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Exploring Construct Validity and Measurement Invariance of the Cyberbullying Experiences Survey

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EXPLORING CONSTRUCT VALIDITY AND MEASUREMENT INVARIANCE OF THE CYBERBULLYING EXPERIENCES SURVEY

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ABSTRACT

Given recent calls for advancing valid instrumentation in the field of cyberaggression, the present study evaluated construct validity and measurement invariance for the Cyberbullying Experiences Survey (CES) in a high school and college student sample. A series of confirmatory factor analyses (CFA), reliability analyses, and a nomological net evaluation were conducted to address these aims. The data did not provide support for the hypothesized four-factor model for cyberaggression or cybervictimization (i.e., unwanted contact, malice, deception, and public humiliation). Upon implementing suggested and theoretically supported modification indices, support for a four-factor solution for both cyberaggression and cybervictimization was provided.

To subsequently evaluate measurement invariance, single-group CFAs were constructed to test invariance of the four-factor structure across college and high school students. Results provided support for the four-factor model solution of cyberaggression and cybervictimization in the college sample but not in the high school sample. Two cyberaggression subscales (i.e., unwanted contact and deception) correlated at $r = .99$, indicating the potential for multicollinearity, and incremental fit indices for the cybervictimization model solution did not meet recommended cut-off values in the high school sample. Revised model results based on statistical and theoretical considerations evaluated a restructured three-factor solution for cyberaggression (i.e., “sexual,” “direct,” and “coercion”) and cybervictimization (i.e., “sexual,” “direct,” and “defamation”). Fit

indices provided initial support for the revised model solution for both CES cyberaggression items (College: MLM χ^2 (163) = 273.01, RMSEA = .04, CFI = .92, SRMR = .06; High School: MLM χ^2 (165) = 196.29, RMSEA = .03, CFI = .96, SRMR = .08) and cybervictimization items (College: MLM χ^2 (163) = 367.81, RMSEA = .05, CFI = .93, SRMR = .06; High School: MLM χ^2 (160) = 256.32, RMSEA = .06, CFI = .92, SRMR = .07).

Utilizing the revised factor solution for the remaining analyses, the CES displayed evidence for internal consistency reliability across college (cyberaggression items: α = .83; cybervictimization items: α = .89) and high school (cyberaggression items: α = .88; cybervictimization items: α = .90), although internal consistencies for the CES cyberaggression subscales ranged from poor to good (α = .54 - .88) and acceptable to excellent (α = .76 - .92) for the CES cybervictimization subscales across both college and high school samples. Evidence for convergent validity with theoretically similar constructs was mixed. Specific areas of model misspecification as well as directions for future cyberaggression measurement research and policy are discussed.

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CHAPTER 1

INTRODUCTION

Electronic technology has become increasingly used as an interface to communicate among adolescents and young adults. With these new mechanisms for communication (e.g., texting, e-mailing, social networking sites), novel forms of aggressive behavior are emerging. In particular, *cyberaggression* has received growing attention from both researchers and behavioral health professionals. In a recent meta-analysis, Modecki et al. (2014) reported the prevalence rates of cyberaggression to be 15.5% among adolescents 12-18 years old. Similar prevalence rates have been observed among college students (5-15%; Schenk & Fremouw, 2012; Schenk, Fremouw & Keelan, 2013; Wensley & Campbell, 2012). Public health concerns surrounding cyberaggression have concurrently risen in response to numerous highly publicized national and international cases (Tokunaga, 2010). Cyberaggression has been linked with negative behavioral health correlates such as depression and suicidal ideation (e.g., Landoll et al., 2015; Schenk et al., 2013). Populations who are more vulnerable to experiencing traditional face-to-face aggression or bullying, such as military connected youth (Atuel et al., 2014; Gilreath et al., 2013), may also be at an increased risk for experiencing cyberaggressive behavior, though these investigations are limited or nonexistent.

Despite its prevalence and psychological impact (Cassidy, Faucher, & Jackson, 2013), a uniform definition of cyberaggression has yet to be established (Tokunaga, 2010). A variety of terms have been described in the literature (e.g., cyberaggression, cyberbullying, cyberharassment; Berne et al., 2013) to represent negative interactions via electronic communication. Other investigations have demonstrated varying interpretations of cyberaggression between middle/high school students and college students (Baldasare, Bauman, Goldman, & Robie, 2012; Grigg, 2010), pointing to potential distinctions in how cyberaggression may be operationalized across age groups. Research in this field is limited given the lack of consensus on the conceptualization of this construct, however, and the measurement and assessment of cyberaggression has been affected. Without sound conceptualization and measurement, furthering research that has the potential to inform clinical practice and policy, such as evaluating how cyberaggression impacts various groups and vulnerable populations, will remain hindered. Therefore, the purpose of this paper is to inform the literature by providing additional exploration into the psychometric properties of a novel scale, the Cyberbullying Experiences Survey (CES; Doane, Kelley, Chiang, & Padilla, 2013). The original psychometric investigation of the CES provided initial evidence for construct validity (Doane et al., 2013).

The current study seeks to extend evaluation of the instrument and of cyberaggression across sociodemographics via three aims. First, in light of nationally and internationally recognized issues of rigor and reproducibility (McNutt, 2014), we seek to evaluate evidence for construct validity of the CES using a novel sample of high school and college students. Second, we seek to examine aspects of measurement invariance of the CES across age (i.e., high school and college) as these issues have yet to explored as well as considering prior qualitative research suggesting varying conceptualizations of aggressive behaviors across developmental periods (Card, 2013). Finally, given inconsistent findings concerning prevalence rates and impact of cyberaggression across demographic characteristics, a tertiary aim of our study seeks to provide additional evidence for cyberaggression experiences among race/ethnic status, sex, and military-connected youth as research has suggested these youth to be at increased risk for experiencing negative peer interactions (Atuel, et al., 2014; Gilreath et al., 2013). We begin our investigation by reviewing the current literature base of definitions, theories, and sociodemographic perspectives on cyberaggression, as well as review psychometric evidence of cyberaggression instrumentation. Results from our study and implications for future research, clinical-community practice, and policy will then be presented.

1.1 DEFINTIONS AND THEORIES OF CYBERAGGRESSION

1.1.1 The Problem The first task in novel fields of inquiry is to conceptually and operationally define the primary constructs of interest. The purpose of a definition is said to specify the essence of a term and to identify the necessary and sufficient conditions for something to be a member of the construct being defined (Bauman, 2013). Definitions provide the foundation for measurement and instruments which are developed for research investigations and clinical applications. It is therefore difficult to appropriately evaluate and generalize findings across investigations without consistent terminology.

The field of cyberaggression is inundated with inconsistency in both the terms used to describe negative behaviors utilizing electronic forms of communication, as well as in the attempts to measure such behavior (Berne et al., 2013; Tokunaga, 2010). Numerous terms including, but not limited to, cyberaggression, cyberbullying, cyberharassment, cyberstalking, internet harassment, and cyber targeting (e.g., Berne et al., 2013; Ybarra, 2013) have been referenced in the literature. Some researchers (e.g., Hinduja & Patchin, 2014; Ybarra, 2013; Ybarra & Mitchell, 2004) distinguish between cyberharassment (single incidents of electronic aggression) and cyberbullying (repeated incidents). Although attempts have been made to measure each of these individually named constructs, recent reviews have suggested that the majority of current instruments actually attempt to measure *cyberaggression* (Bauman, Underwood, & Card, 2013). Given the prevailing use of the term "cyberbullying" in society to refer to the range of behaviors referenced above, the remainder of this section will evaluate the legitimacy of recent definitions of cyberbullying. Informed by various theoretical perspectives and critical differences in the face-to-face versus cyber realms, concerns in defining criteria for cyberbullying will be identified and proposed reasons for alternatively using and defining cyberaggression to address cohesion among researchers in the field will be argued.

1.1.2 Cyberbullying and Traditional Bullying In the beginning stages of research in this field, the original coined term to conceptualize negative interactions via electronic communication was *cyberbullying*. The original definition stated that cyberbullying "involves the use of information and communication technologies to support deliberate, repeated, and hostile behavior by an individual or group that is intended to harm others" (Bauman, 2013). More recently, Smith et al. (2008) defined cyberbullying as "an aggressive, intentional act carried out by a group or individual, using electronic forms of contact, repeatedly and over time against a victim who cannot easily defend him or herself." These definitions inherently rely on the original conceptualization of traditional, face-to-face bullying (Olweus, 1993) and simply integrate the novel *modality* of electronic forms of communication to express behaviors.

