HHS Public Access
Author manuscript
Psychol Assess. Author manuscript; available in PMC 2019 September 01.

Published in final edited form as:
Psychol Assess. 2018 September ; 30(9): 1127–1143. doi:10.1037/pas0000558.

The Online Social Support Scale: Measure Development and Validation

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Abstract

A new measure, the Online Social Support Scale, was developed based on previous theory, research, and measurement of in-person social support. It includes four subscales: esteem/emotional support, social companionship, informational support, and instrumental support. In college and community samples, factor analytic and item response theory results suggest that subtypes of in-person social support also pertain in the online world. Evidence of reliability, convergent validity, and discriminant validity provide excellent psychometric support for the measure. Construct validity accrues to the measure vis-à-vis support for three hypotheses: (1) Various broad types of Internet platforms for social interactions are differentially associated with online social support and online victimization, (2) Similar to in-person social support, online social support offsets the adverse effect of negative life events on self-esteem and depression-related outcome, and (3) Online social support counteracts the effects of online victimization in much the same way that in-person friends in one social niche counterbalance rejection in other social niches.

Keywords

online social support; Internet; social media; depression; self-esteem

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For millions of people around the world, the Internet now plays an enormous role in the development and maintenance of social relations. Online social media platforms have given rise to new and pervasive social niches that appear to operate in ways quite similar to in-person social niches (Gonçalves et al., 2011). Many studies have focused on potential dangers and adverse effects of social media, including cybervictimization, online predators, and Internet addiction (Aboujaoude, Savage, Starcevic, & Salame, 2015; Cassidy, Faucher, & Jackson, 2013; Wingate, Minney, & Guadagno, 2013). Despite the fact that online social relations (like all social relations) convey benefits as well as risks, research on positive aspects of online social relations is only just beginning. One such benefit is what we refer to as *online social support* (OSS), defined as the Internet-facilitated receipt of tangible and intangible assistance from friends, family, and others in one's social circle (House, 1981).

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The empirical studies of OSS that comprise this incipient literature have tended to rely on ad hoc measures often without strong psychometric support. Furthermore, different measures are based upon different theoretical conceptualizations of social support, thus complicating interpretation. The overarching goal of the current study was to develop and validate a new measure of OSS, consisting of four factors that have consistently emerged throughout the rich history of in-person social support research and theory.

Collectively, online social media platforms represent an increasingly popular vehicle for social interactions between people of all ages. In the United States between 2005 and 2015, the use of social networking sites increased from 55% to 76% among adolescents, from 12% to 90% among 18–29 year olds, from 8% to 77% among 30–49 year olds, from 5% to 51% among 50–64 year olds, and from 2% to 35% among people over 65 years old (Lenhart, Purcell, Smith, & Zickuhr, 2010; Lenhart, 2015; Perrin, 2015). Similar trends are evident around the world (Pew Research Center, 2012). The numbers are even larger when other online spaces (e.g., texting, email, multiplayer games) that also enable social interactions are included. The sheer number of online communications is staggering, with over 700,000,000 Snapchat and 500,000,000 Twitter posts per day (Mulshine, 2015; Oreskovic, 2015). Engagement with online spaces is extremely high; for example, 1.13 billion people are "daily active users" of Facebook, meaning they access the site every day (Facebook, 2016). Moreover, 92% of teens use the Internet daily, and 24% report using it "almost constantly" (Lenhard, 2015).

Researchers have noted a variety of ways that online social interactions are similar to in-person interactions (e.g., Gonçalves et al., 2011; Gruzd, Wellman, & Takhteyev, 2011). Most research has focused special attention on negative features. For example, among high school students and young adults, cybervictimization has been associated with most of the same adverse outcomes that have been linked to in-person victimization, including depression, anxiety, somatic complaints, and low self-esteem (Burnett, Yozwiak, & Omar, 2013; Gini, & Espelage, 2014). Some researchers have even suggested that cybervictimization has more severe or farther reaching consequences than does in-person victimization (Cole, Zelkowitz e t al., 2016; Thomas, Connor, & Scott, 2015).

Far less research has focused on positive features of social media, such as its contributions to social support, despite the fact that social support theories (e.g., Cohen & Wills, 1985) and social capital theories (e.g., Ahn, 2012; Donath & Boyd, 2004; Ellison, Steinfield, & Lampe, 2007; Putnam, 2000; Steinfield, Ellison, & Lampe, 2008; cf., Lin, 1999) do not distinguish between online and in-person social phenomena. Cohen and Wills (1985) set forth two broad hypotheses about the ways that social support can mitigate the adverse effects of stress on health-related outcomes, a main effects hypothesis and a buffering hypothesis. The main effects hypothesis is supported when social support has a positive main effect on health and offsets the negative main effect of stress. As such, this model implies that "social resources have a beneficial effect irrespective of whether persons are under stress" or not (p. 310). The buffering hypothesis is supported by a support × stress interaction in which social "support 'buffers' (protects) persons from the potentially pathogenic influence of stressful events" (p. 310). As such, "support is related to well-being only (or primarily) for persons under stress" (p. 310).

With respect to online social support, preliminary research has provided evidence consistent with both models, especially in the context of specific health- and illness-focused interventions. For example, Turner-McGrievy and Tate (2013) demonstrated that participants in a weight-loss program were more successful when they used Twitter to engage with the counselor and other participants (main effect). Graham, Papandonatos, Kang, Moreno, and Abrams (2011) found that participation in an online smoking-reduction social support forum was associated with longer periods of smoking abstinence (main effect). Longman, O'Connor, and Obst (2009) reported that greater online social support among World of Warcraft players was associated with lower depression, anxiety, and stress (main effect). Indian and Grieve (2014) reported that online social support on Facebook had was associated with higher levels of well-being for people with high levels of social anxiety (buffering effect).

In these studies, extant measures of OSS tend to be study-specific and have highly diverse structures. Some treat OSS as a unitary construct (e.g., Graham et al., 2011), whereas others attempt to divide OSS into subtypes based on one theory or another (e.g., Turner-McGrievy & Tate, 2013). To ground our own measure of online social support in social support theory, we began by conducting a literature review of theoretical and empirical attempts to characterize the structure of *in-person* social support. From 22 papers (including eight contained in Barrera & Ainlay's, 1983 previous literature review), we examined the number and nature of identified social support subtypes. After collapsing across conceptually similar subtypes and subtypes with poor discriminant validity, we identified 21 different subtypes of social support. In Table 1, we present a modified stem-and-leaf plot of these results, in which social support subtype names are the stems and numeric representations of the publications are the leaves. Four subtypes were especially prevalent in this literature: (1) *Esteem/Emotional support* (EE) reflects communications from others that convey being held in high esteem, offering help in managing one's emotional state, or expressing acceptance, intimacy, caring, liking, respect, validation, empathy, or sympathy. (2) *Social Companionship* (SC) support conveys a sense of belonging, either directly via expressions of inclusivity or indirectly by spending time together in leisure and recreational activities. (3) *Informational support* (INF) includes help in defining, understanding, and coping with problems; it may take the form of giving advice, offering appraisal support, sharing new information or perspectives, or providing reference to new resources. (4) *Instrumental support* (INS) includes provision of financial aid, material resources, and needed services; it includes offering help in getting necessary tasks done, providing something of use, performing a task, or taking on a responsibility. These four subtypes closely resemble those that derived from Cohen and Wills' (1985) review.

The general purpose of the current study was to develop and validate a new measure of OSS, assessing the online occurrence of these four dimensions of social support: esteem/emotional support, social companionship, informational support, and instrumental support. This overarching goal was accomplished via four specific tasks. First, we identified potential items to represent each of the four subtypes of OSS that have predominated in the in-person social support literature. Second, we used factor analysis and item response theory to affirm the four-factor structure of the new measure and demonstrate that subtypes of social support that pertain in the in-person world also pertain in the online world. Third, we demonstrated discriminant and convergent validity of the resultant measure vis-à-vis other measures of social desirability, dissemblance, and in-person social support. And fourth, we demonstrated construct validity of the measure by examining its anticipated theoretical relations vis-à-vis three hypotheses: (1) Internet use for interacting with others will be positively associated with OSS and negatively associated with cybervictimization; (2) OSS will alleviate the adverse effects of stressful life events on self-esteem and depression-related outcomes; and (3) OSS will offset some of the adverse effects of online victimization, much like having friends in one in-person social niche can counterbalance the negative effects of victimization in a different social niche.

Methods

Online Social Support Scale (OSSS) Item Selection and Measure Construction

In order to obtain items representing all four domains of social support, we derived and adapted items from three sources: pre-existent measures of in-person social support, ad hoc measures of online social support, and published content analyses of online posts and Tweets. From in-person measures, we adapted 179 items from Barrera and Ainlay's (1983) Inventory of Socially Supportive Behaviors; Barrera, Sandler, and Ramsay's (1981) earlier version of the Inventory of Socially Supportive Behaviors; Barling, MacEwen, and Pratt's (1988) questions about social support in response to vignettes; Cohen and Hoberman's (1983) Interpersonal Support Evaluation List; Gottlieb's (1978) classification scheme for informal helping behaviors; Norbeck, Lindsey, and Carrieri's (1981) Norbeck Social Support Questionnaire; Brandt and Weinert's (1981) Personal Resource Questionnaire; and Weinert's (2003) Personal Resource Questionnaire. We reworded in-person social support items to reflect online social support. From extant measures of online social support, we obtained 37 items from Cole et al.'s Social Network Scales (Cole, Nick, Zelkowitz, Roeder, & Spinelli, 2017; Cole, Nick, Varga, et al., 2016); Graham et al.'s (2011) Online Social Support for Smokers Scale; Krämer, Rösner, Eimler, Winter, and Neubaum's (2014) Internet social capital work; and Eastin and LaRose's (2005) modification of the Interpersonal Support Evaluation List (Cohen, Mermelstein, Kamarck, & Hoberman, 1985). From published content analyses of social media material, we derived 63 items from Braithwaite, Waldron, and Finn's (1999) content analysis of message board posts; Gaysynsky, Romansky-Poulin, and Arpadi's (2015) content analysis of Facebook posts; and Turner-McGrievy and Tate's (2013) content analysis based on Cutrona and Suhr's (1992) work on socially supportive Tweets.

