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Investigating Construct Validity of the Cyber--Peer Experiences Questionnaire

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INVESTIGATING CONSTRUCT VALIDITY OF THE CYBER – PEER EXPERIENCES QUESTIONNAIRE

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ABSTRACT

With electronic technology becoming increasingly important in all aspects of modern life, traditional forms of relating with others have crossed into the cyber realm. Within that context, both positive and negative aspects of relational behavior have advanced in ways still largely underexplored in the research literature. One such area, termed "cyberaggression," has recently gained momentum as a research focus. Given the numerous mental health sequelae from being involved in cyberaggression, such as anxiety, depression, and suicidal ideation, there is a clear and compelling need for more research in this area. To date, however, there remains little consensus on the conceptualization and measurement of cyberaggression; in the absence of sound instrumentation for the construct, substantive investigations in this domain are hindered.

Therefore, the primary purpose of this research study was to explore construct validity for the Cyber – Peer Experiences Questionnaire (C-PEQ), a promising new measure that assesses experiences of cyberaggression and cybervictimization via electronic communication. Confirmatory factor analysis of the data did not provide support for the hypothesized two-factor model solution of the instrument (MLM χ^2 = 433.79, RMSEA = .06, CFI = .88, SRMR = .06). However, the C-PEQ displayed evidence for internal consistency reliability (C-PEQ: α = .88; cyberaggression subscale: α = .75; cybervictimization subscale: α = .84). Evidence for convergent validity with theoretically similar constructs was mixed. Specific areas of model misspecification as well as suggestions for future research are discussed.

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LIST OF ABBREIVATIONS

ADHD .... Attention Deficit Hyperactivity Disorder

CESD-R .... Center for Epidemiologic Studies Depression Scale – Revised

CFA...Confirmatory Factor Analysis

CFI .... Comparative Fit Index

C-PEQ .... Cyber-Peer Experiences Questionnaire

CS...Cyberbullying Scale

CSS .... Current Symptoms Scale Self-Report Form

CU .... Callous-Unemotional

DSM-IV .... *Diagnostic and Statistical Manual of Mental Disorders–4th Edition*

DSM-IV-TR *Diagnostic and Statistical Manual of Mental Disorders–4th Edition, text rev.*

FIML .... Full Information Maximum-Likelihood

ICU...Inventory of Callous-Unemotional Traits

ISCS ....Internet Social Capital Scale

LSAS-SR... Liebowitz Social Anxiety Scale: Self-Report Version

MLM .... Mean-Adjusted Maximum Likelihood

MSU.. Michigan State University

RMSEA... Root Mean Square Error of Approximation

R-PEQ .... Revised-Peer Experiences Questionnaire

SN-PEQ...Social Networking-Peer Experiences Questionnaire

SRASBM .... Self-Report of Aggression and Social Behavior Measure

SRMR ....Standardized Root Mean Square Residual

USC.. University of South Carolina

CHAPTER 1

INTRODUCTION

With the ever-increasing use and availability of electronic forms of communication (e.g., texting, e-mailing, social networking sites) among today's youth, novel forms of aggressive behavior are emerging. In particular, "cyberaggression," which uses technology as an interface through which aggressive behaviors are conveyed, has received increasing attention from both researchers and media alike. In a recent meta-analysis of prevalence rates of cyberaggression, Modecki et al. (2014) reported the prevalence of cyberaggression to be 15.5% among adolescents (12-18 years). Among college students, prevalence of cyberaggression has ranged from 5 – 15% (Schenk et al., 2012, 2013; Wensley et al., 2012). Along with general prevalence rates, public health concerns surrounding cyberaggression have risen in response to multiple high impact cases presented in the national and international media (Tokunaga, 2010). Although work has documented the negative health impacts of cyberaggression on victims (e.g., Cassidy, Faucher, & Jackson, 2013), less is known about the psychological sequelae of cyberaggression perpetrators. Initial findings suggest, however, that these individuals are at greater risk for engaging in other antisocial behaviors such as traditional aggression, involvement with less prosocial peer groups, and using illicit substances (Cassidy, Faucher, & Jackson, 2013).

Despite its prevalence and influence, a uniform definition of cyberaggression has yet to be formally proposed (Tokunaga, 2010). Many researchers define cyberaggression as an extension of traditional aggression that utilizes forms of technology (e.g., e-mail, social networking) to purposely exclude, harass, or otherwise harm another individual (e.g., Hemphill et al., 2012; Sontag, Clemans, Graber, & Lyndon, 2011). Although there may be similarities between traditional aggression and aggression in the cyber realm, they differ in important ways. For instance, one form of hostile behavior which is subsumed under the broader construct of traditional aggression is face-to-face bullying (Rivers & Smith, 1994). Utilizing previously identified criteria for traditional bullying provides a useful comparison to conceptualize differences between aggressive forms of behavior in the cyber and physical realms. Traditional forms of face-to-face bullying are often defined by three specified criteria: 1) imbalance of power between victims and perpetrators, 2) repetition, and 3) intention to harm (Olweus, 1994). In electronic mediums, however, the presentation of the first two criteria often differ. For example, a cyberaggressor may not necessarily be physically stronger or socially more popular (i.e., creating a power imbalance) as electronic interactions provide inherent protections from physical retaliations. Further, the traditional face-to-face bullying criterion of repetition may not only be met through the literal repetition of cyberaggressive behaviors, but also through the number of times a negative post, picture, or video is viewed by outside witnesses (Dooley, Pyzalski, & Cross, 2009; Tokunaga, 2010). Other differences between cyber and traditional face-to-face aggression behaviors in the literature include the potential for anonymity of cyberaggressors, the 24/7 nature of cyberaggression, and the lack of capacity for the perpetrator to see the victim's immediate reaction to the aggressive act (Cassidy, Faucher, & Jackson, 2013). Taken together, these distinctions serve to highlight the differences between aggression in face-to-face versus cyber realms, and points to the notion that cyberaggression is a unique construct in need of differentiated instrumentation from its traditional face-to-face counterpart.

In connection with the lack of consensus regarding a definition for cyberaggression, the field is still currently at a stage where no gold-standard assessment measure exists and the development of in-house instruments is common practice (Berne et al., 2013). In the only known review of *cyberbullying* assessment, Berne et al. (2013) presented an overview of existing cyberbullying instruments by investigating the characteristics and psychometric properties of 44 various instruments. Though presented as a review of "cyberbullying instruments," the authors acknowledge that half of the instruments reviewed were not specified to measure cyberbullying explicitly and instead targeted related constructs (e.g., cyberaggression, internet harassment). Considering how the field currently lacks consensus on terminology (Tokunaga, 2010) and that the Berne et al. (2013) review is the only of its kind known to date, it is reasonable to make use of this review for our investigation into a novel measure of cyberaggression.

In their psychometric review, Berne et al. (2013) provided information regarding the instruments' internal consistencies and convergent validity, as well as whether structural analyses (such as exploratory or confirmatory factor analyses) had previously been performed for the instruments examined. Supporting psychometric evidence for the 44 instruments reviewed was scarce. Factor analysis (inclusive of both exploratory and confirmatory) had been conducted for only 12 instruments. The failure to include such analyses implores the question of how the instruments effectively operationalized their respective constructs. Only 18 out of the 44 instruments reported internal consistency reliability and reports of instrument validity were likewise limited (24 out of the 44 instruments), with convergent validity being the only form tested in the publications.

Considering both the numerous public health concerns surrounding cyberaggression, as well as its distinguishing characteristics from traditional aggression, there is a clear need for further inquiry into how cyberaggression operates. Yet as discussed above, with cyberaggression being such a recent phenomenon, there is a dearth of consistent and valid instrumentation within the field (Berne et al., 2013). Without sound psychometric instrumentation, research into cyberaggression is necessarily limited. To that end, the purpose of the present study was to explore psychometric validity evidence for a promising, but not yet fully examined, measure of cyberaggression and cybervictimization: the Cyber-Peer Experiences Questionnaire (C-PEQ; Landoll, La Greca, Lai, Chan, & Herge, 2015). The C-PEQ includes 18 total items on two subscales measuring cyberaggression and cybervictimization. Although the primary focus of our study was to investigate psychometric properties of the cyberaggression items as prior work has only focused on the cybervictimization items of the C-PEQ (Landoll et al., 2015), we extended evaluation of the instrument to also include the set of cybervictimization items to consider how the scale's items operate as a whole. The ultimate goal of our exploration was to advance the field by furthering the development of effective instrumentation in measuring cyberaggression and cybervictimization.

1.1 INSTRUMENT DEVELOPMENT

To understand why we cited the noticeable lack of valid instrumentation in the cyberaggression field, it is useful to discuss the concept of validity as well as the process of proper instrument development more broadly. These considerations are particularly crucial in social science as researchers are often interested in exploring underlying, theoretical constructs rather than those that are directly observable. A construct refers to a variable that is captured by measuring a set of reported responses or observed behaviors. To that end, constructs are latent variables which themselves cannot be measured directly, unlike physical attributes such as height or weight; latent variables must be measured indirectly by a series of item responses. The premise of measuring latent variables in this manner presumes that the latent variable is the cause of observed item responses and, in turn, the responses give an indication of the presence or level of the latent variable. The accuracy by which the latent variable is reflected in the observed item responses is known as the *true score.* In classical measurement theory, a true score is measured by the sum of the observed score (i.e., the item response) plus error variation:

$$X_{pi} = T_p + e_{pi}, \qquad \text{(Eq. 1.1)}$$

where X_{pi} refers to the observed score for person *p* observed under condition i, T_p refers to the person's true score, and e_{pi} refers to the error variation associated with the person's observed score (DeVellis, 2012).

Cyberaggression is an example of a construct. Thus, the measurement of cyberaggression requires instrumentation to capture a set of self or peer-reported item responses, from which the presence or level of cyberaggression can be derived. Poor measurement of constructs like cyberaggression carries numerous costs from a design and statistical perspective, such as imposing a limit on the validity of responses researchers can reach in empirical investigations (DeVellis, 2012). Effective scale development, and thus effective measurement of constructs and latent variables, requires a series of statistical and design considerations that include item development, reliability, and construct validity. The subsections that follow will discuss each of these components in turn through theoretical and applied examples derived from the development of the C-PEQ (Landoll et al., 2015).

1.1.1 ITEM DEVELOPMENT The essence of scale development is to optimize construct measurement by creating appropriate items to be included within a scale. DeVellis (2012) provides sequential guidelines for this process. The first is to identify what one wants to measure conceptually. Utilizing psychological theory is crucial in this step as researchers need to determine a concrete conceptualization of the construct before attempting operationalization. Theory can assist in relating a new construct to existing phenomena, providing information on what hypotheses can be made regarding its nature. Indicating the level of specificity or generality of the construct under study (e.g., social anxiety disorder vs. anxiety symptoms) is also helpful to aid in clarifying the item pool.

The second step is to construct the items themselves. Items should be chosen from the theoretical "universal set" of items relating to the construct of interest. In generating the item pool, researchers should consider item aspects such as redundancy and the number of items. The decisions regarding these attributes should be based on trade-off rules where the costs of a given aspect are considered against their potential benefit. For example, redundancy may be helpful or detrimental to developing an item set depending on how it is used. Consider how relevant redundancy (i.e., expressing a similar idea in somewhat different ways with respect to the variable) has the potential to embellish a construct and optimize its measurement by enhancing inter-item scale reliability, whereas irrelevant redundancy (i.e., expressing a similar idea in different ways with respect to grammatical structure) may do little to enhance the quality of a scale (DeVellis, 2012).

The final step in item development is determining the format for measurement. In this context, researchers must consider what response categories and question types will be included in the measurement of the construct. These decisions should align with the theoretical conceptualization of a construct (e.g., dichotomous item formats would be amenable to characterize the absolute presence or absence of a construct, but not varying levels in between). For continuous response scales, there should be at least five response categories if using a Likert response format (Allen & Seaman, 2007) and judgments concerning a respondent's ability to discriminate meaningfully among too many response options should be considered (DeVellis, 2012).

Following item development, an expert review of the initial item pool should be pursued to: (a) confirm or invalidate the proposed definition of the construct, (b) assess the items' clarity and conciseness, and (c) point out ways of tapping the construct that the researcher has not included. After integration of expert advice, researchers should consider the inclusion of validation items (i.e., items which serve to detect possible test-taking biases and/or to reflect construct validity) into the scale as well as administering the items in a pilot sample (DeVellis, 2012).

With these guidelines in mind, it can be demonstrated that Landoll et al. (2015) followed a similar process in constructing the C-PEQ's items. To explain, it is modeled after two psychometrically sound instruments that assess two constructs conceptually similar to cyberaggression (i.e., cybervictimization and relational/overt aggression; Fanti et al., 2012; Hemphill et al., 2013). Specifically, the C-PEQ was developed in connection to the *Social Networking – Peer Experiences Questionnaire* (SN-PEQ; Landoll, La Greca, & Lai, 2013), which assesses cybervictimization only via social networking sites, and the *Revised – Peer Experiences Questionnaire* (R-PEQ; De Los Reyes & Prinstein, 2004), which assesses relational and overt aggression among peers. Relational aggression refers to covert behaviors aimed to harm others through purposeful manipulation and damage of a peer relationship and overt aggression refers to outward displays of negative behavior such as physical and verbal aggression (Crick & Grotpeter, 1995). These constructs have previously been shown to be conceptually related to cyberaggression and were thus useful to include in our current investigation. To continue, the C-PEQ differs in that it measures both cyberaggression and cybervictimization in a broader context (i.e., through electronic media instead of specifically social networking sites as in the SN-PEQ). Therefore, item development for the C-PEQ was informed from previous instruments which received expert consultation, had been administered in pilot testing, and exhibited evidence for validity and reliability (De Los Reyes & Prinstein, 2004; Landoll, La Greca, & Lai, 2013). These aspects of C-PEQ development mirror the scale development guidelines described by DeVellis (2012).

