Users can also utilize a new pinned comments feature which gives them a way to set a positive tone by pinning a selected number of comments that will appear at the top of their comments thread. The goal of adding this feature was to highlight only positive comments. If mean comments continue to be posted despite utilizing these new positive features reviewed, then there are a couple options that users can further take to stop bullying. Instagram users can directly report the behavior and it will be removed. Also, by clicking on the icon above an undesired post, you can choose to report someone anonymously. Based on research findings similar to the current study, as well as Instagram & Facebook interviewing numerous users, they found that anonymity is the best way to stop cyberbullying. Therefore, Instagram does not block users but rather has a restricted feature (Juhasz, 2019). This allows for two things compared to blocking a user. First, if a bully is blocked, they would know they have been blocked and may retaliate more via in-person bullying. Second, this feature gives agency to the victim while taking control away from a bully because the user becomes invisible and has the ability to see what the bully is doing. Finally, the restriction feature makes it to where comments on any of the users post that were posted by the restricted user requires that persons approval. While Instagram and Facebook have strict policies on content that cannot be posted (e.g., nudity, profanity, cyberbullying-harassment, etc.), Twitter holds a more liberal policy since they pride themselves on allowing users to express their full freedom of speech. However, Twitter does have a couple features to reduce cyberbullying. First, it allows users to block and report offensive tweets. The community standard board will then review the tweet and decide if it should be taken down or not. Also, users can now choose who to tag and this feature notifies you when you are mentioned in another person's tweet. It is also important to note that Instagram, Twitter, and other social media platforms utilize automated detection software to digitally phenotype and therefore monitor cyberbullying. In one study it was found that such software was 64% accurate in detecting experimental cyberbullying posts (Van Hee et al., 2018). Also, in a meta-analysis conducted by Kumar, & Sachdeva (2019), they found that cyber aggression had an accurate rate of detection of approximately 88%. While social media companies certainly have a civil duty in helping to protect users from being or engaging in cyberbullying on their platforms, it is ultimately up to the users themselves to not engage in this type of behavior. Therefore, the findings obtained from Hypothesis Two reiterate the important associations between Instagram and Twitter to predict cyberbullying behaviors of all kinds.

Hypothesis 3a

Next, based on the cumulative deleterious effects postulate, it was estimated that levels of loneliness would directly predict health outcomes. Specifically, increased levels of loneliness would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety). Overall, this hypothesis was supported. As mentioned above, it is important that healthcare providers be on the lookout for signs of chronic loneliness, especially older adults. If signs of chronic loneliness are identified, then proper interventions can be requested by others. For instance, a few “cures” for loneliness entail volunteering, learning a new hobby, getting involved in a religious organization, and/or implementing cognitive behavior therapy (Cacioppo et al., 2015; Cacioppo & Patrick, 2008; Kall et al, 2020). By volunteering the focus is taken off of oneself and a new goal is provided such as feeding the homeless or helping kids learn to read. Also, by engaging in new hobbies or religious organizations this provides an increased opportunity to make positive social connections which can also help to reduce feelings of loneliness, such as an older adult making t-shirt quilts or other personalized items for their grandchildren. Finally, in using CBT it is important to be aware of small victories and build momentum. For example, if a chronically lonely person is not up for the challenge of volunteering then a good starting place would be to hold the door open for a stranger next time they go to the store, then have them identify this instance as a small victory to build upon. Overcoming loneliness happens only in small increments.