From this pool of 279 items, we began to assemble our measure. Some items were included in our measure with minor modifications. Often the content of items, but not wording or structure, inspired new items. Other items were collapsed because of redundancy or culled because of irrelevance. From the remaining items, four of the authors (EN, DC, DS, and GC) independently assembled their own sets of candidate items covering each subtype of social support. After conferring as a group, we converged on a single list of candidate items. In order to refine item phrasing, we consulted with college students and young adults who were knowledgeable about social media. We also piloted the items with 51 local high school students enrolled in an International Baccalaureate psychology class. They provided information about item clarity, redundancy, and acceptability. Culling ambiguous and redundant items resulted in an initial set of 48 items, with 12 items for each OSS subtype.

In order to orient participants to the kinds of online platforms we intended, we began the measure by asking participants to rate how frequently they use various popular social media sites, apps, and games. The instructions and a complete list of sites are the same as for the final version of the measure (see Appendix A). Use of each site was rated on five-point Likert scales (0 = *never*, 1 = *rarely*, 2 = *sometimes*, 3 = *pretty often*, 4 = *a lot*). Following these items, the instructions for the 48 OSS items read, "Now, think about the online spaces you use above. Rate **how often** the following things have happened for you **while you interacted with others** online over the last two months." These instructions were followed by the Esteem/Emotional Support items (e.g., "People show that they care about me online"), Social Companionship items (e.g., "Online, I connect with people who like the same things I do"), Informational Support items (e.g., "When I'm online, people give me useful advice"), and Instrumental Support items (e.g., "Online, people offer to do things for me"). Each item was put on the same 5-point Likert scale as above. Higher scores reflected greater online social support.

Participants

Institutional Review Board approval was obtained for all research protocols involved in this project. In order to ensure a high degree of generalizability, we obtained data from both a college student sample and a young to middle-age community adult sample. After comparing the two samples, we combined them into a single data set (pooling their correlations). We conducted all analyses on the aggregated data (final $N = 404$). For cross validation of the OSSS results we obtained OSSS data on a third sample of young to middle-age community adults.

Sample 1: College student participants and procedures—Participants were 98 undergraduates at a southeastern private university, aged 18–23 (mean age = 19.21, $SD = 1.08$) and 77.6% female. The sample was moderately ethnically diverse: White (77.6%), Asian or Asian-American (14.3%), Hispanic or Mexican-American (9.2%), Black (7.1%), other (4.1%), and American Indian or Native American (0%). Participants could select more than one ethnicity. Most were freshmen (58.3%); fewer were sophomores (27.1%), juniors (7.3%), or seniors (7.3%).

In return for course credit, participants completed all measures online via Qualtrics. We obtained 113 participants, all of whom earned credit for their work. We eliminated 15 participants for invalid patterns of responding (i.e., completing the survey more quickly than we deemed possible, scoring higher than two standard deviations above the mean on a lie scale or a social desirability scale).

Sample 2: Community participants and procedures—Participants were 306 USA adults, aged 18–42 (mean age = 31.98, $SD = 5.18$), 46.4% female. The sample was 77.5% White, 11.8% Asian or Asian-American, 9.5% Black, 3.3% Hispanic or Mexican-American, 2.6% American Indian or Native American, and 1% other (participants could select more than one ethnicity). Most had some post-secondary education (mean years of education =

15.03, *SD* = 1.92). Participants reported working outside the home more than working from home (mean number of hours/week = 28.31, *SD* = 17.55 versus mean = 14.53, *SD* = 16.12).

Participants accessed the Qualtrics survey via a Human Intelligence Task on Amazon's Mechanical Turk (mTurk) system. On mTurk, registered workers across the world can complete computerized tasks, such as online surveys, for small reimbursements. Only USA master workers (workers who have consistently demonstrated accuracy in previous work) could access the study, which was described as intended for workers aged 18–40. We paid each worker $4.00 for their participation, plus a $1.80 fee to Amazon. A total of 315 participants completed enough items for compensation. We eliminated nine participants for invalid patterns of responding (i.e., completing the survey too quickly, scoring higher than two standard deviations above the mean on a lie scale or a social desirability scale).

Sample 3: Community participants and procedures—Participants were 686 USA adults, aged 18–40 (mean age = 29.43, *SD* = 5.94), 50.1% female. The sample was 73.62% White, 12.24% Asian or Asian-American, 5.10% Black, 13.56% Hispanic or Mexican-American, 2.19% American Indian or Native American, and 1.02% other (participants could select more than one ethnicity). Most had some post-secondary education (mean years of education = 14.78, *SD* = 2.73). Participants reported working outside the home more than working from home (mean number of hours/week = 25.71, *SD* = 27.65 versus mean = 6.83, *SD* = 14.05).

Participants accessed the Qualtrics survey via Qualtrics Panels. Research volunteers who have signed up to work with Qualtrics Panels are alerted when they qualify for studies and are compensated for their time with points redeemable as gift cards, skymiles, credit for online games, or similar. We described the survey as intended for adults age 18–40. A total of 812 participants completed enough items for compensation. We eliminated 126 participants for invalid patterns of responding (i.e., completing the survey too quickly, scoring higher than two standard deviations above the mean on a lie scale or social desirability scale).

Measures

In addition to the 48-item version of the OSSS (described above), we administered measures of in-person social support, cybervictimization experiences, life stress, self-esteem, depressive thoughts and symptoms, response style, and time spent online.

Our measure of in-person social support was the Perceived Social Support Scale (PSSS; Procidano & Heller, 1983), which measures the extent to which individuals perceive that their needs for support, information, and feedback are being fulfilled by friends and by family. Items inquire about perceptions of support from friends and family, 20 items each. In the current study, we only used the friends subscale. Participants respond to each item on a three-point scale: no (0), I don't know (1), or yes (2). Higher scores reflect greater support. The scale is well validated and has a high degree of internal consistency, coefficient alpha = .88 (Procidano & Heller, 1983). For our analyses, we recoded answers as yes (1) and no (0). The KR-20 was .94 in sample 1 and .86 in sample 2.

The Cyberbullying Experiences Survey (CES; Doane, Kelley, Chiang, & Padilla, 2013) assesses cyberbullying victimization and perpetration in emerging adults. Twenty-one victimization items and 20 perpetration items make up two subscales. In the current study, we only used the victimization items, reflecting four correlated factors: malice, public humiliation, unwanted contact, and deception (*r*s ranged from .38 to .53; coefficient alphas ranged from .74 to .89). Respondents rate items for frequency of occurrence on seven-point Likert scales from never (0) to every day/almost every day (6). Higher scores reflect greater cyberbullying. The composite CES (summing all four subscales) generated reliable scores with convergent validity, correlating well with other measures of cyberbullying (Doane et al., 2013). In the current study, coefficient alpha was .94 in the sample 1 and .90 in sample 2.

The Life Experiences Survey (LES; Sarason, Johnson, & Siegel, 1978) assesses presence, timing, and impact of positive and negative life events in adults. Sixty-three items (outstanding personal achievements, death of a spouse, etc.) are rated for presence within 0–6 months or 7 months to one year. If present, their impact is rated on seven-point Likert scales ranging from extremely negative (−3) to extremely positive (3). The LES correlates with a variety of relevant dependent measures and has demonstrated good test-retest reliability (e.g., five-week retest correlations ranged from .64 to .88; Sarason et al., 1978). In the current study, we rescaled and summed the negative ratings, so that larger scores reflected *greater* impact of negative events.

The Rosenberg Self-Esteem Scale (RSE; Rosenberg, 1965) measures individual self-esteem. Ten items assess positive and negative self-cognitions. People rate items on four-point Likert scales from strongly agree (1) to strongly disagree (4). Negative items are reverse scored and added to positive items such that higher scores reflect greater self-esteem. In prior research, coefficient alphas have been high (.88) and exploratory factor analysis has resulted in a unidimensional solution (Gray-Little, Hancock, & Williams, 1997). In the current study, coefficient alphas were .95 in sample 1 and .90 in sample 2.

The Cognitive Triad Inventory (CTI; Beckham, Leber, Watkins, Boyer, & Cook, 1986) assesses respondents' view of self, world, and future via positively and negatively phrased items. These components reflect Beck's depressive cognitive triad (Beck, Rush, Shaw, & Emery, 1979). Thirty-six items total (10 for each component plus six filler items that are not scored) are rated on seven-point Likert scales ranging from totally agree (1) to totally disagree (7). Items were rescaled and summed so that higher scores represented more depressive cognitions. Previous research found that coefficient alpha was .95 for the total score (Beckham et al., 1986). In the current study, coefficient alpha was .97 in the sample 1, and .95 in sample 2. To correct for skew, we computed a square-root transformation of the original scores.

The Beck Depression Inventory II (BDI; Beck, Steer, & Brown, 1996) is a commonly used, well-validated measure designed to assess the severity of depressive symptoms in a variety of populations. Twenty-one items describe different depressive symptoms that respondents may have experienced over the last two weeks. Respondents rate the severity of these symptoms on a 0 to 3 scale, with higher scores reflecting greater depressive symptoms. The BDI has been independently validated in a university population (coefficient alpha = .9;

Dozois, Dobson, & Ahnberg, 1998). In the current study, as per IRB requirements, the suicidality item was removed. Coefficient alpha was .96 in the sample 1 and .89 in sample 2. To correct for skew, we computed square root transformations of the BDI scores.