1.1.2 RELIABILITY An important aspect of instrumentation is that a measure consistently performs in predictable ways. An instrument exhibits evidence for statistical reliability if it consistently measures a latent construct similarly across samples and situations. As previously mentioned, classical test theory states that an observed score results from the summation of a true score plus error variability. Reliability is then simply the ratio of the estimated true score to the observed score:

$$\rho_{XT}^2 = \frac{\sigma_T^2}{\sigma_X^2}, \qquad \text{(Eq. 2)}$$

where ρ_{XT}^2 refers to the reliability coefficient, σ_T^2 refers to the variance of the true score, and σ_X^2 refers to the variance of the observed score.

Internal consistency, or a measure of reliability that addresses the reliability of a set of items in a scale, is measured by the widely utilized Cronbach's alpha (α) coefficient (Cronbach, 1951), which mathematically expresses the portion of total variance that is shared among items in the set. Alpha is calculated by determining the proportion of unique variance in the item set, and subtracting this from 1 to determine the proportion of variance that is communal. The quantity is then multiplied by a correction factor to adjust for the number of elements contributing to earlier computations (DeVellis, 2012):

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_{y_i}^2}\right), \qquad \text{(Eq. 3)}$$

With regard to reliability and the C-PEQ instrument, prior research has provided evidence of good internal consistency reliability for the C-PEQ's cybervictimization items in a large adolescent sample from two high schools in a metropolitan area in the Southeastern United States (α = .78 – .82; Landoll et al., 2015). Further evidence for internal consistency reliability for the C-PEQ's cybervictimization items as well as novel internal consistency reliability evidence for the C-PEQ's cyberaggression items is still needed and was thus an aim for this paper.

1.1.3 CONSTRUCT VALIDITY Although establishing evidence for reliability is a necessary component of scale development, it is not sufficient for good instrumentation. Namely, it is possible for an instrument to be reliable but not provide valid scores. Establishing evidence for the validity of scores from a newly developed scale is often considered to be more important. A useful metaphor that differentiates reliability and validity considers a bulls-eye display. Presume that a researcher consistently hits the outer rings of the platform. Though they are reliably measuring something, it is not the construct they originally intended to assess as they are not hitting the target (i.e., the center of the rings). Thus, although a scale might be able to consistently measure a construct, it may be consistently measuring the incorrect construct (i.e., the scale does not provide valid scores). In contrast, consider a situation where a researcher consistently hits the bulls-eye right in the center of the target. In this scenario, the measurement of the construct is both reliable and valid as the researcher is not only measuring something consistently but is also tapping into the construct of interest. Using the bulls-eye metaphor, it is obvious that a scale cannot be considered unreliable but also valid. A second way of visualizing this concept is to consider a situation where a research is hitting across all rings of the bulls-eye so that the "average" measurement was near the center of the rings. Although possible, it is likely that any one measurement point the researcher made will vary in a random way and is thus not the preferred method for establishing valid measurement (Elasy & Gaddy, 1998).

There are three types of validity that are commonly assessed in psychometric research: 1) content validity, 2) criterion-related validity, and 3) construct validity. Historical approaches for investigating validity concerned both content validity (i.e., item-sampling adequacy in reflecting a content domain) as well as criterion-related validity. Applied examples of criterion-related validity usually involve the comparison of a recently developed measure and a "gold-standard" instrument for the construct of interest (DeVellis, 2012). The third common type of validity, which was the primary focus of this paper, concerns construct validity. More modern psychometric approaches indicate that construct validity subsumes both content and criterion-related validity, and thus its investigation suffices to cover those topics. Concerning content validity, the range of content provided within a scale clearly contributes to both score interpretation as well as relations with other variables. Regarding criterion-related validity, the empirical relation between a novel scale and a gold-standard instrument should make theoretical sense in that correlations between them are expected to be strong and positive in nature (Messick, 1995).

1.1.4 DEVELOPING A STRONG PROGRAM FOR CONSTRUCT VALIDITY Benson (1998) describes a strong program for establishing construct validity that was used as a backdrop for the current psychometric investigation of the C-PEQ. The program offers a three component procedure to establish construct validity for newly developed instruments: 1) substantive, 2) structural, and 3) external components. The substantive component concerns how the construct of interest, in our case cyberaggression, is defined, both theoretically and empirically (Benson, 1998). Though the theoretical literature has yet to provide a substantial evidence base for the number of latent factors that may comprise the cyberaggression construct, our review does suggest that cyberaggression and cybervictimization are unique factors from similar constructs such as relational aggression/victimization (e.g., Landoll et al., 2015). It can be argued that Landoll et al. (2015) thoroughly investigated the theoretical literature pertaining to *cybervictimization* as is showcased by the prior development of a psychometrically sound cybervictimization instrument (SN-PEQ) and utilization of the parent measure, the R-PEQ, which has similarly been well-validated (La Greca & Harrison, 2005). Outside research suggests expected relationships between cybervictimization and cyberaggression (e.g., Fanti et al., 2012), and therefore our paper seeks to expand upon Landoll's et al.

(2015) approach and investigate construct validity of cyberaggression. Thus, further exploration into the second aspect of Benson's (1998) program is warranted.

The structural component of Benson's (1998) program refers to the internal consistency of the set of observed variables, or how the set of observed variables co-vary and share common variance. Several statistical procedures can be utilized for assessing the structural component, including intercorrelations between items and subscales, exploratory and confirmatory factor analyses, and item response theory. One advantage of using confirmatory factor analysis is that it complements the substantive component of the strong program and allows researchers to rule out other factor models in favor of the hypothesized/expected model (Benson, 1998). In the initial study, Landoll et al. (2015) performed a confirmatory factor analysis for the C-PEQ cybervictimization items and found that a one-factor model suited the instrument's responses. We aimed to extend that investigation by exploring the structure of the cyberaggression items on the instrument. Positive results obtained from the structural component lend evidence of the *necessary condition* for establishing construct validity but does not meet *sufficient condition* criteria (Nunnally, 1978). That is, all three components (substantive, structural, and external) are necessary for a strong program of construct validity; no single component is sufficient. Accordingly, as no prior research has investigated convergent validity evidence of the C-PEQ's cyberaggression items, the third step of the program is brought into question.

Arguably the most crucial aspect for the strong program of construct validity, the external component, furthers the strong program of construct validity by establishing divergence among item responses on the instrument and related but not redundant domains. For example, by showing how an instrument measuring cyberaggression and cybervictimization is related to constructs on other measures (i.e., a nomological net), evidence for the uniqueness of the constructs of interest are provided. Common procedures for assessing the external component consist of zero-order correlations between a scales' items as well as structural equation modeling (Benson, 1998).

In order to establish a nomological net for both the C-PEQ's cyberaggression and cybervictimization items, several other instruments measuring latent constructs thought to be related to cyberaggression or cybervictimization were included within the overall battery. A logical inclusion in the battery were other measures assessing cyberbullying, cybervictimization, and other forms of aggression (e.g. relational aggression), as prior research has shown that cyberaggression, cybervictimization, and relational aggression are correlated. For instance, Fanti and colleagues (2012) reported that cyberaggression and cybervictimization had a strong correlation of $r = .67$. Similarly, Hemphill et al. (2013) found a moderate correlation between relational aggression and cyberaggression/cybervictimization and Landoll et al. (2015) found the C-PEQ's cybervictimization items to be moderately correlated ($r = .39 – .56$) with overt and relational peer victimization.

Furthermore, measures assessing other externalizing behaviors such as attention deficit hyperactivity disorder (ADHD) and callous-unemotional (CU) traits were also included to assess for convergent validity of the cyberaggression items as previous research has shown that individuals with ADHD are more likely to display aggression towards others (Kokkinos & Panayiotou, 2004; Unnever & Cornell, 2003) and that CU traits are longitudinally associated with cyberaggression (Fanti et al., 2012). Measures of social anxiety and depression were included to investigate convergent validity evidence for the C-PEQ's cybervictimization items. Prior research has discovered associations between cybervictimization, depression, and anxiety (Lam & Li, 2013; Landoll et al., 2013, 2015).

A measure of social capital was also included within the nomological net to investigate evidence for convergent validity for both the cyberaggression and cybervictimization subscales. Social capital is commonly defined as the resources available to people through their social interactions (Valenzuela, Park, & Kee, 2009) and experiences of aggression have been described as a lack of social capital (Kouvonen et al., 2006). Some research has suggested that levels of perceived popularity influence cyberaggression behaviors (particularly for males) such that lower levels of perceived popularity and feelings of peer-rejection were related to increased experiences of both cyberaggression and cybervictimization (Ciucci & Baroncelli, 2014; Wright & Li, 2013). Although popularity does not fully encompass the construct of social capital, it is considered to be a component of individual social capital (Glaeser, Laibson, & Sacerdote, 2002). One study which assessed the relationship between social capital and *traditional* bullying concluded that increased exposure to bullying (either as a victim or witness) led to lower mean levels of the perception of trust and fairness in a school environment (Carney, Jacob, & Hazler, 2011). Therefore, considering both these initial research findings as well as that cyberaggression and cybervictimization have been shown to be moderately to strongly correlate (Fanti et al., 2012; Landoll et al., 2015), we expected similar relationships between cyberaggression/cybervictimization and social capital.

1.2 RESEARCH QUESTIONS AND HYPOTHESES

Utilizing Benson's (1998) strong program as the primary structure of this paper and considering the current needs for measurement validation of cyberaggression instruments, we sought to establish both validity evidence and the nomological net for the C-PEQ. Utilizing a sample of 749 college students, we:

1) Conducted a confirmatory factor analysis using the scores from the C-PEQ's cyberaggression and cybervictimization items in order to investigate the proposed factor structure of this instrument's scores (i.e., two-factor structure),

2) Estimated internal consistency reliability of the C-PEQ, and

3) Examined correlations between C-PEQ items and items from theoretically similar instruments to assess construct validity evidence for the instrument

With respect to these goals, we had several research hypotheses. It is first hypothesized that a two-factor structure will underlie item responses on the C-PEQ, such that one factor underlies the cyberaggression subscale and one factor underlies the cybervictimization subscale. Initial factor analyses indicated a single factor structure for the C-PEQ's cybervictimization items (Landoll et al., 2015) and previous literature has reported a single factor structure in cyberaggression instruments (e.g., Ang & Goh, 2010; Calvete, Orue, Estévez, Villardón, & Padilla, 2010; Erdur-Baker, 2010). Second, considering how the C-PEQ was developed from two psychometrically sound instruments (i.e., SN-PEQ and R-PEQ) as well as the preliminary findings for the C-PEQ's cybervictimization items, I hypothesize that both the C-PEQ cyberaggression subscale and C-PEQ as a full scale will display psychometrically sound properties, including acceptable internal consistency reliability scores.

Utilizing Cohen's (1988) correlation effect size criteria, my third set of hypotheses are that the C-PEQ's cyberaggression items will have moderate (r = .25 – .40) to strong (r = .60 – .80) correlations and show convergent validity with similar constructs (i.e., cyberbullying, cybervictimization, relational aggression, ADHD, callous-unemotional traits, and social capital). Specifically regarding the measure of relational aggression, which includes the three subscales of general relational aggression, proactive relational aggression, and reactive relational aggression, it is hypothesized that the C-PEQ's cyberaggression items will have stronger, positive correlations with the reactive relational aggression subscale as compared to the general and proactive relational aggression subscales. Reasoning for this hypothesis stems from prior qualitative research revealing how cyberaggressors often state that their negative online behaviors are used as a method of revenge and/or reactive aggression (Hinduja & Patchin, 2008; Law, Shapka, Domene, & Gagné, 2012). Further, the C-PEQ's cybervictimization items will show moderate (r = .25 – .40) to strong (r = .60 – .80) correlations and convergent validity with measures of depression, social anxiety and social capital.

CHAPTER 2

METHOD

2.1 PARTICIPANTS

A college population was used to obtain the study sample as there is a dearth of literature concerning cyberaggression and cybervictimization within this age range (e.g., Schenk et al, 2013). It is particularly relevant to assess these constructs within a college population as the vast majority of these individuals participate in at least one form of electronic communication on a regular basis (Lenhart, Purcell, Smith, & Zickuhr, 2010). Participants included undergraduate students (*N* = 749) at the University of South Carolina (USC; Age: *M* = 19.92 years, *SD* = 1.55; 78% females; 79% non-Hispanic White). Further demographic information is included in Table 2.1. The current sample was representative of the undergraduate population at USC concerning race/ethnicity (current sample: 21% minority; USC undergraduate population: 20.6% minority) but females were overrepresented (current sample: 78% females; USC undergraduate population: 54% females). Exclusion criteria were as follows: 1) participants who were graduate students or had another relationship (e.g., faculty, staff, etc.) with USC-Columbia or other USC system schools and 2) participants who were below 18 or above 25 years of age.