Although aspects of traditional bullying may be observed in the cyber realm, they necessarily differ due to distinct properties of electronic communication. An evaluation of how the proposed criteria for traditional bullying (i.e., intent to harm, repetition, and power imbalance as defined by Olweus, 1993) may differentially operate in the cyber realm through several theoretical perspectives will inform our discussion. First considering the criterion of intent to harm, it is generally difficult to determine intent in a bullying situation. That is, intent may only be determined if the perpetrator has admitted to premeditated aggression or if the victim perceives that intent to harm was present. In cyber situations, intent might be particularly difficult to observe. A common example used to support this assertion considers a texting conversation via phone in which one individual sends a text that is interpreted by another individual in a negative manner. The sender, however, had no intention to upset the other individual and without the context of vocal tone and facial expressions which are provided in face-to-face interactions, the sender was unable to effectively communicate that there was no intention to harm on their behalf. In legal proceedings, phrases such as the *reasonable person* standard are often applied to consider whether a hypothetical person who exercises average skill and judgment in conduct would consider whether intent was present to determine liability (Smith, del Barrio, & Tokunaga, 2013). Although practical in some areas, the ambiguity provided in the cyber realm and by other practices for determining intent is not sufficient for empirical investigation. Moreover, social information processing theory posits that aggression is largely due to impairment in social problem solving. Utilizing ambiguous situations such as in the provided example, researchers have recently attempted to discover whether cyberbullying is largely proactive or reactive in nature (Dooley, Pyzalski, & Cross, 2009). The nature of the cyberbullying act, whether proactive or reactive and whether it can be determined, will likely impact how the information is processed, what attributions are made about the perpetrator, and what behavior ultimately emerges from them (Espelage, Rao, & Craven, 2013).

Regarding the criterion of repetition, it is often noted that repetition in traditional bullying is demonstrated by multiple acts of bullying directed towards the victim by the perpetrator. Although applicable in the cyber realm, repetition may operate quite differently. For example, repetition might be met either through the literal repetition of harmful behaviors or through the number of times a negative post, picture, or video is viewed by third-party witnesses (Dooley et al., 2009; Tokunaga, 2010). Social learning theory suggests that aggressive behavior is posited to be a consequence of exposure to socially deviant role models and inappropriate reinforcement of maladaptive behaviors (Bandura, 1977). Applying this perspective to the cyber realm may consider third-party viewers on social networking sites "liking" a post of an embarrassing picture of a cybervictim (Espelage et al., 2013). This reinforcement of negative online behavior could additionally be viewed as a form of repetition in that other individuals are more or less supporting an act of cyberbullying.

The third criterion, an established power imbalance, may likewise be context specific in the cyber realm. In traditional bullying, a power imbalance may refer to differences in physical or social status between a perpetrator and victim which make it challenging for a victim to respond in an effective manner (Cassidy, Faucher, & Jackson, 2013). In the cyber realm, these distinctions may be diminished. A perpetrator, for example, may not necessarily be physically stronger or more socially connected as electronic interactions provide protections from physical retaliations. A more context-specific example considers the technological know-how and internet and communication technology skills of the perpetrator as compared to the victim (Smith, del Barrio, & Tokunaga, 2013). Two other properties of cyber communication may provide a power imbalance: anonymity and the 24/7 nature of electronic communication. It is more difficult to effectively respond if a cybervictim does not know the identity of the perpetrator, and it might be challenging to avoid receiving negative electronic communication as a result of the permanent status of posts or pictures online. These context-specific aspects of cyberbullying relate to a recently proposed theory entitled the online disinhibition effect (Suler, 2004), which refers to diminished internal censorship when communicating in the cyber realm. That is, individuals may choose to interact with others anonymously and therefore avoid the repercussions by the cybervictim that might accompany the bad behaviors if their identity was known (Espelage, Rao, & Craven, 2013). Knowing that the cyber realm offers this form of protection, youth may say or do things via electronic communication that they are more unlikely to do in face-to-face encounters and to limit their sense of responsibility for these actions (Blumenfield, 2005).

1.1.3 The Argument for Cyberaggression Several points have been presented to identify limitations in the utility of the term *cyberbullying* and attempting to define it in connection with proposed traditional bullying criteria (Olweus, 1993). It is apparent that the initial criteria utilized to define cyberbullying contain numerous context-specific intricacies which hinder the ability to develop robust instrumentation to measure this construct. Recent qualitative research (e.g., Grigg, 2010) has further investigated the utility of the term cyberbullying and has identified an issue as to whether children or young people use, or recognize, the term cyberbullying, as well as, what terms they use to describe this behavior. Through a qualitative triangulation methodological approach, Grigg (2010) noted several limitations to the construct of cyberbullying including that the term is vague, inadequate, and restricted for the variety of negative behaviors which may occur via electronic media. Focus group participants further agreed that cyberaggression holds more utility as a construct as it represents a wider range of behaviors (Grigg, 2010).

In practice, the majority of the literature base uses the term "cyberbullying" in research articles. Some suggest that many studies actually measure *cyberaggression*, however, since they do not systematically include measures of imbalance of power or repetition which are required for a cyberbullying event to occur (Smith, del Barrio, & Tokunaga, 2013). It has therefore been recommended that given the inconsistency of terms and difficulty in applying complex criteria to define cyberbullying, the field should shift its focus towards examining cyberaggression (Bauman, Underwood, & Card, 2013). In addition, given how electronic forms of contact have changed and are continuously evolving, utilizing a broader term such as cyberaggression may best capture the variety of negative interactions via electronic communication among youth. Taking a broader approach by evaluating cyberaggression is similar to traditional aggression literature in that bullying, among other forms of aggression (e.g., stalking, harassment, etc.), are subsumed under a broader aggression construct (Smith, del Barrio, & Tokunaga, 2013). We do not suggest removing "cyberbullying" from the literature as it may represent a specific type of cyberaggression; we are emphasizing that the field must first come to an agreement on what construct it is attempting to measure and use consistent terminology to better facilitate future intervention and policy efforts.

Given these recommendations, the present investigation will refer to the primary construct of interest as *cyberaggression*. A recent and well-known definition of cyberaggression offered by Schoffstall and Cohen (2011) states:

> Cyberaggression: *intentional behavior aimed at harming another person or persons though computers, cell phones, and other electronic devices, and perceived as aversive by the victim*.

It is recommended that future definitions of cyberaggression include explicit language pertaining to the act being perpetrated via software or digital applications available through computers, cell phones, and other electronic devices, to avoid any misinterpretation that cyberaggression could be defined through physical (e.g., throwing a cell phone at someone) usage of electronic devices.

1.2 CYBERAGGRESSION INSTRUMENTATION

Considering the lack of consensus regarding a uniform definition and consistent use of terminology, the field is currently at a stage where no gold-standard assessment measure exists (Berne et al., 2013; Card, 2013; Ybarra, 2011). The majority of current instrumentation measures the frequency of cyberaggressive behavior either perpetrated or experienced over a specified time period (Berne et al., 2013). This form of measurement warrants notice given the array of terms used to describe the same behavior and the specific criteria proposed for cyberbullying. That is, current instrumentation which is said to be measuring cyberbullying is in reality measuring cyberaggression because there are often no items representing the criteria of repetition and power imbalance (Bauman, Underwood, & Card, 2013; Smith, Barrio, & Tokunaga, 2013). To further highlight this issue, Table 1.1 provides examples of items from two instruments contending to measure *cyberbullying* (Cyberbullying Experiences Questionnaire (CES), Doane et al., 2013;

Table 1.1

Item Comparisons between the CES, RCBI, and C-PEQ

CES Cyberbullying Subscale (*Report behaviors that occurred in the past year*)	RCBI Cyberbullying Subscale (*Have often have you done the instances described to others?)*	C-PEQ Cyberaggression Subscale (*I…via electronic media*)
Have you sent a rude message to someone electronically?	Sending threatening and/or hurtful text messages	…posted mean things about a peer publicly…
Have you sent an unwanted nude or partially nude picture to someone electronically?	Published online an embarrassing photo without permission	…posted pictures of a peer that made him/her look bad…
Have you posted a picture of someone electronically that they did not want others to see?	Sharing private internet conversations without the other's knowledge (such as chatting with a friend on Skype with other(s) in the room)	…publicly spread rumors about a peer or revealed secrets he/she had told me…

Revised Cyberbullying Inventory (RCBI), Topcu & Erdur-Baker, 2010) and one instrument contending to measure *cyberaggression* (Cyber-Peer Experiences Questionnaire (C-PEQ), Landoll et al., 2015). As shown, item content across all three instruments is markedly similar and no instruments include items specifically designed to assess the complexities of power imbalance or repetition in the cyber realm which are recommended to fully evaluate the construct of cyberbullying. With such similar item content across a multitude of existing instruments, it is defensible that for the field to progress, developing additional instruments may not necessarily inform the current knowledge base. Instead, expanding upon psychometric evidence of existing measures is more readily needed. In the only known psychometric review in this field, Berne et al. (2013) presented an overview of existing cyberbullying and related instruments by investigating 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).

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. 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. Several additional instruments have been published and examined since the Berne et al. (2013) review including the Cyberbullying Experiences Survey (Doane et al., 2013), Cyber – Peer Experiences Questionnaire (Landoll et al., 2015), Cyberbullying Scale (Stewart, Drescher, Maack, Ebesutani, & Young, 2014), and E-Victimization Scale and E-Bullying Scale (Lam & Li, 2013). Overall, these investigations reported preliminary psychometric evidence for all measures.

1.2.1 Methods for Expanding Psychometric Evidence Exploring empirically supported methods for evaluating psychometric evidence of existing measures may inform the research gap of limited psychometric evidence of cyberaggression instrumentation. Benson (1998) describes a three-component procedure to evaluate construct validity for newly developed instruments which involves the following: 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 from similar constructs such as relational or physical aggression/victimization (e.g., Landoll et al., 2015). Thus, further exploration into the second aspect of Benson's (1998) program is warranted.

The structural component of Benson's (1998) method 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 inter-correlations between items and subscales, exploratory and confirmatory factor analyses, and item response theory. One advantage of using confirmatory factor analysis (CFA) 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 model (Benson, 1998).