The Marlowe-Crowne Short Form C (MCSF-C; Reynolds, 1982) is a 13-item short form of the Crowne - Marlowe Social Desirability Scale (Crowne & Marlowe, 1960) that measures culturally approved but infrequent behaviors. Thirteen items on the MCSF-C Form C are answered as true (1) or false (0) with higher scores reflecting a greater tendency to respond in social desirable manner. The measure has adequate reliability (KR-20 = .76) and correlates well with the full Crowne and Marlowe Social Desirability Scale ($r = .93$; Reynolds, 1982). In the current study, KR-20 was .76 in sample 1, .73 in sample 2, and .73 in sample 3.

The Revised Eysenck Personality Questionnaire Lie Scale - Short Form (EPQR-S; Eysenck, Eysenck, & Barrett, 1985) is a short form of the lie scale from the Revised Eysenck Personality Questionnaire (Eysenck & Eysenck, 1975). The EPQR-S includes 12 yes/no items that measure the extent to which participants deliberately attempt to control their responses (e.g., “Are all your habits good and desirable ones?”). Higher scores reflect greater deliberate control. Reliability coefficients range from .73 to.77 (Eysenck et al., 1985) and two-year longitudinal correlations range from .69 to .81 (Roberts, Duffy, & Martin, 1995). In the current study the KR-20 was .78 in sample 1, .67 in sample 2, and .77 in sample 3.

We also measured time spent online (TSO) by asking participants how many hours per week they spent using online spaces such as text/photo/video sharing sites (e.g., Facebook, Instagram, Twitter, Snapchat, Tumblr, Vine, Google+), text communication sites (e.g., Texting, Email, Kik, Groupme, Whatsapp), anonymous discussion apps (e.g., YikYak, Whatsgoodly), forums (e.g., Reddit, 4chan), dating sites (e.g., Match.com, eHarmony), dating/hookup apps (e.g., Tinder, Bumble), sports/fighting/racing games (e.g., FIFA, Call of Duty, Need for Speed, Grand Theft Auto), and role player/battle arena games (e.g., World of Warcraft, League of Legends).

Schedule of assessments—Members of samples 1 and 2 completed the same battery of measures: the 48-item version of the OSSS, CES, PSSS, LES, RSE, CTI, BDI-II, MCSF-C, EPQR-S, and TSO. Members of sample 3 completed a subset of the above measures: a 40-item version of the OSSS (described below), MCSF-C, and EPQR-S. All participants completed the OSSS first; subsequent measures were ordered randomly to minimize the effects of fatigue.

Results

Preliminary Analyses

First, we examined samples 1, 2, and 3 with respect to their use of the Internet (see Table 2). On average, all three samples used the Internet extensively, albeit in somewhat different ways. In sample 1 (college students), the most popular platforms were texting apps, email, SnapChat, GroupMe, Facebook, and Instagram. For sample 2, the most popular platforms were texting apps, email, Facebook, Reddit, Twitter, and YouTube. For sample 3, texting apps, email, Facebook, YouTube, Instagram, Twitter, and Pinterest were the most popular.

Before combining samples 1 and 2, we compared their correlation matrices, on which all subsequent analyses were based. Box's test of homogeneity across the two 48 × 48 item-level OSSS correlation matrices (using full information maximum likelihood estimation) was significant ($\chi^2_{1176} = 1982.25$, $p < 0.001$); however, all other indices suggested that a model with all correlations constrained to be equal across groups provided a good fit to the data: TLI = .91, CFI = .96, RMSEA = .041 (90% CI .038 – .044, $p_{\text{close}} = 1.00$). We conducted a similar cross-group comparison of the scale-level correlations among all 16 primary variables. Again, Box's test was significant, ($\chi^2_{120} = 170.25$, $p < 0.05$); however, all other indices indicated that a fully constrained model provided an excellent fit to the data, TLI = .95, CFI = .97, RMSEA = .031 (90% CI .028 – .036, $p_{\text{close}} = 1.00$).

Exploratory Factor Analyses of the OSSS

Exploratory factor analyses of the 48 OSSS items for samples 1 and 2 were based on the pooled correlation matrices. Analyses were conducted with Mplus, version 7.4, utilizing maximum likelihood estimation and oblique Geomin rotation. Examination of scree plots, parallel analysis results (Horn, 1965; Zwick & Velicer, 1986), factor correlations, and factor loadings all suggested that a four-factor solution was optimal. Models with fewer factors provided significantly worse fits (e.g., a three-factor solution fit the data worse than a four-factor solution, $\Delta\chi^2_{45} = 690.98$, $p < .001$). Models with more factors showed signs of over-factoring (e.g., singlets, doublets, large factor correlations). Furthermore, the addition of more factors yielded only very small changes in the RMSEA (e.g., ΔRMSEA for a four-versus five-factor solution was only = .004.) Interpretability of the resultant factors was excellent, as 47 out of 48 of the items loaded strongly on the factor they were originally designed to represent, and all but one of these primary factor loadings were between .45 and .87. Crossloadings were small, with 139 out of 144 being < .30. Consistent with our *a priori* goals, factors 1 to 4 represented Esteem/Emotional Support, Social Companionship, Informational Support, and Instrumental Support, respectively. Factor intercorrelations ranged from .46 to .69.

To shorten the measure and eliminate problematic items, we dropped two items per factor. Culled items had relatively small primary factor loadings, relatively large crossloadings, or evidence of relatively large residual correlations. Coefficient alphas for the 10-item OSSS subscales were .95 for Esteem/Emotional Support, .94 for Social Companionship, .95 for Informational Support, and .95 for Instrumental Support (and Guttman's L2 lower-bound estimates of reliability were .95, .94, .95, and .95, respectively).

We then factor analyzed the reduced, 40-item OSSS (see Appendix A), using the same methods described above. Scree plots, parallel analysis, and goodness-of-fit statistics for models with 1, 2, 3, 4, 5, and 6 factors (see Table 3) collectively provide strong support for a 4-factor model. Factor loadings for the four-factor model appear in Table 4. Factor correlations ranged from .46 to .69, large enough to justify summing the subscales (if researchers want a measure of total OSS) but not so large as to call into question the discriminant validity of the subscales.[1]

To cross-validate these results, we repeated all analyses for the 40-item OSSS using sample 3. Scree plots, parallel analysis, and goodness-of-fit statistics (Table 3), and the factor loadings and factor correlations in Table 4 were very similar to those for samples 1 and 2, again providing strong support for the anticipated four factors. Coefficient alphas and Guttman L2 estimates were identical (to two digits) to those reported above.

Item Response Theory (IRT) Analyses

We conducted IRT analyses on samples 1, 2, and 3 using Mplus, version 7.4. Specifically, we used weighted least squares with adjusted means and variance (WLSMV) with oblique Geomin rotation to estimate model parameters of an exploratory 4-dimensional graded response model. Estimates of item discriminations and thresholds appear in Table 5. The scale of the estimates was standardized in probit values.

The discrimination parameter estimates the ability of an item to differentiate between people, with higher values reflecting greater differentiation capability. (Standard errors for these estimates were small, ranging from .017 – .047, *Mdn* = .022.) As shown in boldface in Table 5, each set of items had high discriminations only for their respective dimensions.

Item thresholds represent item location information for each item on the sum of the four dimensions weighted by item discriminations. Thresholds in Table 5 represent item location information for each item. Threshold 1 reflects the transition point from a score of 0 (never) to scores 1–4 (rarely, sometimes, pretty often, or a lot); Threshold 2 reflects the transition point from scores of 0–1 to scores of 2–4; Threshold 3 reflects the transition point from scores of 0–2 to scores of 3–4; and Threshold 4 reflects the transition point from scores of 0–3 to a score of 4. For all items, thresholds were in order and well separated. (Standard errors were small, ranging from .017 – .047, *Mdn* = .022.) Thresholds were similar for items designed to represent the same dimension. These results indicate that items having the response anchors *never, rarely, sometimes, pretty often*, or *a lot* behaved as designed to assess individual differences in online social support.

We also plotted Test Information Functions (TIFs) for each dimension, holding the other dimensions constant at their means. A high value of test information and a wide curve on TIFs imply good measurement fidelity across a wide range on the underlying dimension. As shown in the figure, coverage of the EE, SC, and INF dimensions was quite good. Coverage of INS was better in the upper 84% of the dimension (i.e., for people with IRT-scores > −1). For INS, these TIF features are commensurate with its higher thresholds shown in Table 5. (We note, however, that the information in these plots pertain to each construct controlling for the other three constructs. They do not reflect the multidimensional nature of OSS, on which scores are a function of a linear combination of the four subordinate OSS constructs, such that different people can obtain the same observed score in a wide variety of ways.)

[1]To test the uni-dimensionality of the four resultant factors, we repeated the above factor analysis four times, once for each set of scale-specific items. Each of these four analyses provided strong evidence of a single underlying factor. Further, the factor loadings did not change substantially from those reported in Table 4.

Validation of the OSSS and Hypothesis Testing in Samples 1 and 2

Correlations—We examined correlations of the OSSS and its subscales with the MCSF-C (social desirability) and EPQR-S (lie scale) for evidence of *discriminant validity* (see Table 6). The OSSS and its subscales correlated .12–.15 with the MCSF-C and .06–.12 with the EPQR-S. The OSSS scores shared less than 2% variance with these two problematic response styles, consistent with our expectation of relative freedom from bias due to impression management.