Another implication that resulted from the findings of Hypothesis 3a includes the notion that socioeconomic status (i.e., paying one's monthly bills) predicted increased levels of anxiety and stress. Therefore, schools should provide students with the necessary resources to reduce related stressors. For instance, a first semester course could be implemented educating students about how to effectively manage their monthly budget/bills, how school loans work including interest, current and future investment options related to the stock market, etc. By educating students in this manner it is estimated that it would reduce stress and anxieties associated with paying one's monthly bills and thus improve the mental health of students. It was also found that females compared to males drove increased predicted scores of physical symptoms, depression, perceived stress, and trait anxiety. These findings highlight the fact that males and females physically and mentally react to various stressors differently. Therefore, clinicians should not prescribe treatments to the sexes equally (American Psychological Association, 2012). Rather, a tailored approach is preferred. For instance, according to the Mayo Clinic if treating a female client for depression it would be important to understand other influences such as premenstrual problems (e.g., premenstrual syndrome, premenstrual dysphoric disorder), issues related to pregnancy (e.g., miscarriages, dealing with an unwanted pregnancy, if pregnant having to get off antidepressant medication, postpartum depression), and/or other life circumstances that differ for females (e.g., unequal power and status for employment, work overload, sexual abuse, caring for child and aging parents; Mayo Clinic, 2020; Rincón-Cortés et al., 2019; Wellman et al., 2018).

Hypothesis 3b

Moreover, based on Jensen-Campbell's Stress Model of Peer Victimization, it was estimated that increased levels of both cyberbullying perpetration and victimization would be associated with worse predicted physical and mental health outcomes (i.e., obesity, physical symptoms, depression, perceived stress, and anxiety). Overall, this hypothesis was partially supported, because cyberbullying perpetration and victimization behaviors directly predicted only some of the physical and mental health outcomes tested. Because perpetration and victimization behaviors directly predicted physical and mental health outcomes, it reiterates the importance of executing measures to prevent cyberbullying behaviors. This requires a combined effort from schools, social media companies, and parents. Many schools now offer cyberbullying intervention programs to students with great success (Jadambaa et al., 2019). For example, in examining 15 different cyberbullying intervention and prevention programs it was concluded that both perpetration and victimization behaviors were reduced by approximately 9-15%, and 14-15% respectively (Gaffney, Farrington, Ttofi, 2019). Also, social media companies like Instagram are implementing programs to educate all citizens about proper e-etiquette and safety. For instance, Facebook has created over 200 community events in partnership with the National

Parent Teachers Association (Davis, 2018). Additionally, social media companies including Instagram have implemented community standards which include the following concerning cyberbullying,

> "Respect other members of the Instagram community. We want to foster a positive, diverse community. We remove content that contains credible threats or hate speech, content that targets private individuals to degrade or shame them, personal information meant to blackmail or harass someone, and repeated unwanted messages. It is never OK to encourage violence or attack anyone based on their race, ethnicity, national origin, sex, gender, gender identity, sexual orientation, religious affiliation, disabilities, or diseases. Serious threats of harm to public and personal safety are not allowed. This includes specific threats of physical harm as well as threats of theft, vandalism, and other financial harm. We carefully review reports of threats and consider many things when determining whether a threat is credible."

Parents are also critical in preventing cyberbullying and as recommended by the National Association of School Psychologist (2010) can take the following steps. a). Ensure all computers are in a visible part of the household, b). Establish a child-parent internet contract, and c). Talk openly with your children (both young and older) about internet safety. Additionally, parents should take advantage of applications and software tools that monitor and altar cyberbullying behavior. Some examples of applications parents should be aware of include Mobicip, Near-Parent, Software Eyes Mobile, GoGostats, Cybersyncs, Social Shield, Safety Web, and Net-Nanny. These various apps provide features such as sending parents notifications when their children post, get friend request, or are tagged in stories. Also, data from one's phone and computer can be backed-up, shared, stored, and synced so that parents can get reports that have been flagged for content indicating cyberbullying. Another app, Safety Shield, generates an overall safety score between1-10 and that score is then sent to parents with a 1 representing the highest level of threat for cyberbullying activity that can be detected. While these apps are great for child parent dyads, not all parents monitor their child's social media accounts as they grow older, such as when they are in college and beyond. Therefore, it is important from a young age that a child's on-line behavior is monitored so that good habits and e-etiquette are formed. However, no matter the age, we all have the civil responsibility to monitor and engage in appropriate behavior on our social media accounts and should also be utilizing applications that screen for cyberbullying. For example, the application ReThink, which is free, screens for negative messages and in turn provides a more positive message causing people to rethink sending messages that may insinuate cyberbullying aggression or harassment. Many schools as well as many companies have already required this type of technology to be installed on all computers and other devices to monitor cyberbullying in these environments. Clearly then, there are a plethora of ways that cyber bullying can be prevented and based on the current study's findings will improve all of our wellbeing.