In the original investigation of the Cyberbullying Experiences Survey (CES), Doane et al. (2013) initially conducted an exploratory factor analysis (EFA) using weighted least squares with mean and variance adjusted Promax rotation to extrapolate the factors and permit them to correlate. Results revealed three factors for a posited cybervictimization subscale and two factors for a posited cyberbullying perpetration subscale. The authors, however, posited a four-factor structure (i.e., unwanted contact, malice, deception, and public humiliation) for both subscales solely for interpretability purposes without providing theoretical justification (Doane et al., 2013).

During the second phase of their investigation, a CFA was conducted to test for the purported four-factor structure on both the cyberbullying perpetration and cybervictimization subscales. Initial results for the cybervictimization subscale indicated mediocre fit based on appropriate fit indices (comparative fit index [CFI], Tucker-Lewis index [TLI], and root mean square error of approximation [RMSEA]; Doane et al., 2013; Hu & Bentler, 1999). The authors subsequently invoked modification indices, which estimate the amount by which the model's overall χ^2 statistic would decrease if a particular parameter were freely estimated (Kline, 1998). This resulted in the removal of six items which exhibited cross loadings on the subscale. A similar procedure was completed for improving overall model fit of the posited four-factor structure of the cyberbullying perpetration subscale; this procedure resulted in the removal of one item that exhibited a cross loading. The final CFA model results posited a four-factor structure for the cyberbullying perpetration subscale: χ^2 (52) = 185.97, $p < .001$; CFI = .97, TLI = .99, RMSEA = .06 and cybervictimization subscale: χ^2 (73) = 447.89, $p < .001$; CFI = .91, TLI = .98, RMSEA = .09).

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 are necessary for robust evaluation of construct validity. Arguably the most crucial component, the external component, establishes 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 scale's items as well as structural equation modeling (Benson, 1998). In the original psychometric investigation of the CES, initial convergent validity evidence was observed in that the CES cyberbullying and cybervictimization subscales moderately correlated with respective subscales on two other cyberbullying and cybervictimization instruments (r = .21-.41; Doane et al., 2013). To develop a broader nomological net for the CES, several other instruments measuring latent constructs thought to be related to cyberaggression or cybervictimization will be included in our investigation. A logical inclusion involves other measures assessing cyberaggression, cybervictimization, and other forms of aggression (e.g., relational and peer aggression), as prior research has shown that cyberaggression, cybervictimization, and relational aggression are correlated. Fanti and colleagues (2012) reported that cyberaggression and cybervictimization strongly correlated (r = .67). Hemphill et al. (2013) similarly found a moderate correlation between relational aggression and cyberaggression/ cybervictimization, and Landoll et al. (2015) found cybervictimization to be moderately correlated (r = .39-.56) with overt and relational peer victimization. Furthermore, a measure of behavioral health and well-being was included to investigate convergent validity evidence for the CES's cybervictimization items. Prior research has discovered associations between cybervictimization, depression, and anxiety (Lam & Li, 2013; Landoll et al., 2013, 2015).

1.3 DEVELOPMENTAL AND SOCIODEMOGRAPHIC PERSPECTIVES

1.3.1 The Problem In view of the limitations in this field concerning a uniform definition, terminology used, and lack of empirically supported psychometric evaluations of existing measures, inquiries into how cyberaggression differentially operates between groups across various developmental and sociocultural indicators are hindered. This is problematic given the noted prevalence rates and public health concerns of cyberaggression among youth (Modecki et al., 2014; Tokunaga, 2010), as well as the need for further research into how cyberaggression may impact populations particularly vulnerable to experiencing face-to-face aggression such as military-connected youth (Atuel et al., 2014). This section serves to highlight prior investigations into how and/or why cyberaggression may differentially operate among various developmental and sociodemographic groups. An argument for extending evaluation of these potential group differences through robust statistical procedures to compliment Benson's (1998) strong program of measurement will be presented.

1.3.2 Developmental Perspectives With the ever-changing technological and communicative landscape youth experience, exploring whether human development may impact how cyberaggression operates is warranted. Modern day adolescents and young adults have been immersed in a digital culture. These youth have developed a greater literacy and understanding of how the Internet and other forms of technology operate as well as the norms and social practices of digital communication (Lewis, 2015). As social interactions utilizing technology have become commonplace among youth, these individuals may develop a tendency to not view the technology as technological (Lankshear, Snyder, & Green, 2000). For example, 92% of teenagers (defined as 13-17 years old) and 88% of young adults (defined as 18-29) in the United States use the Internet, social networking sites, and other forms of technology (Greenwood, Perrin, & Duggan, 2016; Lenhart, 2015). As such, these forms of communication do not hold the fascination as being novel among young people (Lewis, 2015). Novel modalities of electronic communication and shifts in popularity among social networking sites (Lenhart, Purcell, Smith, & Zickuhr, 2010) are continuously changing, however. These transitions between forms of electronic communication necessarily impact technological literacy rates among youth which may contribute to a power imbalance among Internet users (Lewis, 2015). A power imbalance based on technological literacy may serve as a risk factor for experiencing cyberaggression (Smith, del Barrio, & Tokunaga, 2013).

Despite the majority of both adolescents and young adults utilizing electronic communication, the preponderance of the literature has examined how cyberaggression operates among middle and high school populations (Walker, Craven, & Tokunaga, 2013). This developmental focus likely pertains to theories of face-to-face interactions among youth that posit a higher prevalence rate of aggressive and bullying behaviors at these ages as compared to young adult age groups (MacDonald et al., 2010; Schenk, Fremouw, & Keelan, 2013). Adolescence is a period of numerous physical, social, and interpersonal transformations. Stress from these changes often elicits the development of ineffective coping mechanisms and engagement in risky behaviors such as substance use and aggression (Seiffge-Krenke, 2013). Heightened risk-taking during adolescence is also likely to be normative, biologically driven, and, to some extent, inevitable (Steinberg, 2008). It is therefore plausible that adolescents may also enact more risk-taking and aggressive behaviors in the cyber realm. Connecting with aspects of the online disinhibition effect (Suler, 2004) and properties of electronic communication which may decrease accountability and social responsibility, the Internet and other modes of technology may serve as an effective vessel for adolescents to express negative social interactions.

Research has indicated that forms of aggression do not necessarily decrease in university settings (Wensley & Campbell, 2012). Numerous studies have reported that subtypes of aggression including physical aggression, relational aggression, and sexual aggression are consistently prevalent among both male and female college student populations (Dahlen, Czar, Prather, & Dyess, 2013; Hines & Saudino, 2003). Rates of cyberaggression have also been shown to be similar among high school and college students (Modecki et al., 2014; Schenk & Fremouw, 2012; Schenk, Fremouw & Keelan, 2013; Wensley & Campbell, 2012). Overall, the limited data available suggest that the relation between age and cyberaggression follows a quadratic function, where prevalence rates are initially low, increase until mid-teenage years, and then begin to decrease again over time (Dooley, Cross, Hearn, & Treyvaud, 2009; Walker, Craven, & Tokunaga, 2013).

Given similarities in both prevalence rates and forms of negative peer interactions among adolescents and college students, furthering evaluation of how cyberaggression operates among high school and college student populations is warranted. Investigations have consistently demonstrated that participating in cyberaggression (i.e., as a perpetrator, victim, or perpetrator-victim) results in numerous impacts on behavioral health such as increasing risk for depression, anxiety, and suicidal ideation among both high school and college students (e.g., Landoll et al., 2015; Schenk et al., 2013). Qualitative investigations have highlighted that college students believe cyberaggression to be of greater concern among high school populations, however, likely due to its association with bullying in the extant literature and media portrayal of the issue (Baldasare et al., 2012). Perhaps college student populations do not perceive cyberaggression to be relevant or know how cyberaggression manifests and how it impacts behavioral health. Further inquiry into how cyberaggression may differentially operate across these particular age groups may inform our investigations into a strong program of measurement.

1.3.3 Sociodemographic Perspectives: Sex In addition to how cyberaggression may operate differentially across two distinct periods of the human lifespan, considering sociodemographic variables such as sex, race/ethnicity as well as other culturally vulnerable populations may also hold utility. In research pertaining to traditional forms of aggression, it has been generally accepted that males exhibit more physical (overt) forms of aggression whereas females exhibit verbal and relational (covert) forms of aggression (e.g., Campbell, 2007). In a recent review article, Tokunaga (2010) reported that the majority of research to date has found no differences between males and females in their experiences of cyberaggression. A minority of studies have concluded sex to be a significant predictor of cyberaggression in that females are disproportionately at risk of being victimized (Tokunaga, 2010); other investigations have observed the opposite, however (e.g., Fanti, Demetriou, & Hawa, 2012). These contradictory findings may be informed by cultural risk factors that are present for both sexes. For example, male youth are more likely to report less social support from family or friends as well as be exposed to higher levels of media violence due to television and video gaming (Fanti, Demetriou, & Hawa, 2012). On the other hand, research has demonstrated that females tend to interact more via electronic communication (e.g., e-mail, text messaging), which may predispose females to becoming cyberaggressors or cybervictims as a function of usage of the Internet and other forms of social media (Dooley, Pyżalski, & Cross, 2009).