We also examined the relations of the OSSS and its subscales to the PSSS (perceived social support) for evidence of *convergent validity*. The total OSSS correlated .38 ($p < .01$) with the PSSS, and correlations of the subscales with the PSSS ranged from .23 to .49 (ps < .01). These significant correlations were large enough to suggest convergent validity but are not so large as to suggest redundancy of online and in-person social support.[2]

Is Internet use associated with OSS as well as cybervictimization?—Part of validating a new measure is the demonstration that it relates to other constructs in anticipated ways. In this process, we tested several hypotheses. Our first hypothesis was that greater use of the Internet to connect with other people would be associated with not just greater risk for cybervictimization but greater OSS as well. Specifically, we anticipated that Internet spaces designed to promote social relations or communication (e.g., Facebook, Reddit, email) would be associated with greater OSS. Conversely, sites and apps that tend to facilitate evaluation, criticism, or competition (e.g., YikYak, dating sites/apps, competitive sports games) would increase negative exchanges.

We estimated participants' use of seven broad types of online spaces, by standardizing and averaging usage data from the TSO and the initial part of the OSSS: (1) social media sites like Facebook and Twitter; (2) text communication sites like email and Kik; (3) anonymous discussion apps like YikYak and Whatsgoodly; (4) forums like Reddit and 4chan; (5) dating sites and apps like Tinder, Match, and eHarmony; (6) sports/fighting/racing games like FIFA, Call of Duty, and Need for Speed; and (7) role playing/battle arena games like World of Warcraft and League of Legends. We treated these seven measures as concomitant exogenous variables in a path analysis predicting total OSSS scores and total CES scores (see path diagram in Figure 1). All predictors were allowed to correlate, as were the disturbances for the two endogenous variables. For the regression of OSSS onto the seven predictors, the multiple $R = .44$, $F_{396} = 13.47$, $p < .001$; social media use, text app use, and forum use were all significant predictors. For the regression of the CES onto the same predictors, the multiple $R = .33$, $F_{396} = 6.45$, $p < .001$; anonymous discussion apps, and dating sites/apps, sports/fighting/racing games were all significant predictors.

Does online support alleviate effects of stressful life events on depression-related outcomes?—Our second hypothesis derived from Cohen and Wills' (1985) main effects and buffering models. Construct validity would accrue to our new measure if OSS

[2]Means and standard deviations for the community and college samples are also presented in Table 6. The means for the community sample were significantly larger than the college sample for the SC, INF, INS, and LS measures and significantly smaller on the EE, CTI, Use, and TSO measures.

counteracted the effects of stressful life events by means of either an offsetting main effect or the buffering effect of an interaction. As stressful events have particularly strong effects on depression-related symptoms (Hammen, 2005), we treated the RSE, CTI, and BDI-II as our outcome measures.

We conducted a series of two-step hierarchical regressions, one for each dependent variable. In each, step 1 constituted our test of the main effects for OSSS and LES. In step 2, we added the OSSS × LES interaction (all predictors were centered at 0, as per Aiken & West, 1991). All interactions were small and nonsignificant (*p*s > .10, see top half of Table 7). In every analysis, a significant adverse main effect for LES was counterbalanced by a main effect for OSSS in the opposite direction. (Note that on the RSE, higher scores represent a better outcome, whereas on the CTI and BDI-II positive scores represent less healthy outcomes.) Follow-up analyses revealed that all four OSSS subscales were related to the RSE and CTI, but only the emotional support subscale was related to the BDI-II after controlling for type I error. These results simultaneously extend support for Cohen and Wills' (1985) main effects theory to the online world and support the construct validity of the OSSS.

To confirm that the effects of OSS truly parallel the effects of in-person social support in the current data, we conducted a second series of hierarchical regressions, using the PSSS instead of the OSSS. As above, all interactions with LES were small and nonsignificant (*p*s > .10). All main effects for PSSS and LES were significant and in opposite directions, consistent with Cohen and Wills' (1985) main-effects model (see bottom half of Table 7). The only substantive difference between the online and in-person results was that the main effects of PSSS were stronger than the main effects of OSSS.

Does online support offset the adverse effects of online victimization?— Previous theory and research on in-person relationships suggests that social support can diminish the negative effects of social rejection or peer victimization (Bilsky, et al., 2013; Maurizi, Grogan-Kaylor, Granillo, & Delva, 2013; Rothon, Head, Klineberg, & Stasfeld, 2011). Consequently, we examined the ability of both online and in-person social support to alleviate the effects of online victimization. As peer victimization has some of its strongest effects on depression-related symptoms (Reijntjes, Kamphuis, Prinzie, & Telch, 2010), we again treated the RSE, CTI, and BDI-II as our outcome measures.

We conducted separate hierarchical regression analyses, one set for each dependent variable. In step 1 of each analysis, we entered cyberbullying scores (i.e., the CES) in order to document the total effect of online victimization. As shown in the top half of Table 8, the CES significantly predicted all three dependent variables. In step 2, we added the OSSS. In every analysis, the OSSS and the CES were significant, albeit in opposite directions. Examination of the standardized coefficients reveals that the effect of OSSS was as large as or larger than the effect of CES, suggesting that the salubrious main effect of online social support offset the adverse main effect of online victimization in every analysis (see top of Table 8). In step 3, we tested the CES × OSSS interaction. Follow-up analyses revealed that all OSSS subscales were related to all outcome measures, except that INS and INF were not related to BDI-II scores after controlling for type-I error. In every analysis the interaction was not significant (*p*s > .10) after statistically controlling for the main effects (results not shown in Table 8).

In order to see if the OSSS results (above) resembled the results for in-person social support, we conducted a parallel set of analyses, replacing the OSSS with the PSSS (see bottom half of Table 8). Step 1 again shows the significant adverse effects of CES on all three outcomes. In step 2, the effect of PSSS was large, significant, and in the opposite direction of the CES. In two of the analyses (predicting RSE and BDI-II), the CES was no longer significant when PSSS was in the model. In step 3, the PSSS × CES interaction emerged as a small but significant predictor of all three dependent variables. Both main effects remained significant as well. The nature of these interactions, however, was not consistent with Cohen and Wills' (1985) hypothesized buffering effect (see Figure 2). Instead, the powerful main effect of low PSSS attenuated the effect of CES on the outcomes. Except for these interactions, the results for PSSS were generally similar to but stronger than the effects of OSSS on the three outcome variables.

Discussion

Four key results emerged from the current study about the measurement, validation, and effects of online social support. First, we developed the Online Social Support Scale, the first of its kind that has both deep theoretical roots and strong psychometric properties. The scale has a highly interpretable factor structure, demonstrating that the four main subtypes of in-person social support also exist in the online world. Second, we found that spending more time online not only increases one's risk for cybervictimization but also increases the extent of social support from one's online social network. Third, similar to in-person social support, online social support represents an important positive resource that can offset some of the adverse effects of negative life events. Fourth, online social support (like in-person social support) helps to offset some of the adverse effects of online victimization. Each of these results has implications both for the validation of the OSSS and for the extension of in-person social support theory to the online world of social relations.

Our first goal, the construction of the Online Social Support Scale, was informed by substantial previous empirical and theoretical work on in-person social support plus the small but growing research into online social support. We built the OSSS to represent four major types of social support that have pervaded the in-person social support literature for decades: esteem/emotional support, social companionship, informational support, and instrumental support. Factor analysis of the OSSS revealed strong support for these factors. This result not only helps to validate the OSSS but it augments a growing literature suggesting that online communities function similarly to physical communities (Gruzd et al., 2011). Gonçalves et al. (2011) further noted that the pervasive use of online social media platforms by all layers of society make them "an ideal proxy for the study of social interactions" (pp. 1–2). From the current study, we see that the primary subtypes of social support operating in the in-person world also exist in the online world.

The current study also provides sound psychometric support for the OSSS. The correlation of the OSSS with the PSSS was high enough to suggest good convergent validity but not so high as to call the distinctiveness of the OSSS into question. Correlations of the OSSS with measures of dissemblance and social desirability were small, an important feature given the tendency of some respondents for self-enhancement in survey research. The reliabilities of all four OSSS subscales were quite high.

Our second major finding speaks both to the construct validity of the OSSS and to a larger social issue. Since the emergence of social media, people have (understandably) been very concerned about its abuse. A PsycInfo search for “cybervictimization or cyberbullying” revealed over 1100 studies, dating back to 2006. In contrast, a search for “online social support” found less than 100 citations (most of which emerged since 2013), suggesting that the interpersonal benefits of social media have been somewhat neglected until recently. In the current study, we hypothesized that online social relationships, like in-person social relationships, carry rewards as well as risks. Supporting this contention, we found that increased Internet use was significantly related to not just increased rates of online victimization but increased social support as well.

These results complement a growing literature about the similarities between the in-person and online worlds. For example, research based on social capital theory (Lin, 1999) has shown that social media use predicts bridging social capital and that valence of online communications predicts bonding social capital, in ways similar to face-to-face communications (Ahn, 2012; Donath & Boyd, 2004; Ellison et al., 2007; Putnam, 2000; Steinfield et al., 2008). Gonçalves et al. (2011) further noted that the pervasive adoption of social media by all layers of society “makes it an ideal proxy for the study of social interactions” (pp. 1–2). Reflecting the downside of social media, cyber-victimization can have consequences at least as severe as in-person forms of victimization (Bonanno & Hymel, 2013; Cole, Zelkowitz, Nick, Martin, et al., 2016; Kowalski, Giumetti, Schroeder, & Lattanner, 2014; Kowalski & Limber, 2013). Reflecting the upside, an incipient literature has begun to document the positive effects of OSS, at least as a tool for coping with specific, health-related problems (e.g., Braithwaite et al., 1999; Gaysynsky et al., 2015; Turner-McGrievy & Tate, 2013). The current study suggests that online social support is at least as strongly associated with Internet use as is online victimization. Our results further suggest that online social support and victimization are related to time spent in different online spaces. Whereas online support appears to accrue for those spending more time on classic social media sites and spaces facilitating communication (e.g., email, texting apps; forums), victimization appears to be more highly correlated with time spent on anonymous discussion apps, dating sites/apps, and sports, fighting, and racing games. An important direction for future research would be to study these same online spaces in younger samples, as children’s choice of online environment may have important implications for their experiences of online social support or victimization.