Table 2.1

Sample Demographics (N = 749)

Characteristic	Overall
Mean age (*SD*)	19.92 (1.55)
Age Frequencies (*n*)	
18	163
19	168
20	157
21	156
22+	105
Gender	
Female (*n*, %)	584 (78%)
Male (*n*, %)	165 (22%)
Race (*n*, %)	
Non-Hispanic White	592 (79%)
African-American/Black	82 (11%)
Hispanic/Latino	23 (3%)
Asian/Other	52 (7%)
Sexual Orientation (% Heterosexual)	92%
Student-Athletes (% Student-Athletes)	2%

2.2 MEASURES

Cyber-Peer Experiences Questionnaire (C-PEQ; Landoll et al., 2015). The C-PEQ was designed to assess aversive experiences through electronic communication. The measure originally included 30 items (15 items included in the cyberaggression and cybervictimization subscales) which asked participants how often they have either experienced or perpetrated cyberaggressive behaviors over the past two months. An example of a cyberaggression item states "I sent embarrassing pictures or videos of a peer to others via electronic media." An example of a cybervictimization item includes "A peer posted pictures of me that made me look bad via electronic media." Participants rated occurrences of each item on a 5-point Likert scale (1 = Never, 5 = A few times a week), such that higher scores were indicative of higher frequencies of cyberaggression/ cybervictimization. As mentioned, the C-PEQ's cybervictimization items have initially displayed good internal consistency ($\alpha = .78 – .82$) and moderate test-retest reliability ($r = .59$). In addition, initial factor analyses indicated that not all 15 cybervictimization items displayed adequate fit for this C-PEQ subscale. Specifically, six items were removed resulting in 9 items for the scale (Landoll et al., 2015). In the present study, we utilized these 9 items in the cybervictimization subscale as well as the 9 cyberaggression subscale items which mirrored the finalized cybervictimization items. This resulted in 18 total C-PEQ items, where we used an average summed scale score for each respective subscale (possible range from 9-45 on each subscale) for our factor analysis, internal consistency, and nomological net analyses.

Cyberbullying Scale (CS; Menesini, Nocentini, & Calussi, 2011). The CS is a 20 item instrument which includes two subscales that assess both cyberbullying perpetration and cybervictimization. An example of a cyberbullying perpetration item is "How often in the past 2 months have you sent nasty text messages?", and a cybervictimization example item is "How often in the past 2 months have you received a nasty or rude e-mail?" Participant responses were measured on a 5-point Likert scale and were collapsed to a dichotomous scoring category (0 = never, 1 = only once, only once or twice, two or three times a month, about once a week, or several times a week) to both reflect scoring strategies in prior research (Menesini, Nocentini, & Calussi, 2011) and for usage within our nomological net analysis. Thus, scores could range from 0-10 for both the cyberbullying and cybervictimization subscales. Evidence for a two-factor structure as well as moderate to adequate internal consistency using an adolescent sample has been demonstrated (α = .67 – .86 for cyberbullying perpetration, α = .72 – .87 for cybervictimization). In the current study, the subscales again demonstrated adequate internal consistency reliabilities (α = .86 for cyberbullying perpetration, α = .81 for cybervictimization).

Self-Report of Aggression and Social Behavior Measure (SRASBM; Morales & Crick, 1998). The SRASBM is a 56-item instrument which includes 11 subscales that measure forms of relational aggression and victimization. For the present study, two subscales were utilized: Proactive Relational Aggression (5 items) and Reactive Relational Aggression (6 items). These particular subscales were selected to assess for evidence of convergent validity instead of other scales on the SRASBM (physical aggression, relational and physical victimization, exclusivity, and prosocial behavior) due to both empirical support of the relation between relational aggression and cyberaggression (Hemphill et al., 2013) and consideration of the battery's length.

Respondents rated items based on experiences within the previous year on a 7-point Likert scale (1 = Not at all true, 7 = Very true). These subscales have demonstrated poor to acceptable internal consistencies in adult samples (α = .69 for proactive relational aggression; α = .72 for reactive relational aggression) and construct validity has also been established for the SRASBM in comparison with other theoretically related constructs (Murray-Close, Ostrov, Nelson, Crick, & Coccaro, 2010). Proactive relational aggression scores could range from 5-35 and reactive relational aggression scores could range from 6-42. For the present study's nomological net analyses, the subscales again demonstrated poor to acceptable internal consistency reliabilities (α = .83 for proactive relational aggression; α = .65 for reactive relational aggression) and subscale scores were calculated by computing the mean of all items within the subscale across each participant, similar to prior research (Murray-Close et al., 2010).

Current Symptoms Scale – Self-Report Form (CSS; Barkley & Murphy, 2006). The CSS scale contains the 18 specified symptoms for ADHD in the *Diagnostic and Statistical Manual of Mental Disorders* (4^{th} ed., text rev.; *DSM-IV-TR*; American Psychiatric Association, 2000) which may have been present over the past six months. An example of an ADHD item is, "Have difficulty awaiting turn." All items are scored on a 4-point Likert scale (0 = Never or rarely, 3 = Very often), with a score of 0 or 1 indicating no symptom presence and a score of 2 or 3 indicating symptom presence. Previous research has shown the internal consistencies of the ADHD inattention and hyperactivity/impulsivity symptoms' subscales to be acceptable (α = .84 and α = .78, respectively; Tercyak, Lerman, & Audrain, 2002). For our nomological net analyses, we observed acceptable internal consistency reliabilities for both subscales (α = .78 for the inattention subscale and α = .74 for the hyperactivity/impulsivity subscale) and utilized a summed scale score (possible range from 0-18), similar to prior research which dichotomizes the aforementioned Likert scale where a score of “0” indicates no symptom presence and “1” indicates symptom presence (Barkley & Murphy, 2006).

Inventory of Callous-Unemotional Traits (ICU; Frick, 2004). The ICU was initially developed as a self-report measure for callous-unemotional traits in children and adolescents, though it has preliminary evidence for appropriate usage with college student populations (Kimonis, Branch, Hagman, Graham, & Miller, 2013). It includes 24 items which are scored on a 4-point Likert scale (0 = Not at all true, 3 = Definitely true). Factor analyses have proposed a general callous-unemotional factor and three sub-factors for this instrument: callousness (e.g., the feelings of others are unimportant to me”), unemotional (e.g., “I hide my feelings from others”), and uncaring (e.g., “I try not to hurt others’ feelings;” reverse-scored item) (Ciucci, Baroncelli, Franchi, Golmaryami, & Frick, 2014). Furthermore, the ICU has shown adequate and similar internal consistencies in both adolescents (α = .74 – .85; Kimonis et al., 2008) and college students in previous studies (α = .80; Kimonis et al., 2013) as well as the current study (α = .81). In addition, evidence for construct validity (i.e., factor structure, correlations with aggression and delinquency) in several research studies has also been demonstrated (Essau, Sasagawa, & Frick, 2006; Fanti, Frick, & Georgiou, 2009; Kimonis et al., 2008). To analyze within the nomological net, we utilized a summed scale score (possible range from 0-72) and reverse scored 12 specified items to reflect the method of scoring the ICU in prior research (e.g., Kimonis et al., 2008).

Liebowitz Social Anxiety Scale: Self-Report Version (LSAS-SR; Liebowitz, 1987). The LSAS-SR is a 24-item scale which provides scores for both fear and avoidance in social/performance situations over the previous week. The scale is scored using both performance and social interaction subscales which present various social situations (e.g., "Telephoning in public," "Going to a party") in which individuals may or may not feel anxious or enact avoidance behaviors. Anxiety and avoidance situations have a 4-point Likert scale response format (0 = None/Never, 3 = Severe/Usually). The LSAS-SR has been shown to have adequate internal consistency (α = .71 – .94; Fresco et al., 2001) and strong test-retest reliability (*r* = .83; Baker, Heinrichs, Kim, & Hofmann, 2002) among young adult and adult samples. For our nomological net analysis, we observed strong internal consistency reliability in the LSAS-SR (α = .95) and utilized a summed scale score (possible range from 0-144), as suggested by previous research (Baker et al., 2002).

Center for Epidemiologic Studies Depression Scale – Revised (CESD-R; Eaton, Smith, Ybarra, Muntaner, & Tien, 2004). The CESD-R is a self-administered measure to assess for clinical depression. It consists of 20 items which imitate *DSM-IV* criteria for depression. Responses are measured on a 5-point Likert scale (0 = not at all or less than 1 day, 4 = nearly every day for 2 weeks). Example items include "My appetite was poor" and "I was tired all the time." Investigation into the psychometric properties of the CESD-R have indicated strong internal consistency (α = .92 – .93), strong factor loadings, and theoretically consistent convergent and divergent validity (Van Dam & Earleywine, 2011). In the present study, the CESD-R again demonstrated strong internal consistency reliability (α = .93). For our nomological net analysis, we utilized a summed scale score (possible range from 0-80), reflecting previous scoring strategies for this scale (Van Dam & Earleywine, 2011).

Adaption of the Internet Social Capital Scale (ISCS; Ellison, Steinfield, & Lampe, 2007; Williams, 2006). The ISCS, originally described in Williams (2006), contains 20 items assessing online and offline social capital. Similar to Ellison, Steinfield, and Lampe (2007), an adaptation of the ISCS was utilized as the content of the items better reflected the context of the present study (i.e., use of a college student sample). In Ellison, Steinfield, and Lampe (2007), the adapted version included 11 of the original ISCS items representing the two subscales of bridging (i.e., loose connections between individuals who might provide useful information or new perspectives for one another but usually not emotional support; Ellison, Steinfield, & Lampe, 2007) and bonding (i.e., between individuals in emotionally close relationships, such as family and close friends; Ellison, Steinfield, & Lampe, 2007) social capital, as well as three additional items which were also adapted to reflect the Michigan State University (MSU) context. In the present study, we replaced “MSU” with “USC” in all items to reflect the University of South Carolina context. An example item is, “The people I interact with at USC would be good job references for me.” Furthermore, an additional 5 items were also included from Ellison, Steinfield, and Lampe (2007) to represent a maintained social capital subscale; this resulted in 19 total items for the ISCS version utilized in the present study. This subscale was inspired by the authors’ pilot interviews of MSU students which suggested that keeping in touch with high school friends was a primary use of social networking sites for college students. An example item from this subscale is, “It would be easy to find people to invite to my high school reunion.” All items are scored on a 5-point

Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Research has shown that the internal consistencies of the original and MSU-adapted ISCS are good ($\alpha = .75 – .89$) (Ellison, Steinfield, & Lampe, 2007; Williams, 2006). For our nomological net analysis, we observed strong internal consistency reliability for the USC-adapted ISCS ($\alpha = .91$) and used a summed scale score (possible range from 19-95) which reflects prior research using this instrument (Ellison, Steinfield, & Lampe, 2007).

2.3 PROCEDURE

Data were collected from undergraduate participants at the University of South Carolina using an online survey though Qualtrics (Qualtrics, Provo, UT). The primary investigator contacted various professors, administrators, and student organizations to gain access to potential participants across campus. Specific recruitment strategies for the study included: 1) Posting Qualtrics survey link on the Psychology Subject Pool website; 2) Advertising the survey in various undergraduate courses (the Qualtrics survey link and primary investigator's contact information were given to students during this time); 3) Contacting various Deans of colleges for e-mailing the Qualtrics survey link to their respective listservs, and 4) Posting recruitment fliers around the USC campus.

Given the C-PEQ was the primary instrument of focus, it was administered first for all participants and the remaining measures were randomized in order to counteract any potential effects of participant fatigue. The final battery included 181 items and took on average 20-40 minutes to complete. Participants were able to take the survey at any preferred location and time on their own personal computers. For their efforts, participants had the opportunity to potentially gain extra course credit (as allowed by their instructor) and/or be entered into a drawing to win a $200 Best Buy gift card. All procedural methods were approved by the University of South Carolina Institutional Review Board.

2.4 DATA ANALYSIS

All CFA data analyses were conducted utilizing the Mplus Version 7.2 statistical software package (Muthén, L. K., & Muthén, B. O., 1998-2012). Full information maximum-likelihood (FIML) was utilized to estimate parameter estimates in the model, as this method has been shown to generate the most asymptotically unbiased (i.e., neither overestimates or underestimates model parameters), asymptotically efficient (i.e., the variability of the parameter estimates are minimized), and consistent parameter estimates (i.e., model parameters are the most accurate representation of population parameters, as sample increases) in a variety of circumstances (West, Finch, & Curran, 1995). Moreover, FIML is able to accommodate missing data analysis and is currently recognized as one of two preferred missing data handling techniques (Enders, 2010).

Analyses associated with research goals two and three were conducted utilizing the R Version 3.0.1 statistical software package. Inter-item correlations of the C-PEQ along with participant means, standard deviations, skewness, and kurtosis were also reported. Participants who completed the survey in 5 minutes or less were excluded from data analysis to increase our confidence in the validity of responses. As there were 181 total questions in the entire battery, completed responses in 5 minutes or less was determined to be an unreasonable response time. This led to the exclusion of 145 respondents, the majority of which (n = 135) either were removed as a result of the study's exclusion criteria or selecting to not provide informed consent. After these exclusions, our final sample size was N = 749 participants.

2.4.1 STRUCTURAL ANALYSES OF THE C-PEQ: CONFIRMATORY FACTOR ANALYSIS A two-factor confirmatory factor analysis using the oblique Geomin rotation was analyzed to test the posited two-factor structure underlying the C-PEQ cyberaggression and cybervictimization items. The specified rotation permitted the two factors to correlate. Unstandardized and standardized estimates for the two-factor C-PEQ solution, as well as variances accounted for by the latent factors (i.e., cyberaggression and cybervictimization) in each item, were reported. Both absolute and incremental fit indices were utilized to assess adequacy of model fit. Absolute-model fit judgment is dichotomous in nature and indicates whether a proposed model fits or does not fit the observed data in an absolute sense. These indices consider how well the model accounts for observed covariances in the data and provide a proportion of variance explained statistic (e.g., R^2 in regression analyses; Hu & Bentler, 1995). A chi-square (χ^2) goodness-of-fit test was used to assess absolute model fit, with lower, non-significant χ^2 values indicating acceptable model fit for the two-factor model. Incremental model fit gauges the extent of misfit instead of using an all-or-nothing approach.