It is likewise important to highlight how traditional gender norms may impact cyberaggression perpetration and victimization experiences. Male youth are more likely to become perpetrators and victims of traditional aggression through overt means (Dooley, Pyżalski, & Cross, 2009). Normative views on male behavior in the United States place expectations for males to display dominance (Addis & Mahalik, 2003; Archer, 2004), which may even encourage outwards displays of aggression. Cyberaggression, by definition, has been posited to be a covert form of aggression as physical presence or a power imbalance is not as necessary to act aggressively via electronic communication (Dooley et al., 2009; Spears, Slee, Owens, & Johnson, 2009). Perhaps cyberaggression does not align with masculine forms of aggression as expected from gender norms for male behavior. In connection with the aforementioned cultural risk factors males are more likely to experience (i.e., less likely to seek help and support from friends and family and predisposal to greater media violence; Addis & Mahalik, 2003), males may be particularly vulnerable to negative outcomes after experiencing a cyberaggressive act.

Cultural norms in the United States drastically differ for females as they are not encouraged to exhibit overt aggression derived from expectations of proper feminine etiquette (Archer, 2004). Boulton, Lloyd, Down, and Marx (2012) explored perceptions on aggressive behaviors between female and male youth. Expected sex differences were observed, with females expressing significantly less accepting attitudes towards aggressive behavior and bullying perpetrators and expressed higher rates of acceptance towards victims across all bullying subtypes. Cyberaggression may perhaps be perceived as a more acceptable form of aggressive behavior for females because it is historically viewed as covert in nature as compared to overt aggression. Thus, it may be possible that double-standard gender roles exist and influence female perceptions and attitudes towards face-to-face aggression and cyberaggression where cyberaggression is viewed as a more appropriate form of aggressive behavior among females. In addition, and as noted, females use electronic forms of communication more frequently than males (Dooley, Pyżalski, & Cross, 2009) and reports have indicated that females were more likely to experience certain forms of cyberaggression such as gender-based harassment, exclusion, and having personal information about them posted online (Cassidy, Faucher, & Jackson, 2013). Reported outcomes from these experiences for females include feeling like their reputation was affected, making it harder to establish new friendships, as well as suicidal ideation.

1.3.4 Sociodemographic Perspectives: Race and Ethnicity A less explored sociodemographic indicator of cyberaggression concerns race and ethnicity. Hinduja and Patchin (2008) found no significant differences among White and non-White individuals in rates of both cyberaggression perpetration and cybervictimization. The authors provide a novel interpretation for this observed result. Power imbalances between race and ethnic groups have historically existed in the United States. The authors argue that the cyber realm does not necessarily allow for conventional power dynamics to hold, where one's race may not hold as much meaning as it may in traditional, face-to-face aggressive interactions. Due to equalizing characteristics of the Internet (e.g., potential for anonymity), groups who have historically been marginalized who may also become targets of cyberaggression may hold the ability to "turn the tables" (Hinduja & Patchin, 2008; Nimrod, 2013). Other studies have also observed no statistical differences in overall reporting of cyberaggressive behaviors between racial and ethnic groups (e.g., Bauman, Toomey, & Walker, 2013; Schneider, O'donnell, Stueve, & Coulter, 2012).

1.3.5 Sociodemographic Perspectives: Military-Connected Youth The prior sociodemographic indicators have provided a general approach to investigating whether cyberaggression may operate differently across groups. More focused inquiries into specific populations of interest, such as military-connected youth, are limited or nonexistent. Previous research has examined how military-connected youths experience more negative psychological, emotional, and social outcomes than civilian peers (Astor et al., 2013; Gilreath et al., 2013). Military-connected youth have likewise reported increased levels of traditional bullying victimization and perpetration as compared to civilian students (Atuel et al., 2014). Among a sample of 1,957 students in the 7th, 9th, and 11th grades who were military-connected (i.e., having a parent or sibling in the military), military-connected students endorsed increased levels of feeling harassed and/or bullied because of many demographic factors such as their race/ethnicity, gender, sexual orientation, religion, or mental or physical disability, as compared to civilian peers. Furthermore, as the total number of familial deployments increased, military-connected students' overall reports of discriminatory bullying increased as well (Atuel, 2013). Numerous school transitions may expose military-connected youth to experiencing peer victimization due to social alienation (i.e., difficulty in establishing and maintaining social connections; Atuel et al., 2014; De Pedro, Astor, Gilreath, Benbenishty, & Berkowitz, 2016). Evidence from the literature lends support for further investigation into aggression and bullying discrepancies between military-connected and civilian youth. Therefore, a secondary aim of the present study is to serve as the pioneer investigation to explore the frequency of cyberaggression and cybervictimization among military-connected youth.

1.3.6 Measurement Invariance It is apparent that prior research has provided initial evidence for why cyberaggression may similarly or differentially operate across age, sex, race/ethnicity, and unique populations such as military-connected youth and indicated that additional research is needed to better conceptualize and understand these distinctions. To extend this line of research and in connection with Benson's (1998) recommendations for building a strong program of measurement, another aspect of strong instrumentation, measurement invariance, may serve as a useful next step of inquiry in this field. Measurement invariance has even more limited evaluation and evidentiary support in both face-to-face aggression and cyberaggression research as compared to other aspects of psychometric evaluation (Berne et al., 2013; Card, 2013). Measurement invariance assumes that a scale measures the same trait in all demographic or treatment groups. If that assumption holds, then comparisons and analyses of those scores yield meaningful interpretations; if this assumption is violated, then such analyses do not yield meaningful results. A lack of evaluation of measurement invariance in existing cyberaggression instrumentation would suggest that researchers cannot make robust comparisons across developmental or sociodemographic indicators, or pre- versus post-intervention groups (Card, 2013).

Evaluating measurement invariance entails a multi-sample CFA model with structured means. There are several levels of observed measurement invariance for which researchers may test. A multi-sample CFA model is constructed by progressively introducing equality constraints on parameters; with each additional equality constraint, a stronger level of measurement invariance is tested. The first level is termed *weak* factorial invariance. Under this form of invariance, only factor loadings are constrained to be equal across groups which examines whether that the same latent variables are being measured across groups of interest. The second level is termed *strong* factorial invariance which is tested by applying constraints on both factor loadings and intercepts across groups. By constraining both factor loadings and intercepts, one is testing whether the measurement of the latent variables is the same across groups, as in weak factorial invariance, and additionally testing whether differences in means on the observed variables are attributable to differences in means on the latent variables. A third level of analysis is termed *strict* factorial invariance. This form invokes the additional constraint that unique variances are invariant across groups which suggests that group differences in variances of the observed variables are attributable only to group differences in variances of the latent variables, since error variances are forced to be equal across groups.

As mentioned, few evaluations of measurement invariance on cyberaggression instruments currently exist. Landoll et al. (2015) reported strong measurement invariance over time (i.e., item loadings and means were similar across two time points) for the C-PEQ. Other investigations have demonstrated invariance across sex in path models which posited how low self-control predicts cyberbullying perpetration and cybervictimization (Vazsonyi, Machackova, Sevcikova, Smahel, & Cerna, 2012) and invariance across temporal relationships between cybervictimization and behavioral health sequelae during adolescence (i.e., substance use, depression, and problematic internet use; Gámez-Guadix, Orue, Smith, & Calvete, 2013). No other evaluations of measurement invariance across age for current cyberaggression instruments are known. A consideration of how cyberaggression may differentially operate between groups is warranted given developmental and sociodemographic perspectives on this construct (e.g., Astor et al., 2013; Dooley, Pyżalski, & Cross, 2009; Lewis, 2015; Schenk, Fremouw, & Keelan, 2013).

1.4 PURPOSE OF STUDY

In light of 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 a more 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. In particular, investigation into distinct and vulnerable populations (e.g., military-connected youth) across various developmental and sociodemographic indicators are hindered.

Therefore, the primary purpose of this study is to expand on existing psychometric evidence for a recently developed measure: the Cyberbullying Experiences Survey (CES). Initial evidence for construct validity of the CES has been reported (Doane et al., 2013), yet replication in a novel sample is warranted in light of internationally recognized issues of rigor and reproducibility (McNutt, 2014). In addition, evidence for measurement invariance of the CES has not been evaluated and is thus another research aim for the present investigation. The initial evaluation of the CES indicated that men consistently reported more experiences of cyberaggression as compared to women. Age was also negatively correlated with three of the cybervictimization factors (i.e., public humiliation, malice, and deception) and all four of the cyberbullying factors (Doane et al., 2013). This finding indicates that mean levels of cyberaggression experiences generally decreased as age increased. Doane et al. (2013) suggested that future research should extend investigation of potential differences in cyberaggression between age and sex groups. Evaluating evidence of measurement invariance therefore serves as a natural next step in the overall evaluation of the CES.