Hypothesis four

Fourth, it was estimated that based on the salutary-relationship postulate and the Jensen-Campbell's Stress Model of Peer Victimization, cyberbullying would explain the relationship between loneliness and health outcomes, while at the same time use of social media applications would help explain the effects of loneliness in predicting health outcomes. Overall, this hypothesis was not supported. However, several direct relationships emerged that constitute general implications such that, independently, Instagram and Twitter use, as well as cyberbullying perpetration and victimization predicted physical and mental health outcomes. These direct relationships provide evidence for increased education when it comes to internet-safety to prevent cyberbullying and thus worse predicted health outcomes. One example, of a school intervention program that is being implemented is the National Center on Safe and Supportive Learning Environments program REMS (Readiness Emergency Management for Schools), sponsored by the U.S. Department of Education- rems.ed.gov. Students are taught about digital citizenship as it concerns the following: privacy and safety concerns (e.g., never put your address or social security number on social media), relationships/communication (e.g., only friend people that you personally know), cyberbullying/digital drama (e.g., do not confront a perpetrator instead block them and report their actions to the appropriate authority), digital footprints/reputation (e.g., your IP address is discoverable and once posted things never leave cyberspace), self-image/identity (e.g., how to brand yourself to future employers or colleges), and copyright policies. Another resource being utilized in academic environments includes the U.S. Department of Homeland Security's Campaign " Stop, Think, Connect" (stopthinkconnect.org). Multiple free resources are available that accompany this campaign including blogs, toolkits, and videos educating others about how to prevent cyberbullying from occurring. For instance, a few tips they coin are " Share with Care", " When in Doubt Throw it Out", keep security software up to date, and avoid connecting to public Wi-Fi. While these e-safety skills are traditionally taught at secondary educational institutes, it has been suggested that this same type of educational course be implemented at the college level (Heliweli, 2017). More specific, it was advised that digital citizenship and e-safety be incorporated into a freshman success course. Students are taught about the harmful effects of drugs and alcohol, so they should also be taught about the harmful effects of cyberbullying. Finally, in a recent article

Denworth (2019), reminds readers that social media use itself is not harmful to others when used in moderation, and that we must all remember that this is a relatively new phenomena and therefore the research concerning the effects that social media has on mental and physical health should also be considered at the infant stage. Only time and more thorough research will provide better insight into the impacts social media use really has.

Hypothesis five

Finally, also based on the salutary-relationship postulate and the Jensen-Campbell Stress Model of Peer Victimization, it was estimated that social support would account for the relationship between loneliness and health outcomes, while at the same time use of social media applications, either Twitter or Instagram, would also moderate the effects of loneliness in predicting health outcomes. Overall, this hypothesis was not supported. However, this result itself provides insight. More specific, it confirms that the role of social support in buffering against negative physical and mental health effects caused by stressors such as cyberbullying and loneliness is indeed multifaceted and constitutes more research. For instance, one major problem observed in the current generation is a lack of face-to-face communication. Cacioppo & Patrick (2008), further highlighted two trends pertaining to this issue including para-relationships, and social snacking. Para-relationships include substituting a relationship with something (e.g., pets, computers, social media) in place of a person. For example, due to a large discrepancy in the number of males and females in countries like China, Vietnam, Estonia, etc. males have had a hard time finding females to marry and have thus replaced a real bride with a virtual bride (Smith, 2020). These virtual brides can be programed to wake their partners up, make coffee/dinner, engage in sexual acts, and provide companionship through continual communication. Social snacking, while similar to para-relationships, entails replacing one's time to build connections with bits of human interaction. For example, instead of meeting a friend for coffee to catch-up, you might follow that friend's Insta story and comment. One application trying to combat these trends and provide more face-to-face communication includes MOST – Moderated Online Social Therapy (Bhat, 2019). This application encourages interaction with others as it is arranged similar to Facebook, as well as features a discussion forum to foster conversation. This allows the user to post questions for others to comment on as it relates to helping them overcome their mental health problem, as well as interact with a licensed care professional to virtually manage their chronic mental health condition (e.g., Autism, Major Depressive Disorder, Socialized Anxiety Disorder).