Though useful to understand, limiting analysis of global model fit to an all-or-nothing approach provides no information on the extent of model misfit if found. Moreover, the χ^2 statistic is known to be quite sensitive to sample size (i.e., underestimates goodness-of-fit for $N > 500$ sample sizes and overestimates goodness-of-fit for $N < 100$; Hu & Bentler, 1995). Supplementing the analysis of absolute fit via the evaluation of additional incremental fit indices provides a solution to both of these problems. These indices compare the proposed model to a restricted baseline model that typically assumes no covariation between the observed variables in analysis (Bentler &

Bonett, 1980). In doing so, the fit indices provide a basis from which to understand the extent of global model misfit in the event it is discovered.

Based on Hu and Bentler's (1998; 1999) recommendations, the comparative fit index (CFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA) will be used to further assess the degree of model misspecification (both simple and complex) to supplement the χ^2 statistic. Simple model misspecification involves misspecification of latent factor correlations whereas complex misspecification involves factor loadings (or how much a factor explains a variable in factor analysis).

Hu and Bentler (1998; 1999) recommend reporting these indices as they reflect a good representation of metrics that consider both models. Parsimony, or the desire to explain phenomena utilizing fewer parameters, impacts the various fit indices in different ways. The CFI penalizes models that are less parsimonious so that simpler theoretical processes are favored over more complex ones (i.e., the more complex the model, the lower the fit index). The CFI is measured on a 0 – 1 scale, with higher scores indicating better model fit. Hu and Bentler (1999) recommended that CFI cut-off values at or above .95 are indicative of good model fit. The CFI has found to be sensitive to complex misspecification, and robust to both distributional non-normality and sample size (Hu & Bentler, 1998).

The SRMR is similar to the CFI in that it penalizes models with a higher number of parameters resulting in a decrease in model fit (Hooper, Coughlan, & Mullen, 2008). The measure provides the standardized difference between observed correlations and predicted correlations by computing the average residual covariance, or the differences between the observed and model-implied covariances (Kline, 1998). Unlike the CFI and RMSEA, the SRMR is more sensitive to simple model misspecification. Lower SRMR values are associated with better model fit, with zero indicating perfect fit of a model to the observed data. As the average discrepancy between the observed and model-implied covariances increases, so does the value of the SRMR. Yu (2002) and Hu and Bentler (1999) have suggested cut-off values of .07 and .08 or lower respectively to be considered as good model fit.

Finally, the RMSEA fit statistic is a parsimony-adjusted, residual-based, fit statistic that includes a built-in correction for model complexity. The RMSEA is more sensitive to underparameterized models and relatively unaffected by model overparameterization (Marsh & Balla, 1994), suggesting that it does prefer parsimonious models but does not necessarily penalize for more complex models (Hooper, Coughlan, & Mullen, 2008). Yu (2002) and Hu and Bentler (1999) have recommended RMSEA cut-off values of .05 and .06 and below respectively, with lower RMSEA values indicating better model fit (and less discrepancy between observed and predicted model covariances). Similar to the CFI, the RMSEA has also been shown to be robust to sample size and non-normal distribution.

Along with global measures of misfit (e.g., the CFI, RMSEA, and SRMR), we also explored local sources of misfit in the presence of model misspecification. Two sources of local misfit included standardized estimates and modification indices. Standardized estimates were investigated to examine variance explained in each item by the construct via squaring the loading (R^2 estimate). Likewise, in the presence of misfit, modification indices were assessed to explore where problems exist. A modification index estimates the amount by which the model's overall χ^2 statistic would *decrease* if a particular parameter were freely estimated (Kline, 1998). That is, modification indices indicate potential modifications that would make the hypothesized factor structure more consistent with the factor structure that truly underlies a scale's items.

Conversely, items within an instrument should cluster based upon their intercorrelations (i.e., if a measure, such as the C-PEQ, is supposed to measure several distinct constructs, then the items should form clusters corresponding to these various subscales). If these constructs (e.g., cyberaggression and cybervictimization) are thought to be related yet conceptually distinct, then the subscales should strongly inter-correlate, although not so strongly that they statistically represent the same construct. On the other hand, if items originally developed to cluster on a distinct subscale only weakly inter-correlate, it might be the case that either the instrument is psychometrically poor or these items do not adequately operationalize the construct of interest. It follows that strong inter-item correlations based upon the original conceptualization of the constructs of interest provides evidence for construct validity and will thus improve/increase model specification (Prudon, 2014) (i.e., since a factor loading can be calculated by taking the square root of the mean inter-item correlation, increasing the intercorrelations will subsequently improve absolute and incremental fit indices; Reis & Judd, 2000).

2.4.2 STRUCTURAL ANALYSES OF THE C-PEQ: INTERNAL CONSISTENCY For the second research question regarding internal consistency reliability of the C-PEQ's items, Cronbach's coefficient alpha (α) was evaluated to assess inter-item reliability of the instrument. Judgments of appropriate reliability estimates were based off of recommendations for acceptable, good, and excellent internal consistencies estimates: $0.7 \leq \alpha < 0.8$, $0.8 \leq \alpha < 0.9$, and $\alpha \geq 0.9$ respectively (George & Mallery, 2003).

2.4.3 EXTERNAL ANALYSES OF THE C-PEQ: ESTABLISHING A NOMOLOGICAL NET To establish the nomological net for the C-PEQ, analyses exploring convergent validity were employed. This procedure involved correlating items from the C-PEQ and items from theoretically related instruments. Specifically, we analyzed correlations among items derived from cyberbullying, relational aggression, ADHD, callous-unemotional traits, and social capital scales with the C-PEQ's cyberaggression items to assess for convergent validity. Scales measuring social anxiety, depression, and social capital were also examined for correlations with the C-PEQ's cybervictimization items to assess for convergent validity.

2.4.4 POWER ANALYSES To determine an appropriate sample size to have sufficient power for meeting the recommended cutoff point criteria for the RMSEA fit index, an a priori power analysis was performed. Even though this is not a holistic approach in determining power for all of the recommended CFA fit indices (i.e., CFI, SRMR, and RMSEA; Hu & Bentler, 1999), the RMSEA is one of the most commonly-used fit indices (Kenny, 2011), and provides a good basis for information regarding power for the CFA analyses. Further, previous researchers have developed sample size planning methods for CFA analyses based on this index to understand the power of analysis to reject poorly fitting models and to identify good fitting models (defined by $H_0 = .08$ and $H_1 = .05$, respectively in the test; Browne & Cudeck, 1993; MacCallum, Browne, & Sugawara, 1996; Steiger, 1990). Maxwell, Kelley, and Rausch (2008) state that the idea is not necessarily to test an exact model, but to determine a sample size so that not-good-fitting models can be rejected. Using the conventional field standards of power = $1 - \beta = .8$ and $\alpha = .05$, a priori power analyses based on the model indicated a required sample size of $N = 115$. Given our recruited sample of $N = 749$, results indicated that we were adequately powered for the study.

CHAPTER 3

RESULTS

3.1 MISSING DATA

Missing data for our primary instrument of focus was minimal. Specifically, no missing data was observed on the cyberaggression subscale of the C-PEQ, and the rate of missingness on the cybervictimization subscale items was only 1%. A possible reason for this discrepancy is that some participants completed the cyberaggression subscale (which was presented first) but never completed the remaining parts of the battery, thus resulting in a small portion of missingness on the cybervictimization subscale. Nevertheless, full information maximum-likelihood (FIML) was utilized to estimate model parameters such that missing data could be accommodated in analysis. FIML estimates a likelihood function for each individual case based on the observed variables so that all available information is utilized; variables with no information were not estimated (Newsom, 2015). This method assumes that data are at least missing at random (MAR), such that missing values are unrelated to whether or not a person has missing data on that variable (Rubin, 1976).

3.2 CONFIRMATORY FACTOR ANALYSIS

3.2.1 DESCRIPTIVE STATISTICS Inter-item correlations for the C-PEQ are reported in Appendix A. Means, standard deviations, skewness, and kurtosis for the C-PEQ items are presented in Appendix B. Standard deviations ranged from .45 to .90, indicating some variability in the item responses. Mean values indicated low levels of endorsement for both the cyberaggression and cybervictimization items. Items 6 and 9 on both subscales were highly skewed and kurtotic as compared to recommended normality thresholds for kurtosis and skewness (i.e., skewness $\geq$ 3 and kurtosis $\geq$ 10; Curran, West, & Finch, 1996; Kline, 2005). We conducted additional tests of normality and investigated potential outliers; no outliers were subsequently identified.

In an attempt to satisfy normality assumptions of the inferential techniques employed in the study, we conducted both square root and logarithmic transformations. These data transformations are commonly used for moderate to substantial positive skewness (Tabachnick & Fidell, 2007). Neither data transformation, however, resulted in improvements in normality as a result of substantial floor effects. As such, we decided to employ the original, non-transformed data for inferential tests to preserve interpretability of results and invoked mean-adjusted maximum-likelihood estimation to account for violations of normality. This estimation strategy produces an adjusted absolute fit index termed the Satorra-Bentler scaled chi-square statistic that is robust to the violations of the normality assumption (Satorra & Bentler, 2001). The adjustment involves dividing the normal-theory chi-square statistic by a scaling correction to better approximate chi-square under non-normality and to provide adjusted standard error estimates that correct for artificial attenuation in the presence of non-normality (Satorra & Bentler, 1994; Yuan, Bentler, & Zhang, 2005).

3.2.2 MODEL RESULTS All C-PEQ items are referenced in Table 3.1. The model under analysis considered a two-factor model solution that was hypothesized for the C-PEQ. The structure represents cyberaggression and cybervictimization as two

Table 3.1

C-PEQ Cyberaggression and Cybervictimization Items

Item	Cyberaggression Subscale (*I…via electronic media.*)	Cybervictimization Subscale (*A peer… via electronic media.*)
#1	…ignored a friend request from a peer who wanted to be friends with me…	…I wanted to be friends with via electronic media ignored my friend request.
#2	…removed a peer from my list of friends…	…removed me from his/her list of friends…
#3	…posted mean things about a peer publicly…	…posted mean things about me publicly…
#4	…posted mean things about a peer anonymously…	…posted mean things about me anonymously…
#5	…posted pictures of a peer that made him/her look bad…	…posted pictures of me that made me look bad…
#6	…publicly spread rumors about a peer or revealed secrets he/she had told me…	…publicly spread rumors about me or revealed secrets I had told them…
#7	…sent a mean message to a peer…	…sent me a mean message…
#8	…deliberately excluded a friend from a party or social event, and they found about it…	I found that out that I was excluded from a party or social event…
#9	…made a peer jealous by "messing" with his/her girlfriend/boyfriend…	…made me feel jealous by "messing" with my girlfriend/boyfriend

distinct, yet correlated factors. The fit indices for the two-factor model, as well as the unstandardized/standardized parameters estimates and variance accounted for by each item, are presented in Tables 3.2 and 3.3 respectively. Residual variances for the cyberaggression/cybervictimization items pairs were permitted to correlate as item-pairs

Table 3.2

Goodness-of-Fit Indicators of Model for Cyberaggression and Cybervictimization (N = 729)

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR
Two Factor	433.79*	125	.06	.88	.06

Note: MLM χ^2 = Satorra-Bentler chi square; RMSEA = root mean square error of approximation; CFI = comparative fit index; SRMR = standardized root mean square residual.
*$p < .001$

reflect nearly identical wording across the subscales (See Figure 3.1). The invoked MLM estimator was utilized to handle missing data as this method has been shown to generate the most asymptotically unbiased, asymptotically efficient (i.e., the variability of the parameter estimates are minimized), and consistent parameter estimates (i.e., model parameters are the most accurate representation of population parameters, particularly as sample size increases) of estimation methods in a variety of circumstances (West, Finch & Curran, 1995).

As shown in Figure 3.1, the two factors were strongly correlated yet the paired-items showed weak correlated error terms. Results indicated that only the SRMR fit index associated with the two-factor model fell below the recommended .08 cut-off value (SRMR = .06). The RMSEA fit index approached, but did not meet, the recommended .05 cut-off value (RMSEA = .06); the CFI did not approach the recommended cut-off value of .95 (CFI = .88; Hu & Bentler, 1999). Likewise, the χ^2 difference test did not indicate acceptable model fit for the two-factor solution ($\chi^2 = 433.79$, $p < .001$), such that the observed covariance matrix significantly differed from the model implied covariance matrix. In general, these results might suggest the presence of misspecified factor loadings, construct overlap, or inadequate construct representation within some of the cyberaggression and/or cybervictimization items (See Table 3.2). We explore potential sources of both global and local sources of model misfit in a subsequent section.