1.5 RESEARCH AIMS AND HYPOTHESES

The current investigation considered several tiered research goals:

1) Conduct a CFA to investigate the structural dimensionality of the CES,

Hypothesis 1: A four-factor structure underlies item responses on the CES cyberaggression and cybervictimization subscales

2) In the presence of global or local model misspecification, explore alternative model solutions utilizing information garnered from analysis in our first research goal by incorporating scale revisions as suggested by theoretically relevant modification indices and poor functioning items as defined by low variance accounted for in their respective constructs

3) Contingent upon evidence for construct validity derived from the first two research aims, extend psychometric investigation of the CES by evaluating evidence of measurement invariance across age,

Hypothesis 2: The CES will demonstrate, at minimum, weak measurement invariance across age

4) Predicated on finding support for a well-fitting model from our first and second research goals, evaluate internal consistency reliability of the instrument

Hypothesis 3: The cyberaggression and cybervictimization subscales as well as the full CES will demonstrate acceptable internal consistency

5) Given adequate factor structure and internal consistency reliability, we will examine convergent validity evidence in a nomological net analysis of the refined instrument

Hypothesis 4: The CES cyberaggression items will show moderate (r = .25-.40) to strong (r = .60-.80) correlations and will show convergent validity evidence with theoretically related constructs (e.g., cyberbullying, peer aggression, mental health difficulties)

Hypothesis 5: The CES cybervictimization items will show moderate to strong correlations and convergent validity evidence with theoretically related constructs (e.g., cybervictimization, peer victimization, mental health difficulties)

6) As an exploratory analysis, we will examine the frequency of cyberaggression and cybervictimization between male and female participants, white and non-white participants, as well as among military-connected high school and college youth to serve as a pioneer investigation of cyberaggression in this population

Hypothesis 6: Females, white, and military-connected youth will endorse higher frequencies of cyberaggression and cybervictimization

CHAPTER 2

METHOD

2.1 PARTICIPANTS

2.1.1 HIGH SCHOOL STUDENTS Participants included 225 students from a high school located in a southeastern state. The sample was typical of high school students in this southeastern state with respect to sex (current sample: 47% male; statewide: 51% male) but white participants were overrepresented (current sample: 75% white; statewide: 51% white). Exclusion criteria were: 1) non-English speaking and 2) responses marked as invalid based on checks for random responding which are later described. No participants were removed based on the first exclusion criterion. The second exclusion criterion resulted in 25 participants being removed from analysis resulting in a final sample of n = 200 high school students (see Table 2.1). Of the participants removed who also reported demographic characteristics, there were no significant differences across sex ($\chi^2 = 1.65$, $p > .05$), race/ethnicity ($\chi^2 = 2.01$, $p > .05$), sexual orientation ($\chi^2 = 3.17$, $p > .05$), or military-connected status ($\chi^2 = 1.13$, $p > .05$).

2.1.2 COLLEGE STUDENTS Participants included undergraduate students (n = 495) at the University of South Carolina (USC). The sample was representative of the undergraduate population at USC concerning race/ethnicity (current sample: 22% minority; USC undergraduate population: 20.6% minority) but females were overrepresented (current sample: 82% 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, 2) participants who were below 18 or above 25 years of age, and 3) responses marked as invalid based on checks for random responding. These criteria excluded 32 participants from analysis resulting in a final sample of $n = 463$ college students (see Table 2.1). Of the participants removed who also reported demographic characteristics, there were no significant differences across sex ($\chi^2 = .005$, $p > .05$), race/ethnicity ($\chi^2 = 2.36$, $p > .05$), sexual orientation ($\chi^2 = .01$, $p > .05$), or military-connected status ($\chi^2 = 0.14$, $p > .05$).

2.2 MEASURES

Cyberbullying Experiences Survey (CES; Doane, Kelley, Chiang, & Padilla, 2013) The CES is a 41-item measure which includes two subscales of cyberbullying perpetration (20 items) and cybervictimization (21 items). The additional item on the cybervictimization subscale contains content specific to cybervictimization (i.e., "Have you completed an electronic survey that was supposed to remain private but the answers were sent to someone else?") and does not have a mirrored item on the cyberbullying subscale. Self-reported responses were recorded on a 6-point Likert scale (0 = Never to 5 = Almost every day). Thus, scores could range from 0-100 on the cyberbullying perpetration subscale and from 0-105 on the cybervictimization subscale. Psychometric studies conducted on the CES have demonstrated a four-factor structure in both the cyberbullying perpetration and cybervictimization subscales, as well as evidence for internal consistency reliability across factors ($\alpha = .62$-$.87$) and convergent validity (Doane et al., 2013).

Table 2.1

Final High School (n =200) / College (n = 463) Student Sample Demographics

Characteristic	Overall
Mean age (*SD*)	15.83 (1.23) / 19.94 (1.53)
Age Frequencies (*n*)	
14	34
15	52
16	36
17	66
18 (high school /college)	11 / 83
19	119
20	119
21	74
22+	60
Gender	
Female (*n*, %)	103 (52%) / 379 (82%)
Male (*n*, %)	94 (47%) / 80 (17%)
Race (*n*, %)	
White	149 (75%) / 360 (78%)
African-American/Black	24 (12%) / 54 (12%)
Hispanic/Latino	5 (3%) / 17 (4%)
Asian/Other	22 (11%) / 32 (7%)
Sexual Orientation (% Heterosexual)	92% / 91%
Military-Connected Youth (*n*, %)	16 (8%) / 51 (11%)

Revised Cyberbullying Inventory (RCBI; Topcu & Erdur-Baker, 2010) The RCBI is a 28-item self-report measure which measures cyberbullying and cybervictimization. The cyberbully and cybervictim subscales each include 14 items and ask respondents to answer whether they have performed or received various aspects of cyberbullying during the previous twelve months. Items are scored on a 4-point Likert scale (0 = Never to 3 = More than three times) and summed scores can range from 0-42 with higher scores indicating more frequent cyberbullying or cybervictimization. Previous studies on the RCBI have demonstrated acceptable to strong internal consistency reliabilities across the two subscales (α = .79-.92; Brack & Caltabiano, 2015; Topcu & Erdur-Baker, 2010) and evidence for construct validity in adolescent and young adult populations. We observed acceptable to excellent internal consistency reliabilities in the present study (see Table 2.2).

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/victimization, physical aggression/victimization, exclusivity, and prosocial behavior. We utilized the relational aggression/victimization subscales to inform our investigation of convergent validity evidence for the CES in our college student sample. Respondents rate items based on experiences within the previous year on a 7-point Likert scale (1 = Not at all true to 7 = Very true). These scales have demonstrated poor to acceptable internal consistencies in adult samples (α = .66-.83) and construct validity has been established for the SRASBM in comparison with other theoretically related constructs (Murray-Close, Ostrov, Nelson, Crick, & Coccaro, 2010). We observed poor to good internal consistency reliabilities in this study (see Table 2.2).

Peer Conflict Scale (PCS; Marsee et al., 2004) The Peer Conflict Scale is a 40-item instrument that measures dimensions of peer aggression (i.e., reactive overt, reactive relational, proactive overt, and proactive relational) in youth. We utilized the PCS in our evaluation of convergent validity evidence for the CES among our high school student sample. Items are scored on a 4-point Likert scale (0 = Not at all true to 3 = Definitely true). Possible scores could range from 0-120. The PCS has demonstrated acceptable to good internal consistency reliabilities across all four subscales (α = .79-.83) and evidence for both construct validity and measurement invariance (Marsee et al., 2011). The PCS demonstrated good to excellent internal consistency reliabilities in the present study (see Table 2.2.).

Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997) The Strengths and Difficulties Questionnaire is a 25-item scale that measures aspects of internalizing, externalizing, and pro-social behavior across five subscales. All items are on a 3-point Likert scale (1 = Not true to 3 = Certainly true). Two versions of the scale were used to accommodate the age range of participants: an adolescent (11-17) version and a version adapted for individuals over 18 years of age. The adolescent and adult versions do not differ in item content; they differ in use of age-appropriate pronouns. For example, an item on the adolescent version states “I often offer to help others (parents, teachers, children)” and the adult version states “I often offer to help others (family members, friends, colleagues).” Prior research has indicated satisfactory internal consistency reliability for the SDQ adolescent version (α = .73; Goodman, 2001). No psychometric evaluations for the SDQ 18+ version have been conducted. We observed poor to acceptable internal consistency reliabilities (see Table 2.2).

Table 2.2

Internal Consistency Reliability Estimates for Nomological Net Instruments

Measure	Combined	College	High School
RCBI	.89	.85	.94
Cyberbullying	.85	.80	.88
Cybervictimization	.79	.77	.91
SRASBM	--	.93	--
Reactive Relational Aggression	--	.70	--
Proactive Relational Aggression	--	.79	--
Cross-Gender Relational Aggression	--	.73	--
Relational Victimization	--	.84	--
PCS	--	--	.94
Reactive Overt	--	--	.82
Reactive Relational	--	--	.83
Proactive Overt	--	--	.85
Proactive Relational	--	--	.85
SDQ	--	.72	.77
Total Difficulties	--	.74	.67*
Prosocial	--	.68*	.70

Note: RCBI = Revised Cyberbullying Inventory; Self-Report of Aggression and Social Behavior Measure; PCS = Peer Conflict Scale; SDQ = Strengths and Difficulties Questionnaire. 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.
*All subscales with estimates below 0.7 will not be interpreted for the nomological net analyses.

Military-Connected Youth To identify military-connected participants, several items were included which mirrored content from the California Healthy Kids Survey – Military Module (Gilreath, Estrada, Pineda, Benbenishty, & Astor, 2014). These include:

1) Do you have someone in your immediate family (e.g., father, mother, brother, sister) who is currently in the military (Army, Navy, Marine Corps, Air Force, National Guard, or Reserves)?

2) Who in your family is currently in the military (Army, Navy, Marine Corps, Air Force, National Guard, or Reserves)?