Our third major finding was that online social support (measured by the OSSS) counterbalanced some of the adverse effects of negative life events at least insofar as depression-related outcomes were concerned. This result has two implications. It extends support for Cohen and Wills’ (1985) main effects model to the online world, while simultaneously providing additional construct validation of the OSSS. Cohen and Wills’ main effects model suggests that stressful life events take their toll on human psychological and physical well-being but that strong social support can have an opposite salubrious effect for people at all levels of stress. Similar to Longman et al.'s (2009) research on the benefits of social support in online gaming, the current research found positive effects for all types of online social support. Although the results for online and in-person support were quite similar, the effects of in-person social support were stronger. Not surprisingly, social support that derives from traditional face-to-face relationships appears to be more powerful than social support that is completely online. The fact that channels of online communications are inherently more constrained has been deemed a possible simplifying advantage for people who have difficulty in face-to-face interactions (Mesch & Talmudrence, 2006); however, the current results suggest that, on average, the advantages of face-to-face social support may be greater. An important direction for future research would be to explore individual difference characteristics that moderate the utility of online spaces as a source of social support (e.g., Longman et al., 2009).

Our fourth finding was that both online and in-person social support offset some of the adverse effects of cybervictimization. Social and developmental psychologists have repeatedly shown that interpersonal support from one social niche can make up for ostracism, rejection, and victimization in another social niche (Hodges, Malone, & Perry, 1997; Parker & Asher, 1993; Schwartz, Dodge, Pettit, & Bates, 2000). The current results suggest that a similar compensatory model pertains in the online world. In our data, online victimization was associated with low self-esteem and depressive symptoms in a manner similar to the effects of in-person victimization (cf. Reijntjes et al., 2010, for studies of negative effects of in-person PV). The effects of online social support, however, were just as strong and in the opposite direction, suggesting that the advantages of online social relationships offset their disadvantages. The effects of in-person social support were very similar, except for two things: (1) its main effect was larger and (2) for people with low levels of in-person social support, the additional effect of online victimization was negligible.

Limitations of the current study suggest important avenues for future research. First, we only measured in-person social support from friends. Although the Perceived Social Support Scale (PSSS) has both friends and family subscales, we only used the former. Future research should investigate the relative strengths of different sources of social support (e.g., friends, family, school/work, community, interest/affinity groups) in addition to the means of delivery of that support (in person, online).

Second, in the current study, we validated the OSSS only against depression-related outcomes such as depressive thinking, depressive symptoms, and self-esteem. Within the in-person world, social support relates to an enormous number of mental and physical health-related outcomes (Ganster & Victor, 1988; Schwarzer & Leppin, 1989; Uchino, Bowen, Carlisle, & Birmingham, 2012). A critical direction for future research would be to examine the relation of the OSSS to a wider variety of outcomes, not only to document further the predictive validity of the measure but also to ascertain how broad the beneficial effects of OSS may be (Wright & Bell, 2003).

Third, the current study documents the overarching merits of online social support; however, the mechanisms underlying its benefits are unknown. One possibility is that the benefits of OSS derive from the inclusion of people who are not part of one's in-person social network. Alternatively, the benefits of OSS may reflect the fact that the same people behave differently online than they do in-person (Cummings, Butler, & Kraut, 2002). Both of these possibilities are important and deserve further research.

Fourth, the current study examined the utility of OSS across a wide variety of people; however, it did not test for differential effects of OSS for various subtypes of people. Previous research suggests that social support via Facebook was especially useful to people with high levels of social anxiety, who may have found it easier to develop friendships online than in person (Indian & Grieve, 2014). Future research should examine individual difference characteristics that could moderate the effects of OSS.

Fifth, we intentionally focused on broadband online social support, pooling across a wide variety of online platforms. The OSSS can easily be adapted to focus on a particular type of online experience (e.g., social media, gaming) or even a particular site or app (e.g., Reddit, YikYak). As suggested in the current study, different platforms may confer very different risks and benefits. Such information would be especially useful in middle or high school technology classes, where entry-level users may just be learning about different social media platforms.

Finally, it may be tempting to infer from many of our findings that OSS has a prospective if not causal relation to depression-related outcomes; however, the current study was cross-sectional. A valuable direction for future research would be to design longitudinal or experimental studies to test the degree to which OSS actually predicts changes in social, educational, or health outcomes over time.

Acknowledgments

This work was supported in part by a training grant from the National Institute of Mental Health (T32 MH018921), the Peter and Malina James & Dr. Louis P. James Legacy Scholarship (American Psychological Foundation), and by a Psi Chi Junior Scientist Fellowship (American Psychological Association of Graduate Students).

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Appendix A

Online Social Support Scale (OSSS)

Most sites, apps, services, and games on the Internet can be used in lots of different ways and for different purposes. We're interested in how much you use these online spaces to **connect or interact with other people**.

This means we **are** interested in how much you use these online spaces to talk with people, post, comment, like, send messages, game with others, etc.

This means we are **not** interested in how much you use these online spaces to scroll through other people's posts, watch or read content, or just look up information.

How much do you use the following sites, apps, services, or games to **connect or interact with other people?**

0 = Never 1 = Rarely 2 = Sometimes 3 = Pretty Often 4 = A lot					
Facebook	0	1	2	3	4
Instagram	0	1	2	3	4
Twitter	0	1	2	3	4
SnapChat	0	1	2	3	4
Tumblr	0	1	2	3	4
Vine	0	1	2	3	4
YouTube	0	1	2	3	4
Pinterest	0	1	2	3	4
Reddit	0	1	2	3	4
YikYak	0	1	2	3	4
Kik	0	1	2	3	4
LinkedIn	0	1	2	3	4
GroupMe	0	1	2	3	4
WhatsApp	0	1	2	3	4
Google+	0	1	2	3	4
Whatsgoodly	0	1	2	3	4
Chat services	0	1	2	3	4
Email	0	1	2	3	4
Texting	0	1	2	3	4
Dating sites/apps (e.g., Tinder)	0	1	2	3	4

0 = Never 1 = Rarely 2 = Sometimes 3 = Pretty Often 4 = A lot					
First person shooter games (e.g., Call of Duty)	0	1	2	3	4
Battle arena games (MOBAs: e.g., League of Legends)	0	1	2	3	4
Sports/fighting/racing games (e.g., FIFA, Street Fighter, Mario Kart)	0	1	2	3	4
Role-playing games (RPGs: e.g., World of Warcraft)	0	1	2	3	4
If you interact with people using other sites, apps, services, or games, please write them in and rate how often you use them:					
______________________________	0	1	2	3	4
______________________________	0	1	2	3	4
______________________________	0	1	2	3	4

Now, think about the online spaces you use above. Rate **how often** the following things have happened for you **while you interacted with others** online over the last two months. Use the following scale:

	0 = Never 1 = Rarely 2 = Sometimes 3 = Pretty Often 4 = A lot					
1.	People show that they care about me online.	0	1	2	3	4
2.	Online, people say or do things that make me feel good about myself.	0	1	2	3	4
3.	People encourage me when I'm online.	0	1	2	3	4
4.	People pay attention to me online.	0	1	2	3	4
5.	I get likes, favorites, upvotes, views, etc. online.	0	1	2	3	4
6.	I get positive comments online.	0	1	2	3	4
7.	When I'm online, people tell me they like the things I say or do.	0	1	2	3	4
8.	Online, people are interested in me as a person.	0	1	2	3	4
9.	People support me online.	0	1	2	3	4
10.	When I'm online, people make me feel good about myself.	0	1	2	3	4
11.	When I'm online, I talk or do things with other people.	0	1	2	3	4
12.	People spend time with me online.	0	1	2	3	4
13.	People hang out and do fun things with me online.	0	1	2	3	4
14.	Online, I belong to groups of people with similar interests.	0	1	2	3	4
15.	People talk with me online about things we have in common.	0	1	2	3	4
16.	Online, I connect with people who like the same things I do.	0	1	2	3	4
17.	I am part of groups online.	0	1	2	3	4
18.	When I'm online, people joke and kid around with me.	0	1	2	3	4
19.	People relate to me through things I say or do online.	0	1	2	3	4
20.	Online, people make me feel like I belong.	0	1	2	3	4
21.	When I'm online, people give me useful advice.	0	1	2	3	4
22.	Online, people provide me with helpful information.	0	1	2	3	4
23.	If I had a problem, people would help me online by saying what they would do.	0	1	2	3	4
24.	Online, people would tell me where to find help if I needed it.	0	1	2	3	4
25.	People help me learn new things when I'm online.	0	1	2	3	4
26.	People offer suggestions to me online.	0	1	2	3	4

	0 = Never 1 = Rarely 2 = Sometimes 3 = Pretty Often 4 = A lot					
27.	People tell me things I want to know online.	0	1	2	3	4
28.	When I'm online, people help me understand my situation better.	0	1	2	3	4
29.	If I had a problem, people would share their point of view online.	0	1	2	3	4
30.	People help me see things in new ways when I'm online.	0	1	2	3	4
31.	People online would help me with money or other things if I needed it.	0	1	2	3	4
32.	When I'm online, people help me with school or work.	0	1	2	3	4
33.	Online, people help me get things done.	0	1	2	3	4
34.	If I needed a hand doing something, I go online to find people who will help out.	0	1	2	3	4
35.	Online, people offer to do things for me.	0	1	2	3	4
36.	Online, people help me with causes or events that I think are important.	0	1	2	3	4
37.	When I'm online, people have offered me things I need.	0	1	2	3	4
38.	When I need something, I go online to find someone who might lend it to me.	0	1	2	3	4
39.	When I need a hand with school or work things, I get help from others online.	0	1	2	3	4
40.	I contact people online to get help or raise money for things I think are important.	0	1	2	3	4

Public Significance Statement

This study introduces a new self-report questionnaire to measure four broad types of online social support, similar to those found for in-person social support: esteem/emotional support, social companionship, informational support, and instrumental support. Different online sites and apps provide opportunities for different types and amounts of social support. Similar to in-person social support, online social support helps people cope with adversity.