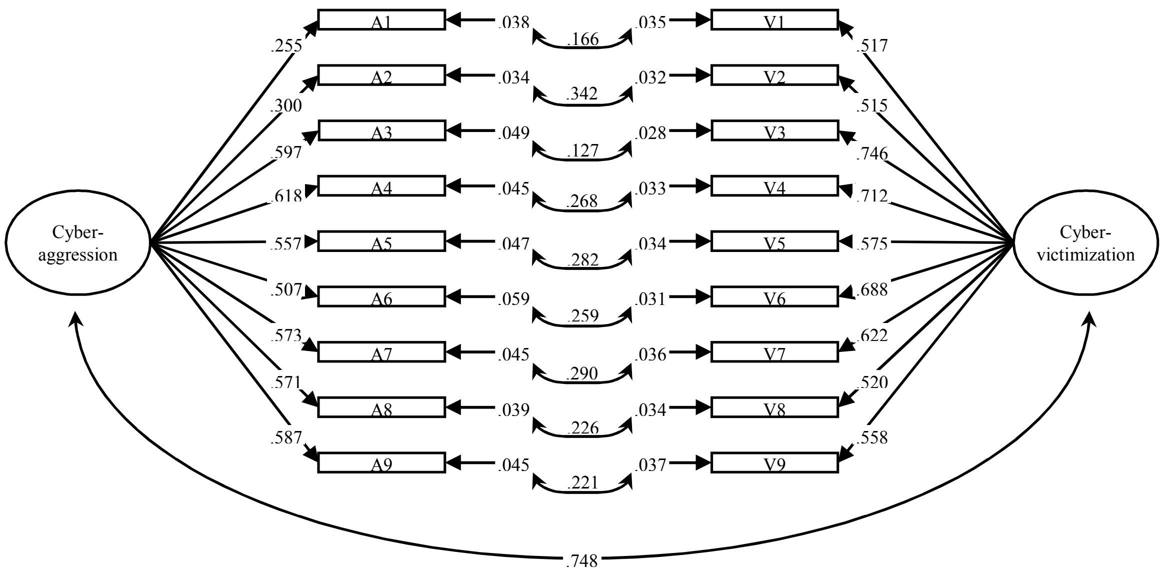

Figure 3.1. Results from the two-factor solution modeled for the C-PEQ. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

Looking at item-level statistics for the model, all unstandardized parameter estimates for the items were significant at α = .05. All standardized parameter estimates, or the correlation between an item and its respective latent factor for which it serves as an indicator, were moderate to strong (ranging from .26 to .75).

3.2.3 EXPLORING MODEL MISSPECIFICATION Given model misspecification, we explored both variance explained in the solution where model misfit was identified as well as suggested modification indices. To acquire information on the variance accounted for in an item by the latent factor, we squared the standardized parameter estimates to obtain an R^2 value. These values are presented in the last column of Table 3.3. The variance accounted for in the items by the latent factors ranged from

.07 to .56, indicating that 7% and 56% of the observed variance in the items was accounted for by the cyberaggression and cybervictimization constructs. Previous methodological work has indicated that a minimum of 50% variance explained in a given item by a latent factor for which is serves as an indicator is an appropriate standard (Hair, Anderson, Tatham, & Black, 1995). Further investigation into standardized error variances (i.e., $1 - R^2$, or the amount of unexplained variance in a given item by its hypothesized latent factor) indicated that items 1, 2, and 6 (all specified to load on the cyberaggression latent factor), as well as items 1, 2, and 8 (all specified to load on the cybervictimization latent factor), had 73 – 94% of the variance not accounted for by their respective latent factors. Examination of these items is further considered in the discussion.

We sought to gain additional insight into identified areas of model misspecification through the analysis of modification indices. A modification index estimates the amount by which the model's overall χ^2 statistic would decrease if a particular parameter were freely estimated (Kline, 1998) and can further provide information on the source of model misspecification. Though research cautions against blindly implementing these indices to improve fit (MacCallum, Roznowski, & Necowitz, 1992), they can act as a useful tool to understand areas in the model that could yield improvement. Examination of the suggested modification indices revealed that items 1 and 2 on the cyberaggression and cybervictimization subscales had correlated error terms, such that if we permitted the model to incorporate this relationship, fit would improve. Specifically, the proposed modification indices suggested adding a correlated error term between items 1 and 2 on the cyberaggression subscale (decrease in $\chi^2 = 86.38$) as well as adding a correlated error term between items 1 and 2 on the cybervictimization subscale (decrease in $\chi^2 = 73.42$). These results suggest that the items shared common variance beyond that of the latent factor for which they were developed to be indicators.

Table 3.3

Unstandardized Loadings (Standard Errors) and Standardized Loadings for the 2-Factor Confirmatory Model of Cyberaggression and Cybervictimization

Item	Cyberaggression		Cybervictimization		Item R^2 Values
	Un-standardized	Standardized	Un-standardized	Standardized	Aggression/ Victimization
#1	1.00 (--)	.26	1.00 (--)	.52	.07/.27
#2	1.21 (.17)	.30	.96 (.08)	.52	.09/.27
#3	1.44 (.29)	.60	1.31 (.13)	.75	.36/.56
#4	1.80 (.34)	.62	1.26 (.13)	.71	.38/.51
#5	1.61 (.34)	.56	1.06 (.12)	.58	.31/.33
#6	1.03 (.26)	.51	.99 (.11)	.69	.26/.47
#7	1.90 (.36)	.57	1.28 (.14)	.62	.33/.39
#8	1.65 (.32)	.57	1.14 (.13)	.52	.33/.27
#9	1.23 (.28)	.59	1.03 (.12)	.56	.35/.31

Note. $N = 729$. Standard errors for model estimates appear in parentheses. R^2 represents the variance accounted for in an item by the latent factor for which it serves as an indicator.

Finally, the modification indices also detected one additional item-cross loading, meaning that a particular item written to serve as an indicator of the cyberaggression latent factor also served as an indicator for the cybervictimization latent factor, or vice versa. In the present analysis, the modification index suggested adding a path, or cross-loading, between item 9 on the cyberaggression subscale and item 6 on the cybervictimization subscale (decrease in χ^2 = 13.74).

In considering values of both the error variances and modification indices, it appears that items 1 and 2 on both subscales are primary sources of model misspecification. In light of these findings, further assessment of the modification indices is subsequently warranted. As previously mentioned, although research cautions against blindly implementing modification indices to improve fit (MacCallum, Roznowski, & Necowitz, 1992), they can act as a useful tool to understand specific areas in the model that could potentially generate improvement. As such, we explore these issues further in the discussion and, in line with the suggested modification indices, present a possible solution for the C-PEQ to consider in future work.

3.3 INTERNAL CONSISTENCY OF THE C-PEQ SUBSCALES

Table 3.4 presents intercorrelations of the latent factors, means, standard deviations, reliability estimates, and the variance accounted for in the C-PEQ subscale items by the respective latent factors. Cronbach's coefficient alpha estimates of internal consistency for the C-PEQ's cybervictimization items was good (α = .84) and reflected estimates reported in prior research (Landoll et al., 2015). Internal consistency for the C-PEQ's cyberaggression items was acceptable (α = .75) and internal consistency for the overall instrument was good (α = .88). The variance accounted for by the latent factors was less than 50% for both the cyberaggression subscale (.05) and the cybervictimization (.16) subscale, however. This is likely a product of the various low R^2 values presented in Table 3.2.

Table 3.4

Correlations, Reliability, Means, and Standard Deviations of the C-PEQ Subscales

	Cyberaggression Subscale	Cybervictimization Subscale
Cyberaggression Subscale	1.00	
Cybervictimization Subscale	.75	1.00
Cronbach's Coefficient α	.75	.84
Factor Mean	13.82[a]	13.66[a]
Standard Deviation	3.41	4.39
Variance Accounted For by the Latent Factors	.05	.16

***$p < .001$. *Note*. $N = 729$. a = possible range of scores: 9 – 45.

3.4 NOMOLOGICAL NET: CONVERGENT VALIDITY EVIDENCE

3.4.1 C-PEQ CYBERAGGRESSION SUBSCALE We originally hypothesized that the C-PEQ cyberaggression subscale scores would moderately ($r = .25 – .40$) to strongly ($r = .60 – .80$; Cohen, 1988) correlate with other instruments measuring cyberbullying (CS), attention-deficit-hyperactivity-disorder (CSS), callous-unemotional traits (ICU), relational aggression (SRASBM), and social capital (ISCS) to demonstrate convergent validity evidence. There were mixed results regarding these predictions. As predicted, the correlation between the C-PEQ cyberaggression scores and the CS cyberbullying scores was moderate ($r = .41$). Also as predicted, a moderate correlation was observed with scores from the measure of proactive/reactive relational aggression ($r = .37$). Moderate support was given for the hypothesis predicting stronger correlations with reactive relational aggression (r = .36) versus proactive relational aggression (r = .33). Contrary to prediction, there was a weak correlation between the C-PEQ cyberaggression scores and ADHD (r = .18), callous-unemotional (r = .24), and social capital scores (r = -.02). These results are summarized in Table 3.5.

3.4.2 C-PEQ CYBERVICTIMIZATION SUBSCALE We originally hypothesized that the C-PEQ cybervictimization subscale scores would moderately (r = .25 – .40) to strongly (r = .60 – .80; Cohen, 1988) correlate with instruments measuring cybervictimization (CS), social anxiety (LSAS – SR), depression (CESD – R), and social capital (ISCS) to demonstrate convergent validity evidence. Similar to the observed results for the C-PEQ cyberaggression subscale, there were mixed results regarding these hypotheses. As predicted, a moderate correlation was observed with the CS cybervictimization scores (r = .39). Contrary to predictions, weak correlations were observed between the C-PEQ cybervictimization scores and scores on the measures of social anxiety (r = .16), depression (r = .24), and social capital (r = -.03). These results are also summarized in Table 3.5. Overall, investigation into the nomological net did not provide sufficient construct validity evidence for the C-PEQ scores and the majority of hypotheses were not supported.

Table 3.5

Correlations between the C-PEQ subscales and Related Measures

Measure	C-PEQ Cyberaggression Subscale	C-PEQ Cybervictimization Subscale
CSS	.18*	NP
ICU	.24*	NP
SRASBM	.37*	NP
Proactive	.33*	NP
Reactive	.36*	NP
ISCS	-.02	-.03
CS Subscales		
Cyberbullying	.41*	NP
Cybervictimization	NP	.39*
LSAS-SR	NP	.16*
CESD – R	NP	.24*

Note: N = 729. NP = no prediction hypothesized; CSS = Current Symptoms Scale; ICU = Inventory of Callous-Unemotional Traits; SRASBM = Self-Report of Aggression and Social Behavior Measure; ISCS = Internet Social Capital Scale; CS = Cyberbullying Scale; LSAS-SR = Liebowitz Social Anxiety Scale – Self-Report Version; CESD – R = Center for Epidemiologic Studies Depression Scale – Revised.
*$p < .01$

CHAPTER 4

DISCUSSION

The present study had three goals:

1) Conduct a confirmatory factor analysis using the scores from the C-PEQ's cyberaggression and cybervictimization items to investigate the purported two-factor structure of the instrument's scores,

2) Estimate internal consistency reliability for the C-PEQ, and

3) Given adequate support for the scale's internal structure, examine correlations between C-PEQ items and items from theoretically similar instruments to assess construct validity evidence for the instrument.

We found adequate support for the second goal of our study, but analyses yielded mixed results with respect to our first and third goals. Concerning the first goal of our study, results indicated that the majority of both absolute and incremental fit indices did not meet recommended standards. These results generally suggest that the proposed two-factor model solution did not adequately fit the observed covariance matrix and that there were several areas of model misspecification. The amount of variance accounted for in the C-PEQ items by their respective latent factors was less than .50 for each subscale, indicating that a low proportion of observed variance in each of the items was explained by the latent factors. This overall issue with low variance explained was likely influenced by several particular items. These included items 1, 2, and 6 on the cyberaggression subscale and items 1, 2 and 8 on the cybervictimization subscale which had 73 – 94% of the variance not accounted for by their respective latent factors.

Further reflecting on both the content of these indicators and suggested modification indices lends insight into these problems. Item 1 on the cyberaggression subscale states “I ignored a friend request from a peer who wanted to be friends with me via electronic media” and item 2 on the cyberaggression subscale reads “I removed a peer from my list of friends via electronic media.” Items 1 and 2 on the cybervictimization subscale assess the same behavior but from the cybervictim’s point of view (i.e., item 2 reads “A peer removed me from his/her list of friends via electronic media”). Given the low amount of variance explained in this set of items, perhaps altering one’s friend list via electronic media does not optimally capture a form of cyberaggression. Consider that many individuals may ignore friend requests from those who they do not personally know as well as remove those from their friend list who they have not spoken to in a long time (McLaughlin & Vitak, 2012; Sibona & Walczak, 2011).

It is likewise possible that many individuals utilizing electronic communication do not perceive these actions as a form of aggression but rather as socially acceptable forms of behavior via electronic media. Qualitative research on socially acceptable and unacceptable behavior utilizing electronic forms of communication as determined by users provides a useful backdrop for this consideration. For instance, Stern and Taylor (2007) discussed how individuals who use Facebook do not view “friends” or “friend requests” to be very important as most people using the social networking site are not their friends in real life. Individuals decide to include or request friends for their social networking friend list for various reasons. Establishing this connection via electronic media may be a result of various weak or strong personal ties with the individual such as having attended the same high school or college, liking similar hobbies, activities, or sports teams on the social networking site fan pages, as well as having brief face-to-face encounters with the individual whom users felt they might see again in the future (e.g., Ellison, Steinfield, & Lampe, 2011; West, Lewis, & Currie, 2009). There are a multitude of reasons for why individuals may be included as part of a social networking friend list, and research shows that the median number of friends per Facebook user for young adults is approximately 300 friends (Smith, 2014). It is therefore plausible that many social networking users do not share a strong connection with a number of individuals included within their friend list. As such, being removed from a person's social networking friend list may not be perceived as insulting as a result of not sharing strong connections with a proportion of the individuals included within one's friend list. This point of view may further support the conclusion that altering or editing one's "friends list" via social media is often not perceived as either a form of cyberaggression (i.e., if one ignores a friend request) or cybervictimization (i.e., if one has their friend request ignored).