3) In what branch (Army, Navy, Marine Corps, Air Force) of the military is your family member(s) serving or have served?

4) As far as you can remember, how many times in the last 10 years did any member of your family leave home or serve (deploy) outside of the USA?

5) In the last five years, how many times did you change your school because your family had to move?

2.3 PROCEDURE

2.3.1 HIGH SCHOOL RECRUITMENT The primary investigator submitted research proposals to four public school districts and one private high school located in the southeastern United States. Permission to recruit participants was only granted at the private high school. All public-school districts cited the following reasons for denying access to students: 1) impediment on instructional time, 2) survey was not aligned with state-mandated school curricula, or 3) survey included sensitive information (e.g., gender, sexual orientation, and cyberaggression). Data collection procedures at the participating school involved students completing the online survey during their homeroom periods. Parental opt-out forms were sent via the high school's email listserv to all parents of the students. No opt-out forms were returned.

2.3.2 COLLEGE RECRUITMENT Data were collected from participants in the Psychology Subject Pool at USC as well as from several other academic departments. The primary investigator contacted professors and student organizations to gain access to potential participants across campus. Specific recruitment strategies included:

1) Posting survey link on the Psychology Subject Pool website

2) Advertising the survey in undergraduate courses (the survey link and primary investigator contact information were provided to students during this time)
3) Posting recruitment fliers around the USC – Columbia campus

Participants took the survey at a preferred location and time on their own personal computers. Participants were given the opportunity to potentially gain extra course credit (as allowed by their instructor) and be entered in a drawing to win one of three available $50 Best Buy gift cards.

2.3.3 SURVEY ADMINISTRATION The survey was administered online using Qualtrics (Qualtrics, Provo, UT). As the CES was the primary instrument of focus, it was administered first. The remaining measures were randomized in order to account for potential effects of participant fatigue and order effects across conditions. The final battery included 140 items for college student participants and 143 items for high school participants and took on average 20-40 minutes to complete. All procedures were approved by the University of South Carolina Institutional Review Board.

2.2.4 DATA ANALYSIS In line with strategies for monitoring random responding on online surveys (Meade & Craig, 2012), we employed several controls in the present study. First, 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 140-143 total questions in the entire battery, completed responses in 5 minutes or less were determined to be an unreasonable response time. An additional check to control for random responding included a self-reported single item indicator which states "I put forth my best effort in responding to this survey" which was scored on a 5-point Likert Scale (0 = Strongly Disagree to 4 = Strongly Agree; Meade & Craig, 2012). These two strategies are recommended as a minimum for monitoring random responding. Given the complex nature of the proposed analyses, we also incorporated a more robust strategy which involved including three instructed items (e.g., “To monitor quality, please respond with a two for this item”). Meade and Craig (2012) recommend the use of instructed items as they are designed to indicate whether participants make an effort to read item stems. Questionnaires were deemed invalid based on these controls if participants did not respond with at least 75% (3 out of 4) correct responses. As previously mentioned, a total of 25 high school participant responses and 32 college participant responses were removed from analyses based on these controls.

2.2.4.1 STRUCTURAL ANALYSES OF THE CES: CONFIRMATORY FACTOR ANALYSES CFA analyses were conducted utilizing Mplus Version 7.2 (Muthén & Muthén, 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). A confirmatory factor model using the oblique Geomin rotation was analyzed to test the posited four-factor structure underlying the CES cyberaggression and cybervictimization items, permitting the factors to correlate as theoretically supported (Berne et al., 2013; Doane et al., 2013). Unstandardized and standardized estimates as well as variances accounted for by the latent factors in each item were reported. Both absolute and incremental fit indices were utilized to assess adequacy of model fit. 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 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, & Hoyle, 1995). Supplementing the analysis of absolute fit via the evaluation of additional incremental fit indices provides a solution to both of these problems. 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) were used to further assess the degree of model misspecification (both simple and complex) to supplement the χ^2 statistic.

The CFI is measured on a 0 – 1 scale, with higher scores indicating better model fit. CFI values close to .90 (Bollen, 1989) or .95 (Hu & Bentler, 1999) 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 prefers parsimonious models but does not necessarily penalize 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). The RMSEA has been shown to be robust to sample size and non-normal distributions.

Along with global measures of misfit, we also explored local sources of misfit in the presence of model misspecification via 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). Modification indices were assessed to investigate specific, problematic parameters. 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).

2.2.4.2 MEASUREMENT INVARIANCE OF THE CES To address the research question of whether the CES measures the same trait across age, we constructed a multi-sample CFA model with structured means. To test measurement invariance, a sequence of models, beginning with an unconstrained model and progressively introducing equality constraints on parameters based on a priori hypotheses, were evaluated. That is, a null hypothesis test of equality of the population covariance matrices (i.e., factor loadings, unique variances, and factor variances and covariances) was first carried out. If this model is not rejected, it is plausible to conclude evidence for measurement invariance across these model parameters. If this null model is rejected, we will examine a series of models to determine what model parameters may be invariant. Recent investigations have recommended using ΔCFI, ΔRMSEA, and ΔSRMR as indices to evaluate evidence for measurement invariance. For testing weak invariance, observing $\Delta CFI \geq -.010$, $\Delta RMSEA \geq .015$, or $\Delta SRMR \geq .030$ would indicate noninvariance. For testing strong and strict invariance models, observing $\Delta CFI \geq -.010$, $\Delta RMSEA \geq .015$, or $\Delta SRMR \geq .010$ would indicate noninvariance (Chen, 2007).

2.2.4.3 STRUCTURAL ANALYSES OF THE CES: INTERNAL CONSISTENCY For the research question regarding internal consistency reliability of the CES'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).

2.2.4.4 EXTERNAL ANALYSES OF THE CES: ESTABLISHING A NOMOLOGICAL NET To establish the nomological net for the CES, analyses exploring convergent validity were employed. This procedure involved correlating items from the CES and items from theoretically related instruments. We analyzed correlations among items derived from peer aggression, cyberaggression, and mental health difficulties scales with the CES's cyberaggression items to assess convergent validity. Scales measuring peer victimization, cybervictimization, and mental health difficulties were also examined for correlations with the C-PEQ's cybervictimization items to assess convergent validity.

2.2.4.5 POWER ANALYSES To determine an appropriate sample size to have sufficient power for meeting the recommended cut-off 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, Kaniskan, & McCoach, 2015), and generally 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 $\alpha = .05$ (e.g., Cohen, 1988), a priori power analyses based on the model indicated a required sample size of $n = 97$. To answer our research questions involving measurement invariance analysis, prior simulation research has indicated that samples as small as $n = 50$ or $n = 100$ will allow researchers to detect large model violations whereas a sample size of at least $n = 200$ is required to detect small model violations (Koller, Maier, & Hatzinger, 2015). Given our sample sizes of 200 high school and 463 college students, this study was adequately powered for addressing all research questions.

CHAPTER 3

RESULTS

3.1 MISSING DATA

Missing data for the CES was minimal (<1%). Nevertheless, full information maximum-likelihood (FIML) was utilized to estimate model parameters. FIML estimates a likelihood function for each individual case based on the observed data so that all available information is utilized; variables with no information were not estimated (Newsom, 2015).

3.2 CONFIRMATORY FACTOR ANALYSIS FOR CES

3.2.1 DESCRIPTIVE STATISTICS Inter-item correlations for the CES are reported in Appendix A. Means, standard deviations, skewness, and kurtosis for the CES items are presented in Appendix B. All CES items are referenced in Appendix C. We conducted both square root and logarithmic transformations in an attempt to satisfy normality assumptions (Tabachnick & Fidell, 2007). Neither data transformation resulted in improvements in normality as a result of substantial floor effects. We therefore decided to employ the original, non-transformed data 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).

3.2.2 MODEL RESULTS CFA results for the hypothesized four-factor cyberaggression model solution as suggested by Doane et al. (2013) indicated model misfit: χ^2 (164) = 349.72, $p < .001$. Both the RMSEA (.04) and SRMR (.07) fell below recommended cut-off values; the CFI did not approach recommended cut-off values (.89). We assessed the variance accounted for in the items by their respective latent factors to identify weak items. This investigation suggested that items 10, 11, 14, 16, and 17 had 85 – 97% observed variance *not* accounted for by their respective latent factors.

CFA results for the hypothesized four-factor cybervictimization model solution indicated model misfit: χ^2 (183) = 562.55, $p < .001$). Both the RMSEA (.06) and SRMR (.06) fell below recommended cut-off values; the CFI did not approach recommended cut-off values (.89). We again assessed the variance accounted for in the items by their respective latent factors. This investigation noted that cybervictimization items 1, 4, 5, 6, and 8 had 75 – 94% observed variance *not* accounted for by their latent factor.

3.2.3 MODEL REFINEMENT Given model misspecification, we explored modification indices. These suggested adding correlated error terms between items 12/13 on the cyberaggression scale, as well as items 10/11 and 13/14 on the cybervictimization scale. The addition of these correlated error terms made theoretical sense as these item pairs shared similar item stems and content. We subsequently investigated a modified four-factor solution for the CES items with invoked modifications indices. Though the cyberaggression model Satorra-Bentler χ^2 was significant, χ^2 (163) = 327.75, $p < .001$, results indicated that all incremental fit indices met or approached recommended cut-off values (SRMR = .06, RMSEA = .04, CFI = .90). Likewise, though the cybervictimization model Satorra-Bentler χ^2 was significant, χ^2 (181) = 422.33, $p < .001$, results indicated that all incremental fit indices met or approached recommended cut-off values (SRMR = .06, RMSEA = .05, CFI = .93). These results support the revised models. We utilized these modified solutions to inform our remaining research aims.