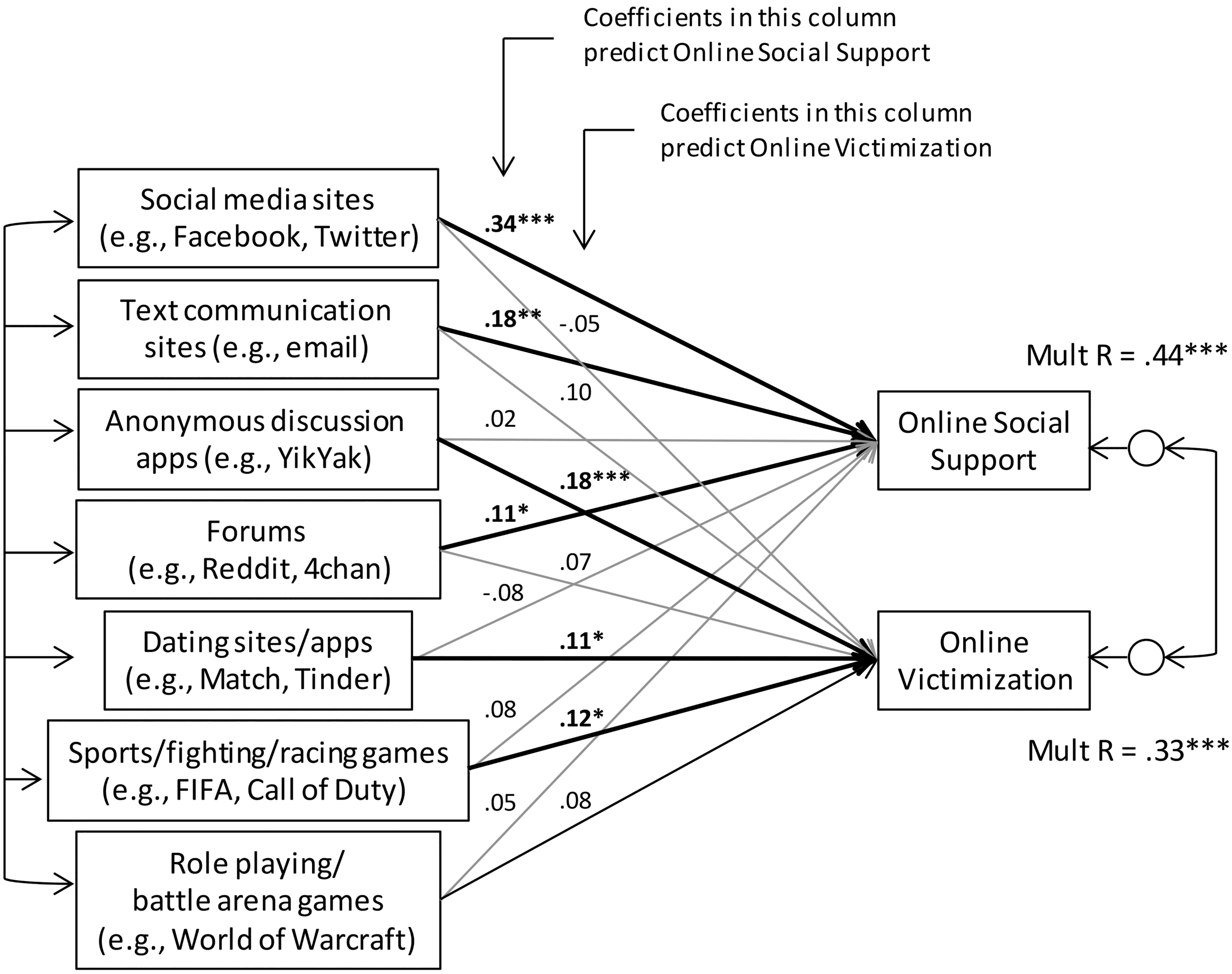

Figure 1.
Path analysis of differential effects of online platform use on online social support versus online victimization (samples 1 and 2).

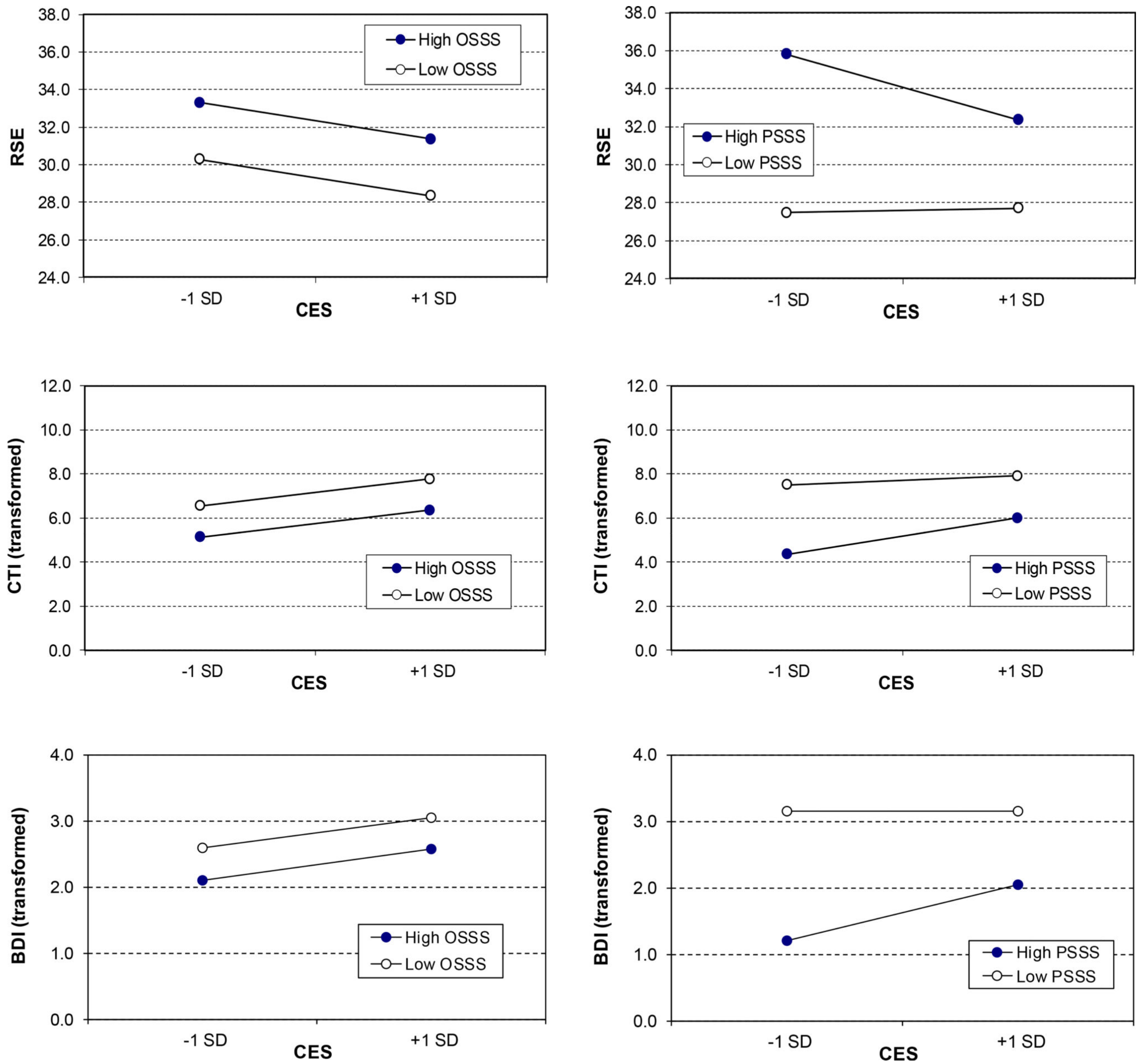

Figure 2.

Main Effect of Online Social Support and Moderating Effect of In-person Social Support in the Relation of Cybervictimization (CES) to Self-esteem (RSE), Depressive thoughts (CTI), and Depressive Symptoms (BDI-II) (samples 1 and 2).

Table 1

Stem-and-leaf Plot of Literature Supporting Different Subtypes of Social Support

Subtype	Numeric code for supporting citations														
Esteem/Emotional	01	02	03	04	<u>05</u>	<u>06</u>	<u>07</u>	08	09	<u>10</u>	<u>11</u>	12	13	14	15
	16	<u>17</u>	18	19	20	22									
Social Companionship	01	02	03	<u>05</u>	06	07	08	09	10	13	17				
Informational	<u>01</u>	02	<u>06</u>	08	09	10	11	12	<u>13</u>	<u>14</u>	15	<u>17</u>	<u>18</u>	19	20
	21														
Instrumental	<u>01</u>	02	05	06	<u>07</u>	08	09	10	<u>11</u>	13	14	15	17	19	20
	22														
Assistance[a]	03														
Worth	03	22													
Nurturance	03	22													
Appreciation	04														
Social companionship/help[b]	04														
Ideology	06														
Help with problem solving[c]	06														
Reference and control	06														
Active	07														
Environmental action	12														
Indirect personal influence	12														
Aid[d]	16														
Affirmation	16	17													
Dependable social network	17														
Normative fit	17														
Support[e]	21														
Social integration[f]	22														

<u>Note</u>: Underlined citations denote the authors have split a particular subtype further into two or more types.