Regarding the correlated error terms between items 1 and 2 on both the cyberaggression and cybervictimization subscales, the suggested modification indices indicate that these items share common variance above and beyond that of variance accounted for by their respective latent factors. Considering both the amount of observed item variance that was not accounted for by the respective latent factors in this study and Landoll's et al. (2015) investigation, as well as the suggested modification indices, we explored another two-factor solution of the C-PEQ with these four items removed from the model. Though the model χ^2 was significant ($\chi^2 = 124.54$, $p < .001$), results indicated that all incremental fit indices met recommended cut-off values, suggesting that although there was no evidence for absolute model fit, the misfit across model-implied and observed covariance matrices was negligible. Specifically, the SRMR fit index fell below the recommended cut-off value of .08 (SRMR = .04); the RMSEA met the recommended .05 cut-off value (RMSEA = .03); and the CFI also met the recommended cut-off value of .95 (CFI = .97). These results strongly support the exclusion of these items in terms of adequate model specification and suggest that the items appear to account for noticeable amounts of construct irrelevant variance within the C-PEQ instrument. Further investigation into the properties of these items appears warranted and is a suggestion for future research of the C-PEQ. Specifically, replicating the methodology of the present investigation by assessing evidence for construct validity of the C-PEQ with items 1 and 2 removed on both subscales within a novel sample may prove useful in future research.

Regarding items 6 ("I publicly spread rumors about a peer or revealed secrets he/she had told me via electronic media") on the cyberaggression subscale and item 8 ("I found out that I was excluded from a party or social event via electronic media") on the cybervictimization subscale, these items seem to involve public instead of private matters or behaviors. Although research has demonstrated that acts of cyberaggression can be both public and private in nature (Menesini et al., 2012), perhaps the wording of these items could be interpreted in other ways. Concerning item 6, perhaps the rumor or secret was positive in nature. For example, an individual may have spread a rumor that another individual was being promoted at their job or was recently engaged. For item 8, perhaps an individual was simply not invited versus directly being told they were not wanted at the party or social event. Overall, it appears that assessing the aforementioned constructs within the above items might not optimally represent the latent constructs of cyberaggression and cybervictimization or rather may contain construct irrelevant variance that obscures measurement of the constructs. If these items are measuring an extraneous construct that is not relevant to cyberaggression or cybervictimization, then their removal from the instrument should be considered. Alternatively, if these items are thought to truly assess a dimension of cyberaggression or cybervictimization, then additional items that directly measure the dimension might be included. The inclusion of differently worded items which were created to measure other aspects of the friend list items' dimension might tap into other construct relevant variance which would subsequently decrease the amount of variance unexplained in the items by their respective latent factor. For example, consider an item that states "I removed one of my friends from my list of friends after we had an argument via electronic media." This item measures the original dimension of "friend lists" but portrays a reactive form of aggression. Thus, including additional items such as this example to the measure may attend to construct irrelevant variance by resulting in larger R^2 values for the items, or the amount of variance explained in the items by their respective latent factors.

A third potential explanation for the presence of model misspecification concerns the correlation between the cyberaggression and cybervictimization subscale. These subscales shared a strong correlation ($r = .75$), suggesting that the C-PEQ may be measuring much of the same construct in both of its subscales. Researchers suggest that subscales correlating $r \geq .85$ show aspects of poor discriminant validity and yield consequences such as multicollinearity (Kenny, 2012). This strong correlation between the cyberaggression and cybervictimization subscales might possibly be explained by the nature of item wording and structure. That is, the C-PEQ subscales include item pairs that measure the same concept from opposing viewpoints of the cyberaggressor and cybervictim, as well as share the same grammatical stem (i.e., the C-PEQ utilizes sister item pairs). Perhaps a point of future investigation would be to develop two, one-factor versions of the C-PEQ subscales which separately address cyberaggression and cybervictimization. Altering the item stems for one of the subscales would remove some potential overlap in construct measurement due to similar item content and phrasing as well as remove the usage of sister item pairings. A one-factor solution for both of these C-PEQ versions might also be hypothesized, similar to the proposal suggested in Landoll et al. (2015).

Beyond the aforementioned issues, it is useful to consider similarities and distinctions across our investigation and the original Landoll et al. (2015) study to gain more context for our CFA results. First, the Landoll et al. (2015) did not explore the C-PEQ's cyberaggression items. Further, error terms that were allowed to correlate in Landoll's et al. (2015) investigation were not invoked in the current study. These error term correlations included: item 1 correlated with items 2 and 8; item 2 correlated with item 5; item 3 with items 4, 5, and 6; item 4 with items 5 and 6; and item 5 correlated with item 8 on the cybervictimization subscale. Interestingly, several of these error term correlations reflect some of the suggested modification indices and areas of model misspecification for the cybervictimization subscale in our investigation. This might suggest that these particular items relate in some manner that is unexplained by their respective latent factor. We chose not to correlate the aforementioned error terms here, however, as implementing modification indices or allowing such error terms to correlate without a strong theoretical rationale is generally not recommended (MacCallum, Roznowski, & Necowitz, 1992). Lastly, the cybervictimization items analyzed in the original Landoll et al. (2015) study also displayed noticeable amounts of unexplained variances, similar to our findings. Considering both of these investigations, further psychometric evaluation of the instrument is still warranted to explore how these items operate in both adolescent and young adult populations.

One lasting issue to address is the differences between the utilized samples within the present study and the original psychometric investigation of the C-PEQ (Landoll et al., 2015). Undergraduate college students were used within the present study whereas high school adolescents (14-18 years of age, $M = 15.80$, $SD = 1.18$) participated in Landoll's et al. (2015) investigation. A majority of the prior literature assessing cyberaggression has focused on middle school and high school age ranges as a result of theories suggesting that face-to-face forms of aggression are more prevalent among these individuals as compared with young adult populations (Schenk et al., 2013). However, prevalence studies have demonstrated that rates of cyberaggression and/or cybervictimization are just as frequent among young adults (Kowalski, Giumetti, Schroeder, Reese, 2012; Schenk & Fremouw, 2012; Schenk et al., 2013). This finding makes conceptual sense as some social networking sites such as Facebook were originally intended for use among college students (Ellison, Steinfield, & Lampe, 2007) as well as that the vast majority of young adults use at least one form of electronic communication on a regular basis (Lenhart, Purcell, Smith, & Zickuhr, 2010).

From a developmental perspective, prior research has investigated how adolescents and young adults interpret various negative behaviors in which they have experienced or are currently experiencing. Since adolescence is an important time for developing healthy relationships, self-esteem, and other developmental factors, these studies have concluded that high school-age students might be hypersensitive to aggressive forms of behavior (e.g., Feiring, Deblinger, Hoch-Espada, & Haworth, 2002). Other researchers have suggested that young adults also perceive that there are much higher rates of cyberaggression in high school compared to college (Kowalski et al., 2012). It is therefore plausible that the high school students utilized in Landoll et al. (2015), as compared to the young adult sample within the present investigation, may have been more apt to report cybervictimization and relate more to aspects of cyberaggression and cybervictimization that were measured in the items which displayed large amounts of unexplained variance in the current study (i.e., items 1, 2 and 6 on the cyberaggression subscale and items 1, 2, and 8 on the cybervictimization subscale). That is, perhaps adolescents perceive the alteration of friend lists or behaviors involving invitations to social events as less socially acceptable behavior via electronic communication as compared to young adults.

Likewise, cultural distinctions between the current study's sample and the sample utilized in Landoll et al. (2015) are worth noting. The present study's sample predominantly included Caucasian participants whereas the majority of Landoll's et al. (2015) sample was Hispanic. It is possible that cultural differences may exist in both the participation in cyberaggression or cybervictimization as well as interpretation of those experiences. For instance, demographic studies show that proportionally speaking, Hispanic populations in the United States interact through social networking sites (e.g., Facebook, Twitter, and Instagram) at greater percentages than Caucasian individuals

(Duggan, Ellison, Lampe, Lenhart, & Madden, 2014). Simply by utilizing electronic forms of communication more frequently may result in higher rates of cyberaggression or cybervictimization among Hispanic individuals. Prior research suggests that both cyberaggressors and cybervictims spend more time online as compared to non-involved persons, although it is also important to consider that having a larger repertoire of electronic activities (e.g., an individual utilizing numerous social networking sites, texting, email, and online chat rooms for communication) may also impact the involvement in cyberaggression (Festl, Scharkow, & Quandt, 2013; Livingstone, Haddon, Görzig, & Olafsson, 2011; Walrave & Heirman, 2011). As the C-PEQ measures the *frequency* of involvement in cyberaggression or cybervictimization, perhaps the increased usage of electronic communication among Hispanic populations was indeed reflected in responses to the C-PEQ cybervictimization items in Landoll's et al. (2015) study. However, although there were few Hispanic participants in the present investigation (N = 21), these participants did endorse higher frequencies of cyberaggression but lower frequencies of cybervictimization experiences as compared to Caucasian participants. Further investigations utilizing the C-PEQ may therefore continue seek to explore the frequency of cyberaggression and cybervictimization experiences among Hispanic individuals.

4.1 IMPLICATIONS OF NOMOLOGICAL NET ANALYSES With respect to our mixed results from the nomological net investigation of the C-PEQ instrument, we have several considerations. Concerning the weak correlation found between cyberaggression and ADHD and CU traits, prior research has suggested both a predictive relationship between ADHD behaviors and traditional forms of aggression (Kokkinos &

Panayiotou, 2004; Unnever & Cornell, 2003) as well as longitudinal associations between cyberaggression and CU traits (Fanti et al., 2012). A potential explanation for our results may be that our sample was predominantly female, as both ADHD and CU traits are overwhelmingly found to be more prevalent in males as compared to females (Faraone & Biederman, 2005; Frick & White, 2008). Community samples utilizing the ICU have observed means of 27.12 (*SD* = 7.7) for males and 21.64 (*SD* = 6.0) for females (Essau et al., 2006); norming samples of 17-29 year olds utilizing the CSS have observed means and standard deviations of *M* = 6.4 and *SD* = 5.1 respectively. Our sample thus displayed lower levels of endorsed CU and ADHD traits (ICU: *M* = 18.01, *SD* = 7.67, possible range of scores from 0-72; CSS: *M* = 3.39, *SD* = 3.53, possible range of scores from 0-18), potentially influencing the intercorrelations with items from the C-PEQ. Perhaps these forms of externalizing behaviors are also inconsistent with aggressive behavior in the cyber realm. However, social science research often describes weak to moderate correlations and low amounts of variance explained among constructs (Cohen, 1988), sometimes as a result of processes such as equifinality and multifinality. These processes suggest that a single outcome may be linked to several variables or that a single variable may lead to several outcomes, respectively. As such, although our findings suggest only weak relationships between these constructs, they may have important clinical meaning in that the cyberaggression items on the C-PEQ are still capturing some explained variance in complex constructs such as CU traits and ADHD in a young adult population.

Concerning the null correlation between the cyberaggression and cybervictimization subscales and the measure of social capital (ISCS; Ellison, Steinfield, & Lampe, 2007), although prior literature supports a relationship between these constructs (e.g., Ciucci & Baroncelli, 2014; Glaeser, Laibson, & Sacerdote, 2002; Wright & Li, 2013), perhaps being involved in cyberaggression has no relation to the level of popularity or perceived social support in one's environment. Although researchers have suggested that negative indicators of a lack of social capital include aggressive and bullying behaviors (Kouvonen, 2006), considering the unique aspects of electronic communication may provide a potential explanation for our results. For example, those who have traditionally been marginalized (i.e., often less popular or minority populations) might have the ability to "turn the tables" as a result in the unique changes in power dynamics of online interactions as compared to face-to-face interactions (Hinduja & Patchin, 2008). Furthermore, another point is to consider how the constructs of social capital and/or popularity appear in a college environment. As part of the ISCS instrument, Ellison, Steinfield, & Lampe (2007) included a maintaining social capital subscale to measure an aspect of social capital where individuals seek to remain in contact with prior social relationships. As high school students transition to a college environment, and particularly to a large public university such as the University of South Carolina, the need to maintain prior social friendships as well as form new social networks is salient. During this transition, popularity may therefore take on a new meaning. In high school, for example, a "popular" student is often well known and/or well liked among a noticeable portion of the school's students. At large public universities, however, popularity might be determined by different mechanisms such as likeability within a person's specific social group (e.g., fraternity/sorority) or the numerous novel opportunities college offers which subsequently allows for the restructuring of social relationships (Astin, 1993). Therefore, considering how a college environment influences social relationships, perhaps social connections in college which involve cyberaggression are also influenced to a degree that the frequency of experiencing cyberaggression is not related to developing or maintaining aspects of social capital.

Our hypotheses predicting moderate to strong correlations between cybervictimization and depression and social anxiety were also not supported. It should be noted, however, that the observed correlations in the present study are similar to those found in Landoll's et al. (2015) original investigation, suggesting that the relationships between these constructs might generalize across adolescent and young adult age groups. It remains important to consider the complexities of these constructs and how those facets may influence the observed relationships in the present investigation. That is, depressive and anxiolytic symptomatology may develop as a result of numerous factors such as genetic predispositions, general psychological vulnerabilities, and specific vulnerabilities (e.g., learned situations; Beck & Alford; Suárez, Bennett, Goldstein, & Barlow, 2009). With such varying etiologies for the cause of depressive and anxiolytic responses, natural variation in our sample as compared to other investigations may have existed, which subsequently led to weak correlations between these constructs. As previously mentioned with regards to our findings on the relationships between cyberaggression and both CU traits and ADHD, the complexities of social science constructs like depression and anxiety often result in lower amounts of variance explained as compared to other scientific fields of inquiry; these findings, however, might still prove important for psychological intervention. Further research should therefore continue to establish whether cybervictimization, as a construct, is or should be more strongly correlated with measures of depression and social anxiety.