3.3 SINGLE-GROUP CONFIRMATORY FACTOR ANALYSES BY AGE

3.3.1 CYBERAGGRESSION MODEL RESULTS All model results are reported in Table 3.1. The first step in evaluating measurement invariance is to investigate configural invariance through conducting single-group CFAs for the hypothesized four-factor cyberaggression model across both college and high school samples. The model Satorra-Bentler chi-square statistics were significant for both college (χ^2 (163) = 246.46, $p < .001$) and high school (χ^2 (163) = 226.11, $p < .001$) samples, although all incremental fit indices met or approached acceptable cut-off recommendations in both samples (Hu & Bentler, 1999). Results also indicated that the "unwanted contact" and "deception" cyberaggression subscales correlated at $r = .99$ in the high school model. Researchers suggest that subscales correlating $r \geq .85$ may result in multicollinearity due to poor discriminative validity (Kenny, 2012). Configural invariance for cyberaggression was therefore not supported between college and high school participants as a result of the hypothesized model differing for high school students. We subsequently employed an exploratory approach to determine a factor solution which provided acceptable fit across both college and high school samples.

3.3.2 MODEL REFINEMENT We used the following analytic method to investigate a revised model solution for the CES cyberaggression model:

Step 1: Conducted an exploratory factor analysis (EFA) for the high school sample to uncover the underlying structure of the CES cyberaggression items.

Table 3.1

Goodness-of-Fit Indicators of Models for CES Cyberaggression Items

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR
Hypothesized Model Solutions					
Single-Group College 4-Factor	246.46*	162	.03	.94	.05
Single-Group High School 4-factor[#]	226.11*	162	.05	.91	.08
Final Model Solutions[##]					
CFA 3-Factor Solution College	**273.01***	**163**	**.04**	**.92**	**.06**
CFA 3-Factor Solution High School	**196.29***	**165**	**.03**	**.96**	**.08**

*$p < .001$
[#]"Unwanted contact" and "deception" subscales correlated at $r = .99$.
[##]"Sexual cyberaggression," "direct cyberaggression," and "coercion" subscales.

Step 2: Integrated EFA results with theoretical considerations and item intercorrelations to conduct an EFA with target rotation for the high school sample. The Target EFA places additional restrictions on model parameters compared to a traditional EFA where items are partially specified to serve as indicators for the proposed latent variable structure.

Step 3: Performed a CFA for both college and high school samples with the revised model solution as informed by the previous two steps. A CFA is more restrictive compared to the Target EFA where items are now fully specified to serve as indicators for the proposed latent variable structure.

Rationale for and results from Steps 1 and 2 are explained in Appendix D and only results from the final model solutions are reported in this section.

Final Model Results: Given evidentiary support from our EFA and Target EFA solutions, we subsequently performed a revised three-factor CFA solution for both the high school and college samples for the proposed latent variable structure (i.e., "sexual cyberaggression," "direct cyberaggression," and "coercion"). Although the Satorra-Bentler chi-square did not indicate acceptable model fit for either the high school (χ^2 (165) = 196.29, $p < .001$) or college sample (χ^2 (163) = 273.01, $p < .001$), incremental fit indices met or approached recommended cut-off values in both samples (High School: RMSEA = .03, CFI = .96, SRMR = .08; College: RMSEA = .04, CFI = .92, SRMR = .06). As shown in Figures 3.1 and 3.2, factors correlated from r = .23-.56 which is consistent with psychometric research in this field (Berne et al., 2013) and several item error variances were correlated in the college and high school models. These correlations were added to the model based on theoretical considerations and similar item stems to reflect variance shared between those items that are unrelated to the latent variable for which they serve as indicators. Overall, these results support the revised three-factor model solution for the CES cyberaggression items in both samples. We subsequently utilized this modified solution to inform our third and fourth research aims. Appendix C includes the CES item configurations for the final revised cyberaggression solutions across college and high school samples. Table 3.2 presents standardized factor loadings and variance explained in each item by the latent variables.

3.3.3 CYBERVICTIMIZATION MODEL RESULTS A similar analytical approach was used for determining an acceptable model solution for the cybervictimization items. All model results are reported in Table 3.3. Single-group CFAs for the hypothesized four-factor cybervictimization models for college and high school samples were performed first. The Satorra-Bentler chi-squares were significant for both college (χ^2 (181) = 329.84, $p < .001$) and high school (χ^2 (181) = 351.97, $p < .001$)

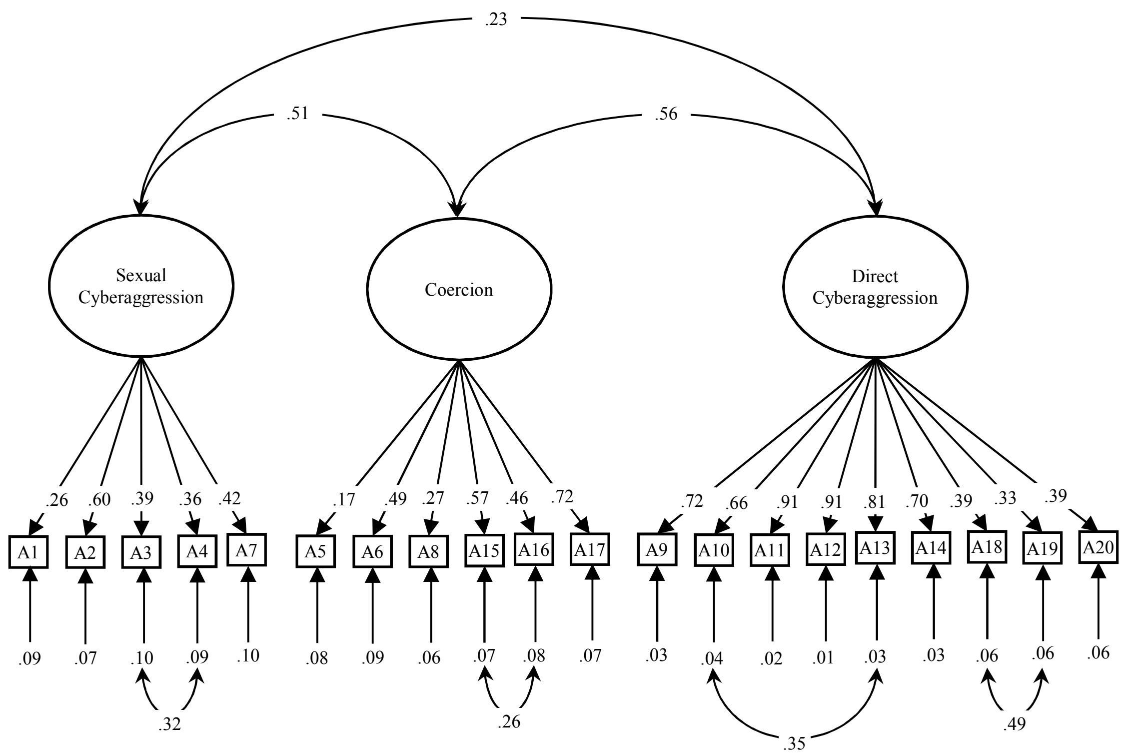

Figure 3.1. Results from the revised CES cyberaggression three-factor solution for college students. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

models. Incremental fit indices met acceptable cut-off recommendations (Hu & Bentler, 1999) in the college sample (RMSEA = .04, CFI = .95, SRMR = .05), but not in the high school sample (RMSEA = .07, CFI = .85, SRMR = .08), indicating the presence of model misspecification. Configural invariance was therefore not supported between college and high school participants as a result of the hypothesized model differing for high school students. We subsequently employed a similar exploratory approach to determine a factor solution for the cybervictimization items which provided acceptable fit across both college and high school samples.