01: Barrera & Ainlay, 1983 (theoretical structure informed by literature review); 02: Barrera & Ainlay 1983 (empirical structure informed by factor analysis); 03: Brandt & Weinert, 1981; 04: Weinert, 2003; 05: Brim, 1974; 06: Caplan, 1976; 07: Cobb, 1976; Cobb, 1978; 08: Cohen & Hoberman, 1983; 09: Cohen & Wills, 1985; 10: Cutrona & Suhr, 1992; 11: Foa, 1993; 12: Gottlieb, 1978; 13: Hirsch, 1980; 14: House, 1981; 15: Jacobson, 1986; 16: Kahn & Antonucci, 1980; 17: Kaplan, Cassel, & Gore, 1977; 18: Killilea, 1975; 19: McCallister & Fischer, 1978; 20: Pinneau, 1975; 21: Tolsdorf, 1976; 22: Weiss 1973.

[a]Assistance combines Emotional, Informational, and Instrumental support

[b]Social companionship and help combines Social Companionship and Instrumental support

[c]Guidance and mediation in problem solving combines Informational and Instrumental support

[d]Aid combines Informational and Instrumental support

[e]Support combines Esteem/Emotional and Instrumental support

[f]Social Integration combines Social Companionship, Informational, and Instrumental support

Table 2

Hours/week Spent Using Online Sites, Apps, and Games

Type of Internet Use	Sample 1		Sample 2		Sample 3	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
Text/photo/video sharing sites (e.g., Facebook, Instagram, Twitter, Snapchat, Tumblr, Google+)	11.78	11.14	6.82	6.55	11.10	18.65
Text communication sites (e.g., Texting, Email, Kik, Groupme, Whatsapp)	12.61	12.60	4.79	6.08	7.03	12.02
Anonymous discussion apps (e.g., YikYak, Whatsgoodly)	0.97	2.55	0.22	1.34	0.70	2.85
Forums (e.g., Reddit, 4chan)	0.55	1.70	5.45	7.08	1.95	5.00
Dating sites and apps (e.g., Match.com, eHarmony, Tinder)	0.13	1.23	0.11	0.66	1.09	2.49
Sports/fighting/racing games (e.g., FIFA, Call of Duty, Need for Speed, Grand Theft Auto)	0.35	1.19	1.42	4.20	2.89	5.74
Role player/battle arena games (e.g., World of Warcraft, League of Legends)	0.81	3.88	1.91	4.54	2.92	7.01

Table 3

Goodness-of-fit Information for Exploratory Factor Analyses of 40-item OSSS.

Model	χ^2	df	$\Delta\chi^2$	RMSEA	CFI	TLI	SMR
			Samples 1 and 2				
1 factor	6096.55	740		.134	.63	.61	.105
2 factors	4018.81	701	2077.74	.108	.77	.74	.066
3 factors	2627.40	663	1391.41	.086	.86	.84	.042
4 factors	1840.88	626	786.52	.069	.92	.90	.026
5 factors	1579.55	590	261.33	.064	.93	.91	.023
6 factors	1350.94	555	228.61	.060	.94	.92	.021
			Sample 3				
1 factor	7997.57	740		.120	.72	.70	.080
2 factors	5242.54	701	2755.03	.097	.82	.80	.050
3 factors	3699.41	663	1543.13	.082	.88	.86	.036
4 factors	2422.40	626	1277.01	.066	.93	.91	.023
5 factors	2052.09	590	370.31	.060	.94	.92	.020
6 factors	1789.00	555	263.09	.057	.95	.93	.018

Table 4

Exploratory Factor Analysis of the 40 Online Social Support Scale Items

	Samples 1 and 2				Sample 3			
Items	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
EE1	**.73**	.01	.01	.10	**.70**	.05	−.03	.04
EE2	**.77**	−.02	.01	.12	**.71**	.06	.03	.03
EE3	**.60**	.05	.11	.12	**.74**	.07	.06	−.01
EE4	**.66**	.21	.04	−.08	**.71**	.08	.05	.03
EE5	**.79**	−.01	.00	−.02	**.79**	−.07	.02	.00
EE6	**.82**	.01	−.03	−.03	**.83**	−.04	.01	−.04
EE7	**.78**	.02	.05	−.01	**.74**	.00	.08	.03
EE8	**.75**	.16	.01	.02	**.80**	.04	.02	.02
EE9	**.73**	.11	.10	−.01	**.82**	.06	−.01	.04
EE10	**.77**	.04	.09	−.01	**.82**	.02	.05	.00
SC1	.26	**.63**	−.06	.07	.14	**.71**	−.04	.03
SC2	.18	**.69**	−.07	.10	.05	**.78**	−.07	.12
SC3	.05	**.70**	−.01	.10	−.07	**.79**	−.04	.19
SC4	−.04	**.82**	.04	−.10	−.03	**.72**	.15	−.02
SC5	.01	**.77**	.11	.01	.01	**.68**	.26	−.07
SC6	.04	**.73**	.15	−.08	.04	**.68**	.21	−.09
SC7	−.04	**.72**	.04	.01	−.04	**.63**	.16	.02
SC8	.20	**.49**	.01	.10	.09	**.58**	.18	.00
SC9	.20	**.66**	−.01	.06	.09	**.52**	.28	.04
SC10	.23	**.57**	.08	.04	.20	**.52**	.16	.07
INF1	.09	−.11	**.84**	.05	.02	.01	**.74**	.03
INF2	.08	−.09	**.86**	.03	.01	.00	**.79**	.01
INF3	.00	.07	**.81**	−.03	.10	−.03	**.79**	−.02
INF4	.10	.03	**.75**	.01	.10	−.05	**.79**	.01
INF5	.02	−.03	**.78**	.07	−.04	.05	**.80**	.05
INF6	.01	.04	**.83**	−.01	.04	.12	**.69**	.04

	Samples 1 and 2				Sample 3			
Items	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
INF7	.10	.11	**.72**	−.05	.12	.03	**.72**	.01
INF8	−.02	.00	**.76**	.14	.00	.08	**.68**	.12
INF9	−.03	.11	**.67**	.02	.07	.05	**.72**	−.02
INF10	−.07	.11	**.64**	.13	−.01	.02	**.75**	.11
INS1	.06	.02	.03	**.67**	.04	.08	−.03	**.74**
INS2	.02	−.03	.09	**.74**	−.05	−.01	.15	**.74**
INS3	−.13	.08	.24	**.69**	−.11	.11	.22	**.68**
INS4	−.05	.02	.18	**.71**	.03	.00	.17	**.70**
INS5	−.04	.17	.10	**.69**	.02	.06	.02	**.80**
INS6	.09	.04	.06	**.71**	.14	.01	.14	**.64**
INS7	.03	.08	.06	**.78**	.13	.04	−.05	**.77**
INS8	.02	−.03	−.02	**.86**	.06	−.05	.01	**.80**
INS9	.03	.05	.00	**.79**	−.04	−.02	.10	**.79**
INS10	.29	−.21	−.14	**.74**	.14	−.05	−.07	**.80**

Note. Loadings > .30 are in boldface.

Factor correlations for samples 1, 2: $r_{12} = .69$, $r_{13} = .61$, $r_{14} = .46$, $r_{23} = .65$, $r_{24} = .51$, $r_{34} = .61$.

Factor correlations for sample 3: $r_{12} = .70$, $r_{13} = .74$, $r_{14} = .55$, $r_{23} = .72$, $r_{24} = .56$, $r_{34} = .60$.

Table 5

IRT Estimates of Item Discriminations and Thresholds for Samples 1, 2, and 3

Item	Discriminations				Thresholds			
	EE	SC	INF	INS	1	2	3	4
EE1	**0.77**	0.02	−0.03	0.08	−1.74	−0.98	0.22	1.24
EE2	**0.80**	0.02	−0.01	0.09	−1.78	−0.94	0.23	1.25
EE3	**0.73**	0.05	0.09	0.05	−1.70	−0.85	0.22	1.31
EE4	**0.71**	0.14	0.06	−0.01	−1.81	−0.96	0.16	1.30
EE5	**0.87**	−0.05	0.00	−0.04	−1.74	−1.03	−0.06	0.98
EE6	**0.92**	−0.04	−0.01	−0.07	−2.01	−1.28	−0.12	1.06
EE7	**0.79**	0.02	0.06	0.02	−1.70	−0.92	0.29	1.30
EE8	**0.80**	0.10	0.02	0.01	−1.63	−0.86	0.21	1.33
EE9	**0.81**	0.09	0.05	0.02	−1.68	−0.95	0.09	1.27
EE10	**0.81**	0.05	0.09	0.00	−1.68	−0.98	0.22	1.26
SC1	0.19	**0.66**	−0.01	0.10	−1.89	−0.93	0.08	1.04
SC2	0.08	**0.82**	−0.11	0.21	−1.63	−0.63	0.37	1.29
SC3	−0.03	**0.80**	−0.04	0.23	−1.30	−0.38	0.53	1.44
SC4	−0.06	**0.72**	0.28	−0.07	−1.44	−0.75	0.02	1.00
SC5	0.04	**0.62**	0.25	−0.05	−1.57	−0.85	0.08	1.10
SC6	0.04	**0.63**	0.24	−0.10	−1.67	−1.04	−0.01	1.04
SC7	−0.07	**0.66**	0.27	−0.01	−1.40	−0.68	0.09	1.02
SC8	0.15	**0.52**	0.20	0.04	−1.63	−0.90	0.08	1.01
SC9	0.17	**0.53**	0.24	0.06	−1.61	−0.90	0.10	1.20
SC10	0.24	**0.48**	0.21	0.09	−1.56	−0.88	0.23	1.24
INF1	0.04	−0.08	**0.87**	0.04	−1.57	−0.67	0.53	1.51
INF2	0.02	−0.08	**0.90**	0.02	−1.66	−0.86	0.30	1.38
INF3	0.06	−0.01	**0.85**	−0.02	−1.43	−0.69	0.33	1.37
INF4	0.12	−0.02	**0.79**	0.01	−1.54	−0.76	0.23	1.23
INF5	0.00	0.02	**0.79**	0.09	−1.53	−0.74	0.31	1.27
INF6	0.03	0.07	**0.77**	0.05	−1.54	−0.73	0.33	1.31