Descriptive statistics revealed similar rates of depressive symptomatology (CESD-R: *M* = 16.60, *SD* = 14.42) compared to validation samples of undergraduate college students for the CESD-R instrument (Van Dam & Earleywine, 2011). Rates of social anxiety, however, were actually higher than observed prevalence rates in several other investigations (LSAS-SR: *M* = 42.81, *SD* = 22.6; Caballo, Salazar, Irurtia, Arias, & Nobre, 2013; Fresco et al., 2001). The LSAS-SR mean score indicated that our sample average was considered to fall in the nongeneralized social anxiety disorder range according to established cutoffs (Caballo et al., 2014). College is a particularly stressful time during development as a result of newfound independence, responsibility, and novel experiences which may have elevated the observed responses of social anxiety. Future investigations of the C-PEQ should seek to analyze correlations between these constructs in populations who are not at increased risk for developing thoughts and feelings related to social anxiety. Overall, our sample mirrors previously established rates of depression and displays expected, elevated rates of social anxiety in young adult populations. Our observed results concerning evidence of convergent validity between the cybervictimization subscales and measures of depression and social anxiety, therefore, are more likely a result of the aforementioned biological and psychological vulnerability factors than either the lack of endorsement or variability of these constructs.

As a continuation of the discussion on differences between the utilized samples in the current investigation and Landoll's et al. (2015) study, aspects of individualistic culture as commonly observed in Caucasian Americans (such as the desire for individual expression and lower concern for in-groups) and collectivistic culture as more commonly seen in Hispanic populations (such as focusing on in-group harmony or respect/dignity) may also have an impact on both involvement in and reactions to experiences of cyberaggression (Triandis, Bontempo, Villareal, Asai, & Lucca, 1988). That is, perhaps those from individualistic cultures may experience elevated negative reactions to being cybervictimized as compared to those from collectivistic cultures as a result of less support from in-group systems (Li, 2007). This point focuses on the *valence* or emotional reaction of being involved in cyberaggression or cybervictimization. As mentioned, the C-PEQ measures frequencies of these constructs yet the content of several items involve language which appeals to emotions (e.g., I sent a *mean* message to a peer via electronic media). Future research should therefore consider both qualitative and quantitative methods to discern any cultural differences concerning cyberaggression and cybervictimization, potential differential item functioning in these constructs, and whether this influences aspects of convergent validity. Concerning the latter, it may be the case that interpretations and reactions to the C-EPQ items which involve emotional valence affects how item responses of the C-PEQ covary with measures of anxiety and depression.

4.2 OVERALL IMPLICATIONS Generally, there was mixed support for construct validity evidence of the C-PEQ. CFA results did not support the proposed two-factor solution and several hypothesized relationships between the C-PEQ and other measures included within the nomological net were unsubstantiated. However, the C-PEQ did display good internal consistency reliability, both for the whole instrument as well as for each subscale, as well as substantiated several other hypothesized correlations with measures included in the nomological net comprising of a measure of cyberbullying and cybervictimization as well as relational aggression. Although several hypotheses were not supported, specifically within the nomological net analysis, the final results appear consistent with initial findings in Landoll's et al. (2015) investigation of the C-PEQ, including potential *clinically* significant findings despite not meeting Cohen's (1988) suggestions for moderate to strong correlational effects. As further evidenced by our exploratory analyses, revisions of the scale should be considered in order to address the identified areas of model misspecification. Specifically, the removal of items 1 and 2 on both subscales as well as item multidimensionality (i.e., how items may be differentially interpreted) might be considered. These revisions may subsequently increase the variance accounted for in the items by the latent factors as well as strengthen the internal structure of the instrument.

4.3 STRENGTHS AND LIMITATIONS There are several various strengths of the present study. First, our study was one of the pioneer investigations to fully examine a novel measure of cyberaggression and cybervictimization utilizing previously validated methodologies for assessing construct validity evidence. As previously mentioned, the current state of valid measurement within this field is noticeably lacking (e.g., Berne et al., 2013) and our primary goal was to address this research gap by advancing psychometric investigation of cyberaggression instrumentation. Second, this is one of the first studies to address both cyberaggression and cybervictimization in a young adult sample. The majority of prior research has utilized middle and high school samples as a result of theory suggesting that traditional forms of aggressive behavior most commonly occur during these periods of development (e.g., Kowalski et al., 2012; Schenk et al., 2013). Our results indicated that aggressive behaviors in the cyber realm are prevalent enough in young adult populations to warrant further investigation, similar to prior research findings (e.g., Kowalski et al., 2012). Furthermore, despite our sample not being fully representative of the University of South Carolina's undergraduate student gender demographic, having a majority-female sample may actually be perceived as a strength of the study given research has shown that females tend to utilize electronic forms of communication more often, as well as experience higher rates of cyberaggression and cybervictimization, as compared to males (e.g., Dooley, Pyżalski, & Cross, 2009). Thus, we are capturing information from individuals who may be more likely to experience or respond to the primary constructs of interest.

Although the utilization of a young adult sample can be argued as a strength of this study, the generalizability of a largely homogenous college sample may be limited. The correlations between scores from the C-PEQ subscales and scores from related measures, for example, may have been attenuated as a result of low variation in scores, as the current sample had uniformly low endorsement of cyberaggression and cybervictimization. In addition, other measures such as the ICU and CSS also displayed low variance in scores. The homogeneity of the sample (i.e., predominantly female and Caucasian) might explain the observed non-normal, skewed score distributions. For example, callous-unemotional and ADHD traits have both been shown to have higher prevalence rates among adult males than females (e.g., Faraone & Biederman, 2005; Frick & White, 2008). Due to the fact that our sample was predominantly female, it is not surprising that there were generally lower levels of endorsement of these traits as compared to a more gender representative sample. Lastly, a third limitation is that the present investigation did not directly investigate discriminative validity evidence for the C-PEQ. With the novel state of the cyberaggression and cybervictimization field, future research should seek to concurrently assess for both convergent and divergent validity evidence to establish a broader nomological net for these constructs. Until the construct is more concretized and supporting theory lays the foundation for these examinations, these investigations may remain largely exploratory in nature during initial stages.

4.4 FUTURE RESEARCH AND CONCLUSION Considerations for future research have been addressed throughout our discussion. Further reflecting on the findings of the present study, there are several other specific areas for future research. First and foremost, the replication of our results is needed to produce more concrete conclusions regarding construct validity evidence for the C-PEQ. Targeted investigation into the aforementioned areas of model misspecification may prove useful for this goal. Furthermore, although our results did not indicate evidence for convergent validity between the C-PEQ's cyberaggression subscale and a measure of ADHD or callous-unemotional traits, it may be of interest to investigate whether other distinctive externalizing disorders such as oppositional defiant disorder and conduct disorder more highly correlate with cyberaggression. Researchers have even suggested a connection between psychopathy and cyberaggression (Pabian, De Backer, & Vandebosch, 2015), and thus these antisocial constructs may prove to be additional areas of investigation. Future research should also consider age and cultural differences in the development of instruments measuring cyberaggression and cybervictimization. These investigations may allude to the necessity for specified versions of cyberaggression instruments such as the C-PEQ to best assess for these behaviors among diverse populations.

A lasting area for future research should involve further psychometric work into novel measures of cyberaggression and cybervictimization. The field is in further need for instrumentation which has been vigorously assessed for evidence of reliability and validity. More specifically, investigation of discriminative validity within subscales is of importance. As many current instruments measuring cyberaggression also attempt to measure cybervictimization (Berne et al., 2013), it will important to ensure that various subscales included on novel measures are not so highly correlated that the instrument's scores are impacted by multicollinearity. As previously suggested, a potential strategy to diminish this possibility is to consider one subscale versions of the instruments which address cyberaggression and cybervictimization without utilizing sister item pairings. This may remove any potential overlap in construct relevant variance due to similar item content and phrasing.

In addition, although Berne et al. (2013) provided a thorough overview of the current state of measurement in this field, an additional instrument not included within the review was discovered since conclusion of the study. Lam and Li (2013) developed the E-Victimization Scale and E-Bullying Scale which are designed to measure cybervictimization and cyberbullying among a sample of 484 Chinese adolescents. The authors mentioned that these scales displayed adequate fit for the hypothesized one-factor solution of the cybervictimization subscale as well as the two-factor solution of the cyberbullying subscale, poor to excellent internal consistency reliabilities (α = .55 – .96), and convergent validity evidence with measures of depression and anxiety (Lam & Li, 2013).

An interesting point of note is that these authors developed two separate, one-subscale instruments to assess for these constructs as aforementioned as a potential strategy to diminish the effects of multicollinearity between these correlated constructs. Secondly, the authors constructed a unique conceptualization of the E-Bullying Scale two-factor solution by hypothesizing that one factor would underlie “mild” forms of cyberbullying and a second factor would underlie “serious” forms of cyberbullying. To explain, an example of mild cyberbullying might involve a perpetrator teasing someone whereas a more serious form of cyberbullying may involve physically threatening or making up rumor about someone to make others not like them via electronic media (Lam & Li, 2013). Future research involving the C-PEQ and other novel measures of cyberaggression and cybervictimization might also consider various intensities or harshness of behaviors displayed via electronic communication as a way of conceptualizing these constructs.

In all, electronic technology is ever changing and it will be important to develop instruments which provide broad assessments of technological use and experiences. The C-PEQ is one of the few, if not only, measures of cyberaggression and cybervictimization to both be thoroughly analyzed through validated statistical methodologies and include a broad assessment of technological experiences. However, the C-PEQ is still in an ongoing development phase but reflects an important step in improving cyberaggression and cybervictimization instrumentation. As such, similar procedures should be adopted to further statistical and substantive investigations within this novel field.

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APPENDIX A: INTER-ITEM CORRELATIONS FOR THE C-PEQ ITEMS

	CPEQ1	CPEQ2	CPEQ3	CPEQ4	CPEQ5
CPEQ1	1.000				
CPEQ2	0.494	1.000			
CPEQ3	0.142	0.178	1.000		
CPEQ4	0.119	0.147	0.437	1.000	
CPEQ5	0.079	0.145	0.382	0.404	1.000
CPEQ6	0.059	0.111	0.218	0.301	0.314
CPEQ7	0.144	0.154	0.353	0.362	0.269
CPEQ8	0.208	0.167	0.250	0.302	0.287
CPEQ9	0.077	0.101	0.381	0.327	0.281
CPEQ10	0.256	0.275	0.239	0.243	0.248
CPEQ11	0.262	0.421	0.217	0.170	0.237
CPEQ12	0.197	0.228	0.402	0.331	0.367
CPEQ13	0.152	0.179	0.338	0.441	0.288
CPEQ14	0.143	0.210	0.261	0.280	0.456
CPEQ15	0.087	0.146	0.292	0.271	0.266
CPEQ16	0.084	0.117	0.238	0.281	0.278
CPEQ17	0.216	0.242	0.150	0.169	0.232
CPEQ18	0.128	0.178	0.297	0.261	0.269

	CPEQ6	CPEQ7	CPEQ8	CPEQ9	CPEQ10
CPEQ6	1.000				
CPEQ7	0.335	1.000			
CPEQ8	0.349	0.312	1.000		
CPEQ9	0.347	0.353	0.406	1.000	
CPEQ10	0.142	0.190	0.278	0.223	1.000
CPEQ11	0.133	0.233	0.320	0.149	0.563
CPEQ12	0.262	0.325	0.310	0.328	0.363
CPEQ13	0.238	0.276	0.253	0.260	0.296
CPEQ14	0.220	0.230	0.297	0.278	0.285
CPEQ15	0.403	0.276	0.336	0.410	0.306
CPEQ16	0.217	0.434	0.272	0.265	0.293
CPEQ17	0.146	0.167	0.376	0.206	0.359
CPEQ18	0.238	0.239	0.345	0.420	0.266

	CPEQ11	CPEQ12	CPEQ13	CPEQ14	CPEQ15
CPEQ11	1.000				
CPEQ12	0.401	1.000			
CPEQ13	0.322	0.608	1.000		
CPEQ14	0.264	0.418	0.431	1.000	
CPEQ15	0.281	0.498	0.486	0.407	1.000
CPEQ16	0.289	0.482	0.432	0.361	0.451
CPEQ17	0.391	0.301	0.333	0.363	0.363
CPEQ18	0.267	0.369	0.381	0.287	0.441

	CPEQ16	CPEQ17	CPEQ18
CPEQ16	1.000		
CPEQ17	0.316	1.000	
CPEQ18	0.337	0.383	1.000

APPENDIX B: DESCRIPTIVE STATISTICS FOR THE C-PEQ ITEMS

Table B.1

Item means, standard deviations, skewness, and kurtosis for the C-PEQ items

Item	Mean	SD	Skewness	Kurtosis
#1	2.48	.87	.27	.35
#2	2.44	.90	.15	0
#3	1.24	.54	2.63	8.06
#4	1.33	.64	2.22	5.36
#5	1.29	.65	2.78	8.55
#6	1.13	.45	4.23	19.69
#7	1.39	.73	2.15	4.92
#8	1.38	.63	1.78	3.22
#9	1.16	.47	3.15	10.32
#10	1.75	.77	.88	.81
#11	1.83	.75	.52	- .23
#12	1.38	.70	1.86	3.08
#13	1.36	.70	2.06	4.27
#14	1.48	.73	1.39	1.03
#15	1.25	.57	2.33	5.01
#16	1.52	.81	1.68	2.79
#17	1.71	.87	1.15	.91
#18	1.38	.74	2.00	3.83

Note: N = 729. Items 1-9 = Cyberaggression, Items 10-18 = Cybervictimization

APPENDIX C: MEASURES

C-PEQ

These questions ask about some things that often happen between young adults. Please rate how often you have done these things to others and how often these things have happened to you in the past two months.