Conclusion

To conclude, the current study aimed to understand the simultaneous rise in levels of loneliness and cyberbullying behaviors. It was reported that Generation Z is the loneliest generation yet, despite having increased opportunities to grow one's social network via applications like Instagram and Twitter (Cigna Loneliness Index, 2019). One reason speculated for this co-occurrence was that social media is being used to engage in cyberbullying perpetration and victimization behaviors. It was specifically expected that more selfish applications including Instagram would be associated with increased cyberbullying perpetration compared to less selfish apps like Twitter. It was also reasoned that social support would moderate the relationship between levels of loneliness and health outcomes. Contrary to what was hypothesized, no moderated, mediated, or moderated-mediation relationships emerged between loneliness, social media, cyberbullying, or social media use. However, as discussed above, several insightful direct effects emerged such as loneliness predicting increased levels of cyberbullying perpetration and victimization. Also, increased time on Instagram was associated with lower perceived levels of depression, while the opposite relationship was observed with increased time spent on Twitter. It was initially stated that, “millennials expect to create a better future using the collaborative power of digital technology.” Results from the current study support the notion that in order to create a better future using the power of collaborative digital technology, interventions should be targeted at reducing loneliness and cyberbullying behaviors. By being upstanders, as well as outstanding digital citizens, Generation Z has the potential to change course and go down in history as the happiest generation yet, due to decreased levels of loneliness, and cyberbullying behaviors fostered through the collaborative use of digital technology. Let’s continue the work of creating a better future!

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Biographical Information

Danielle Brecht was born and raised in Rogers, Arkansas and graduated from Rogers Heritage High School in 2011. She then attended the University of Arkansas Fort Smith where she ran cross-country and earned her Bachelor of Arts degree in Psychology with a minor in Communication in 2015. While at UAFS, she earned Heartland Conference cross-country honors, participated in debate competitions, presented her research at UAFS Research events, and graduated Cum Ladue. After graduating UAFS, Danielle Brecht continued her education at the University of Arkansas earning a Master of Arts degree in Communication, with an emphasis in Healthcare Communication in 2017. During her time at the UofA, she published her first academic article and was research presenter at the National Communication Association conference while also working as a teaching assistant and UofA athletic tutor. Due to her continued interest in Healthcare Communication and Neuroscience, she pursued an additional Master of Sciences degree in Experimental Psychology with an emphasis in Health Psychology and Neuroscience at the University of Texas Arlington and graduated in 2020. While studying at UTA, she earned a doctoral fellowship, participated in various research projects/labs, published work in various academic journals, including co-authoring a book chapter, presented research at the American Psychological Association conference, and had the opportunity to teach various courses in the UTA Psychology department. Additionally, Danielle participated in several workshops and training courses with UTA’s CIRTL network (Center for the Integration of Research, Teaching and Learning), as well as earned certifications including CAPS-5 (Clinical Administered PTSD scale for DSM-5 Clinician Training), and QPR (QPR Gatekeeper Training for Suicide Prevention Certification). Her future plans include continuing to teach and educate students and the public in subjects concerning Communication and Psychology.