Item	Discriminations				Thresholds			
	EE	**SC**	**INF**	**INS**	**1**	**2**	**3**	**4**
INF7	0.11	0.05	**0.74**	0.02	−1.60	−0.78	0.36	1.46
INF8	0.00	0.05	**0.72**	0.15	−1.32	−0.49	0.56	1.57
INF9	0.04	0.06	**0.75**	0.00	−1.49	−0.85	0.18	1.26
INF10	−0.02	0.05	**0.72**	0.14	−1.50	−0.71	0.41	1.39
INS1	0.07	0.05	0.02	**0.74**	−0.45	0.37	1.12	1.79
INS2	−0.06	0.01	0.12	**0.80**	−0.65	0.03	0.83	1.70
INS3	−0.14	0.10	0.25	**0.74**	−0.82	−0.06	0.84	1.73
INS4	−0.01	0.02	0.19	**0.73**	−0.79	−0.11	0.71	1.62
INS5	0.02	0.08	0.07	**0.79**	−0.64	0.15	0.99	1.72
INS6	0.16	−0.01	0.10	**0.70**	−0.93	−0.18	0.76	1.56
INS7	0.12	0.03	0.00	**0.81**	−0.74	0.00	0.87	1.80
INS8	0.07	−0.05	−0.02	**0.86**	−0.56	0.06	0.91	1.90
INS9	−0.02	0.02	0.05	**0.84**	−0.65	−0.02	0.82	1.63
INS10	0.24	−0.09	−0.15	**0.82**	−0.41	0.22	0.90	1.65

Note. EE = Esteem/Emotional, SC = Social companionship, INF = Informational, INS = Instrumental social support. Boldface highlights discrimination estimates > .30. Correlations among the dimensions were 0.623 (*SE*=0.022) between EE and SC, 0.652 (*SE*=0.018) between EE and INF, 0.619 (*SE*=0.027) between SC and INF, 0.517 (*SE*=0.022) between EE and INS, 0.485 (*SE*=0.030) between SC and INS, and 0.616 (*SE*=0.019) between INF and INS.

Table 6

Pooled Sample Correlations and Separate Sample Means and Standard Deviations for All Study Variables for Samples 1 and 2

	OSSS	EE	SC	INF	INS	PSSS	CES	RSE	CTI	BDI	LES	Use	TSO	SD	LS
OSSS	1.00														
EE	.80**	1.00													
SC	.89**	.71**	1.00												
INF	.87**	.56**	.71**	1.00											
INS	.83**	.50**	.59**	.66**	1.00										
PSSS	.38**	.49**	.35**	.24**	.23**	1.00									
CES	.17**	.02	.16**	.15**	.22**	−.15**	1.00								
RSE	.20**	.28**	.17**	.14**	.10*	.48**	−.11*	1.00							
CTI	−.27**	−.37**	−.25**	−.17**	−.12*	−.62**	.18**	−.80**	1.00						
BDI	−.10*	−.14**	−.10	−.06	−.06	−.42**	.14**	−.71**	.75**	1.00					
LES	−.02	.01	−.06	−.02	−.01	−.09	.16**	−.23**	.25**	.41**	1.00				
Use	.33**	.46**	.31**	.17**	.20**	.27**	.10	.11*	−.22**	.00	.10	1.00			
TSO	.23**	.17**	.20**	.18**	.22**	.13*	.08	.05	−.04	.03	.07	.20**	1.00		
SD	.15**	.14**	.13**	.13*	.12*	.09	−.02	.19**	−.17**	−.23**	−.10	.05	−.04	1.00	
LS	.11*	.06	.10*	.12*	.11*	−.01	−.05	.07	−.05	−.16**	−.13*	−.04	−.08	.73**	1.00
							Sample 1								
M	77.58	**26.45**	**21.27**	**17.45**	**12.08**	**18.29**	7.87	30.80	**168.2**	10.16	5.66	**14.13**	**27.48**	4.12	**2.46**
SD	25.56	7.04	8.17	8.27	8.39	2.72	8.78	5.06	4.28	7.54	4.74	3.12	24.41	2.51	2.11
							Sample 2								
M	83.40	**22.69**	**23.99**	**22.32**	**14.45**	**15.51**	9.81	30.20	**158.5**	9.52	4.72	**10.42**	**21.00**	4.62	**4.56**
SD	27.71	7.17	7.98	7.73	8.77	5.54	2.86	7.24	34.19	10.94	6.20	3.42	7.24	3.12	2.76

Note. OSSS = Online Social Support Scale total, EE = OSSS Esteem/Emotional, SC = OSSS Social Companionship, INF = OSSS Informational, INS = OSSS Instrumental, PSSS = Perceived Social Support Scale, CES = Cyberbullying Experiences Survey, CTI = Cognitive Triad Inventory, RSE = Rosenberg Self Esteem Scale, BDI = Beck Depression Inventory, LES = Life Events Scale, Use = OSSS social media use, TSO = time spent online, SD = Social Desirability Scale, LS = Lie Scale. Numbers in boldface indicate that means are significantly different between the two samples at $p \leq 0.05$.

* $p < 0.05$

** $p < 0.01$ (2-tailed).

Table 7

Regression of Self-esteem (RSE), Depressive thoughts (CTI), and Depressive Symptoms (BDI-II) onto Negative Life Events (LES) and either Online Social Support (OSSS) or In-person Social Support (PSSS) for Samples 1 and 2

Outcome	Predictor	*B*	*SE(B)*	*β*
	Online Social Support (OSSS) was a predictor			
RSE	OSSS	0.05	0.01	0.21***
	LES	−0.27	0.06	−0.23***
CTI	OSSS	−0.03	0.00	−0.31***
	LES	0.09	0.02	0.25***
BDI-II	OSSS	−0.01	0.00	−0.12*
	LES	0.12	0.02	0.39***
	In-person Social Support (PSSS) was a predictor			
RSE	PSSS	0.59	0.07	0.46***
	LES	−0.24	0.06	−0.21***
CTI	PSSS	−0.24	0.02	−0.55***
	LES	0.08	0.02	0.22***
BDI-II	PSSS	−0.14	0.02	−0.39***
	LES	0.10	0.02	0.34***

Note. RSE = Rosenberg Self Esteem Scale, CTI = Cognitive Triad Inventory, BDI = Beck Depression Inventory, LES = Life Events Scale, OSSS = Online Social Support Scale, PSSS = Perceived Support Scale. All OSSS × LES and PSSS × LES interactions were nonsignificant (*p*s > .20)

* $p < .05$

** $p < .001$

*** $p < .001$

Table 8

Regression of Self-esteem (RSE), Depressive thoughts (CTI), and Depressive Symptoms (BDI-II) onto Online Victimization (CES) and either Online Social Support (OSSS) or In-person Social Support (PSSS) for Samples 1 and 2

Outcome	Step	Predictor(s)	*B*	*SE(B)*	*β*
		Results for Online Social Support (OSSS)			
RSE	1	CES	−0.07	0.03	-0.13^{*}
	2	CES	−0.09	0.03	-0.16^{**}
		OSSS	0.06	0.01	0.24^{***}
CTI	1	CES	0.05	0.01	0.25^{***}
	2	CES	0.06	0.01	0.29^{***}
		OSSS	−0.03	0.00	-0.32^{***}
BDI-II	1	CES	0.02	0.01	0.12^{*}
	2	CES	0.02	0.01	0.14^{*}
		OSSS	−0.01	0.00	-0.14^{*}
		Results for In-person Social Support (PSSS)			
RSE	1	CES	−0.07	0.03	-0.13^{*}
	2	CES	−0.03	0.03	−0.06
		PSSS	0.64	0.07	0.49^{***}
	3	CES	−0.08	0.03	-0.13^{*}
		PSSS	0.63	0.07	0.49^{***}
		PSSS*CES	−0.02	0.01	-0.16^{**}
CTI	1	CES	0.05	0.01	0.25^{***}
	2	CES	0.03	0.01	0.17^{***}
		PSSS	−0.25	0.02	-0.57^{***}
	3	CES	0.05	0.01	0.25^{***}
		PSSS	−0.25	0.02	-0.57^{***}

Outcome	Step	Predictor(s)	*B*	*SE(B)*	*β*
		PSSS*CES	0.01	0.00	0.16 **
	1	CES	0.02	0.01	0.12 *
BDI-II	2	CES	0.01	0.01	0.06
		PSSS	−0.15	0.02	−0.43 ***
	3	CES	0.02	0.01	0.13 *
		PSSS	−0.15	0.02	−0.42 **
		PSSS*CES	0.00	0.00	0.13 *

Note. RSE = Rosenberg Self Esteem Scale, CTI = Cognitive Triad Inventory, BDI = Beck Depression Inventory, CES = Cyberbullying Experiences Survey, OSSS = Online Social Support Scale, PSSS = Perceived Support Scale. OSSS × CES interactions were nonsignificant.

* $p < .05$

** $p < .001$

*** $p < .001$