How often has this happened to you?	How often have you done this to another peer?
1. A peer I wanted to be friends with via electronic media ignored my friend request.	I ignored a friend request from a peer who wanted to be friends with me via electronic media.
1. Never 2. Once or twice 3. A few times 4. About once a week 5. A few times a week	1. Never 2. Once or twice 3. A few times 4. About once a week 5. A few times a week
2. A peer removed me from his/her list of friends via electronic media.	I removed a peer from my list of friends via electronic media.
1. Never 2. Once or twice 3. A few times 4. About once a week 5. A few times a week	1. Never 2. Once or twice 3. A few times 4. About once a week 5. A few times a week
3. A peer posted mean things about me publicly via electronic media.	I posted mean things about a peer publicly via electronic media.
1. Never 2. Once or twice 3. A few times 4. About once a week 5. A few times a week	1. Never 2. Once or twice 3. A few times 4. About once a week 5. A few times a week

4. A peer posted mean things about me anonymously via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

I posted mean things about a peer anonymously via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

5. A peer posted pictures of me that made me look bad via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

I posted pictures of a peer that made him/her look bad via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

6. A peer publicly spread rumors about me or revealed secrets I had told them via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

I publicly spread rumors about a peer or revealed secrets he/she had told me via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

7. A peer sent me a mean message via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

I sent a mean message to a peer via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

8. I found out that I was excluded from a party or social event via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

I deliberately excluded a friend from a party or social event, and they found out about it via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

9. A peer made me feel jealous by “messing” with my girlfriend/boyfriend via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

I made a peer jealous by “messing” with his/her girlfriend/boyfriend via electronic media.

1. Never
2. Once or twice
3. A few times
4. About once a week
5. A few times a week

Cyberbullying Scale

0 = Never 1 = Only once or twice 2 = Two or three times a month 3 = About once a week 4 = Several times a week

How often in the past 2 months have you been involved in sending:

1. Nasty text messages	0	1	2	3	4
2. Phone pictures/photos/video of violent scene	0	1	2	3	4
3. Phone pictures/photos/video of intimate scene	0	1	2	3	4
4. Silent/prank phone call	0	1	2	3	4
5. Nasty or rude e-mail	0	1	2	3	4
6. Insults on Web sites	0	1	2	3	4
7. Insults on instant messaging	0	1	2	3	4
8. Insults in chatrooms	0	1	2	3	4
9. Insults on blogs	0	1	2	3	4
10. Unpleasant pictures/photos on Web sites	0	1	2	3	4

How often in the past 2 months have you received:

1. Nasty text messages	0	1	2	3	4
2. Phone pictures/photos/video of violent scene	0	1	2	3	4
3. Phone pictures/photos/video of intimate scene	0	1	2	3	4
4. Silent/prank phone call	0	1	2	3	4
5. Nasty or rude e-mail	0	1	2	3	4
6. Insults on Web sites	0	1	2	3	4
7. Insults on instant messaging	0	1	2	3	4
8. Insults in chatrooms	0	1	2	3	4
9. Insults on blogs	0	1	2	3	4
10. Unpleasant pictures/photos on Web sites	0	1	2	3	4

Inventory of Callous-Unemotional Traits (Youth Version)

Please read each statement and decide how well it describes you. Mark your answer by selecting the appropriate number for each statement. Do not leave any statement unrated.

0 = Not at all true 1 = Somewhat true 2 = Very True 3 = Definitely True

1. I express my feelings openly.	0	1	2	3
2. What I think is "right" and "wrong"	0	1	2	3
is different from what other people think.				
3. I care about how well I do at school or work.	0	1	2	3
4. I do not care who I hurt to get what I want.	0	1	2	3
5. I feel bad or guilty when I do something wrong.	0	1	2	3
6. I do not show my emotions to others.	0	1	2	3
7. I do not care about being on time.	0	1	2	3
8. I am concerned about the feelings of others.	0	1	2	3
9. I do not care if I get into trouble.	0	1	2	3
10. I do not let my feelings control me.	0	1	2	3
11. I do not care about doing things well.	0	1	2	3
12. I seem very cold and uncaring to others.	0	1	2	3
13. I easily admit to being wrong.	0	1	2	3
14. It is easy for others to tell how I am feeling.	0	1	2	3
15. I always try my best.	0	1	2	3
16. I apologize ("say I am sorry") to persons I hurt.	0	1	2	3
17. I try not to hurt others' feelings.	0	1	2	3
18. I do not feel remorseful when I do something wrong.	0	1	2	3
19. I am very expressive and emotional.	0	1	2	3
20. I do not like to put the time into doing things well.	0	1	2	3
21. The feelings of others are unimportant to me.	0	1	2	3
22. I hide my feelings from others.	0	1	2	3
23. I work hard on everything I do.	0	1	2	3
24. I do things to make others feel good.	0	1	2	3

Current Symptoms Scale – Self-Report Form

Instructions: Please select the number next to each item that best describes your behavior *during the past 6 months.*

Items:	**Never or Rarely**	**Sometimes**	**Often**	**Very Often**
1. Fail to give close attention to details or make careless mistakes in my work	0	1	2	3
2. Fidget with hands or feet or squirm in seat	0	1	2	3
3. Have difficulty sustaining my attention in tasks or fun activities	0	1	2	3
4. Leave my seat in situations in which seating is expected	0	1	2	3
5. Don’t listen when spoken to directly	0	1	2	3
6. Feel restless	0	1	2	3
7. Don’t follow through on instructions and fail to finish work	0	1	2	3
8. Have difficulty engaging in leisure activities or doing fun things quietly	0	1	2	3
9. Have difficulty organizing tasks and activities	0	1	2	3
10. Feel “on the go” or “driven by a motor”	0	1	2	3
11. Avoid, dislike, or am reluctant to engage in work that requires sustained mental effort	0	1	2	3
12. Talk excessively	0	1	2	3
13. Lose things necessary for tasks or activities	0	1	2	3

14. Blurt out answers before questions have been completed	0	1	2	3
15. Am easily distracted	0	1	2	3
16. Have difficulty awaiting turn	0	1	2	3
17. Am forgetful in daily activities	0	1	2	3
18. Interrupt or intrude on others	0	1	2	3

Center for Epidemiologic Studies Depression Scale – Revised (CESD-R)

Below is a list of the ways you might have felt or behaved. Please check the boxes to tell me how often you have felt this way in the past week or so.	Last Week: Not at all or less than 1 day	1 – 2 days	3 – 4 days	5- 7 days	Nearly every day for 2 weeks
My appetite was poor.	0	1	2	3	4
I could not shake off the blues.	0	1	2	3	4
I had trouble keeping my mind on what I was doing.	0	1	2	3	4
I felt depressed.	0	1	2	3	4
My sleep was restless.	0	1	2	3	4
I felt sad.	0	1	2	3	4
I could not get going.	0	1	2	3	4
Nothing made me happy.	0	1	2	3	4
I felt like a bad person.	0	1	2	3	4
I lost interest in my usual activities.	0	1	2	3	4
I slept much more than usual.	0	1	2	3	4
I felt like I was moving too slowly.	0	1	2	3	4
I felt fidgety.	0	1	2	3	4
I wished I were dead.	0	1	2	3	4
I wanted to hurt myself.	0	1	2	3	4

I was tired all the time.	0	1	2	3	4
I did not like myself.	0	1	2	3	4
I lost a lot of weight without trying to.	0	1	2	3	4
I had a lot of trouble getting to sleep.	0	1	2	3	4
I could not focus on the important things.	0	1	2	3	4

Liebowitz Social Anxiety Scale – Self-Report Version

This measure assesses the way that social phobia plays a role in your life across a variety of situations. Read each situation carefully and answer two questions about that situation. The first question asks how anxious or fearful you feel in the situation. The second question asks how often you avoid the situation. If you come across a situation that you ordinarily do not experience, we ask that you imagine "what if you were faced with that situation," and then, rate the degree to which you would fear this hypothetical situation and how often you would tend to avoid it. Please base your ratings on the way that the situations have affected you in the last week. Fill out the following scale with the most suitable answer provided below.

	Fear or Anxiety	**Avoidance**
	0 = None, 1 = Mild, 2 = Moderate, 3 = Severe	0 = Never (0%), 1 = Occasionally (1-33%), 2 = Often (34-67%), 3 = Severe (68-100%)
Telephoning in public	0 1 2 3	0 1 2 3
Participating in small groups	0 1 2 3	0 1 2 3
Eating in public Places	0 1 2 3	0 1 2 3
Drinking with others in public public	0 1 2 3	0 1 2 3
Talking to people in authority	0 1 2 3	0 1 2 3
Acting, performing, or giving a talk in front of an audience	0 1 2 3	0 1 2 3
Going to a party	0 1 2 3	0 1 2 3
Working while being observed	0 1 2 3	0 1 2 3
Writing while being observed	0 1 2 3	0 1 2 3
Calling someone you don’t know very well	0 1 2 3	0 1 2 3
Talking with people you don’t know very well	0 1 2 3	0 1 2 3
Meeting strangers	0 1 2 3	0 1 2 3

Urinating in a public bathroom	0	1	2	3	0	1	2	3
Entering a room when others are already seated	0	1	2	3	0	1	2	3
Being the center of attention	0	1	2	3	0	1	2	3
Speaking up at a meeting	0	1	2	3	0	1	2	3
Taking a test	0	1	2	3	0	1	2	3
Expressing a disagreement or disapproval to people you don't know very well	0	1	2	3	0	1	2	3
Looking at people you don't know very well in the eyes	0	1	2	3	0	1	2	3
Giving a report to a group	0	1	2	3	0	1	2	3
Trying to pick up someone	0	1	2	3	0	1	2	3
Returning goods to a store	0	1	2	3	0	1	2	3
Giving a party	0	1	2	3	0	1	2	3
Resisting a higher pressure salesperson	0	1	2	3	0	1	2	3

Adaption of Internet Social Capital Scale

Items:	Strongly Disagree					Strongly Agree
I feel I am part of the USC community	0	1	2	3	4	5
I am interested in what goes on the University of South Carolina	0	1	2	3	4	5
USC is a good place to be	0	1	2	3	4	5
I would be willing to contribute money to the University of South Carolina after graduation	0	1	2	3	4	5
Interacting with people at USC makes me want to try new things	0	1	2	3	4	5
Interacting with people at USC makes me feel like part of a larger community	0	1	2	3	4	5
I am willing to spend time to support general USC activities	0	1	2	3	4	5
At USC, I come into contact with new people all the time	0	1	2	3	4	5
Interacting with people at USC reminds me that everyone in the world is connected	0	1	2	3	4	5
There are several people at USC I trust to solve my problems	0	1	2	3	4	5

If I needed an emergency loan of $100, I know someone at USC I can turn to	0	1	2	3	4	5
There is someone at USC I can turn to for advice about making very important decisions	0	1	2	3	4	5
The people I interact with at USC would be good job references for me	0	1	2	3	4	5
I do not know people at MSU well enough to get them do anything important	0	1	2	3	4	5
I'd be able to find out about events in another town from a high school acquaintance living there	0	1	2	3	4	5
If I needed to, I could ask a high school acquaintance to do a small favor	0	1	2	3	4	5
I'd be able to stay with a high school acquaintance if traveling to a different city	0	1	2	3	4	5
I would be able to find information about a job or internship from a high school acquaintance	0	1	2	3	4	5
It would be easy to find people to invite to my high school reunion	0	1	2	3	4	5

Self-Report of Aggression & Social Behavior Measure

Directions: This questionnaire is designed to measure qualities of adult social interaction and close relationships. Please read each statement and indicate how true each is for you, **now and during the last year**, using the scale below. Write the appropriate number in the blank provided. IMPORTANT. The items marked with asterisks (*) ask about experiences in a current romantic relationship. **If you are not currently in a romantic relationship, or if you have not been in a relationship during the last year, please leave these items blank** (but answer all of the other items). Remember that your answers to these questions are completely anonymous, so please answer them as honestly as possible!

Not at All True			Sometimes True			Very True
1	2	3	4	5	6	7

1. ______ My friends know that I will think less of them if they do not do what I want them to do.

2. ______ When I want something from a friend of mine, I act "cold" or indifferent towards them until I get what I want.

3. ______ I have threatened to share private information about my friends with other people in order to get them to comply with my wishes.

4. ______ I have spread rumors about a person just to be mean.

5. ______ I have intentionally ignored a person until they gave me my way about something.

6. ______ When I am not invited to do something with a group of people, I will exclude those people from future activities.

7. ______ When I have been angry at, or jealous of someone, I have tried to damage that person's reputation by gossiping about him/her or by passing on negative information about him/her to other people.

8. ______ When someone does something that makes me angry, I try to embarrass that person or make them look stupid in front of his/her friends.

9. ______ When I have been mad a friend, I have flirted with his/her romantic partner.

10. ______ When I am mad at a person, I try to make sure s/he is excluded from group activities (going to the movies or to a bar).

11. ______ When someone hurts my feelings, I intentionally ignore them.