3.3.4 MODEL REFINEMENT The method used to determine a revised model solution for the cybervictimization items was identical to the method employed for the cyberaggression model revisions. All analytical steps and preliminary model results

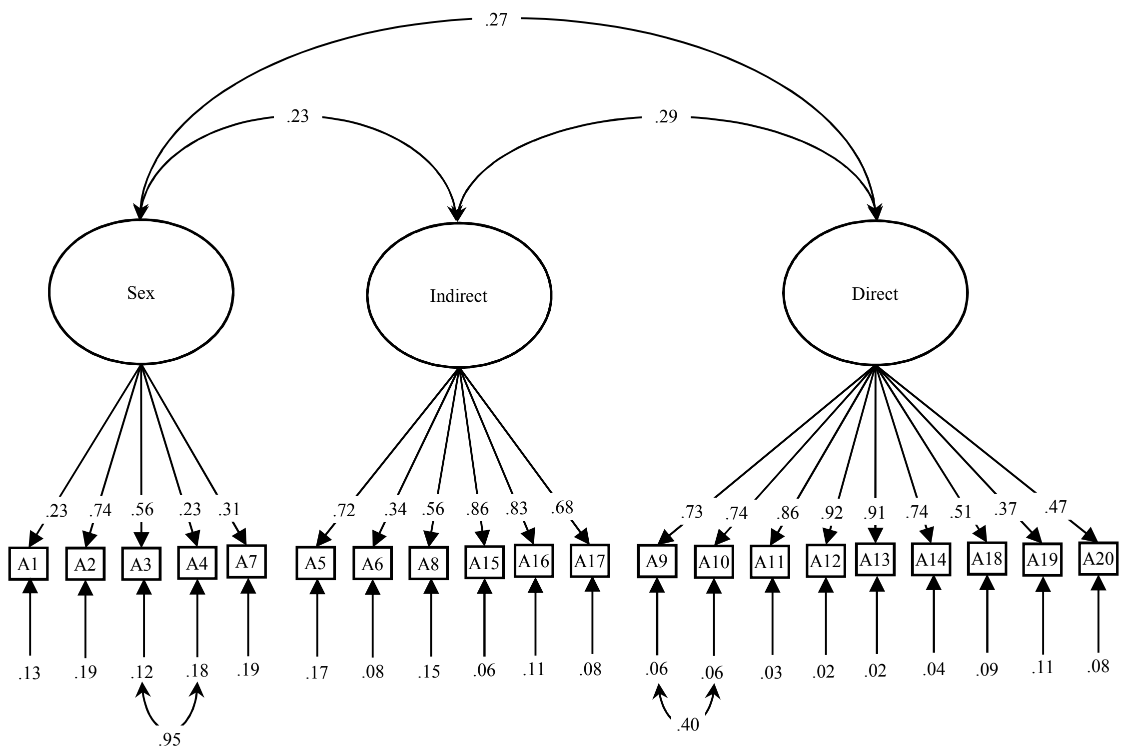

Figure 3.2. Results from the revised CES cyberaggression three-factor solution for high school students. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

garnered from those procedures are also described in Appendix D. Results from the final model solutions are reported in this section.

Final Model Results: We performed a three-factor CFA solution for both high school and college samples for the revised latent factor structure (i.e., "sexual cybervictimization," "direct cybervictimization," and "defamation" subscales). Although the Satorra-Bentler chi-square did not indicate acceptable model fit for either the high school (χ^2 (160) = 256.32, p < .001) or college sample (χ^2 (163) = 367.81, p < .001), incremental fit indices met or approached recommended cut-off values in both samples (High School: RMSEA = .06, CFI = .92, SRMR = .07; College: RMSEA = .05, CFI = .93, SRMR = .06). As shown in Figures 3.3 and 3.4, factors correlated from r = .46-.78 and several item error variances were correlated in the college and high school models.

Table 3.2

Standardized Loadings and Item Variance for the 3-Factor Confirmatory Model of Cyberaggression

Item	Sexual Cyberaggression		Coercion		Direct Cyberaggression		Item R^2 Values	
	High School	College	High School	College	High School	College	High School	College
#1	.23	.26	--	--	--	--	.05	.07
#2	.74	.60	--	--	--	--	.55	.37
#3	.56	.39	--	--	--	--	.31	.16
#4	.23	.36	--	--	--	--	.05	.13
#5	.31	.42	--	--	--	--	.09	.17
#6	--	--	.72	.16	--	--	.52	.03
#7	--	--	.34	.49	--	--	.11	.24
#8	--	--	.56	.27	--	--	.32	.07
#9	--	--	.86	.57	--	--	.73	.32
#10	--	--	.83	.46	--	--	.69	.21
#11	--	--	.68	.72	--	--	.46	.52
#12	--	--	--	--	.73	.72	.53	.52
#13	--	--	--	--	.74	.66	.54	.44
#14	--	--	--	--	.86	.91	.74	.83
#15	--	--	--	--	.92	.91	.84	.84
#16	--	--	--	--	.91	.81	.82	.65
#17	--	--	--	--	.74	.70	.55	.50
#18	--	--	--	--	.51	.39	.26	.15
#19	--	--	--	--	.37	.33	.14	.11
#20	--	--	--	--	.47	.39	.22	.15

Note. R^2 represents the variance accounted for in an item by the latent factor for which it serves as an indicator.

These correlations were added to the model based on theoretical considerations and similar item stems to reflect variance shared between those items that is unrelated to the latent variable for which they serve as indicators. Overall, these results support the revised three-factor model solution for the CES cybervictimization items in both samples. We utilized this modified solution to inform our third and fourth research aims. Appendix

Table 3.3

Goodness-of-Fit Indicators of Models for CES Cybervictimization Items

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR
Hypothesized Model Solutions					
Single-Group College 4-Factor	329.84*	181	.04	.95	.05
Single-Group High School 4-factor	351.97*	181	.07	.85	.08
Final Model Solutions#					
CFA 3-Factor Solution College	**367.81***	**163**	**.05**	**.93**	**.06**
CFA 3-Factor Solution High School	**256.32***	**160**	**.06**	**.92**	**.07**

**p* < .001
#"Sexual cybervictimization," "direct cybervictimization," and "defamation" subscales.

C includes the CES cybervictimization item configurations across college and high school samples. Table 3.4 presents standardized factor loadings and variance explained in each item by the latent variables.

3.4 INTERNAL CONSISTENCY OF THE CES

Tables 3.5 and 3.6 present inter-correlations of the latent factors, means, standard deviations, and reliability estimates. Cronbach's coefficient alpha estimates of internal consistency for the CES cyberaggression items was good in both high school ($\alpha = .88$) and college ($\alpha = .83$) samples. Internal consistency for the CES cybervictimization items was excellent in the high school sample ($\alpha = .90$) and good in the college sample ($\alpha = .89$). Internal consistencies among the cyberaggression subscales, however, ranged from poor to good across both samples ($\alpha = .54 – .88$) and ranged from acceptable to excellent among the cybervictimization subscales across both samples ($\alpha = .76 – .92$). These findings reflect observed results in the original investigation (Doane et al., 2013).

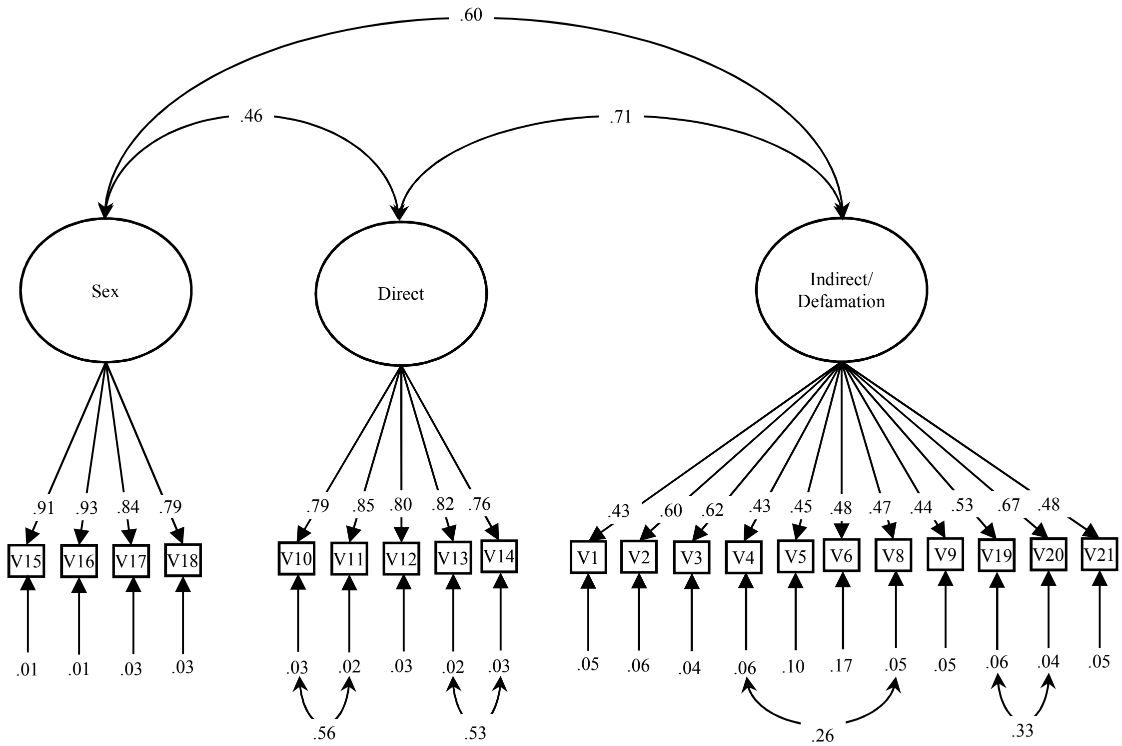

Figure 3.3. Results from the revised CES cybervictimization three-factor solution for college students. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

3.5 NOMOLOGICAL NET: CONVERGENT VALIDITY EVIDENCE

3.5.1 CES CYBERAGGRESSION SUBSCALE As reliability is a necessary but not sufficient component of evaluating construct validity (Nunnally, 1978), subscales indicating unacceptable reliability (i.e., $\alpha \geq .70$) were not considered for our nomological net analyses. Thus, the sexual cyberaggression and coercion subscales in the college sample and the sexual cyberaggression subscale in the high school sample were not considered. All reported results are summarized in Tables 3.7 and 3.8.

There were mixed results regarding our hypotheses. As predicted, a moderate correlation was observed between the direct cyberaggression subscale and the RCBI cyberbullying subscale in both samples. Mostly moderate correlations were also observed

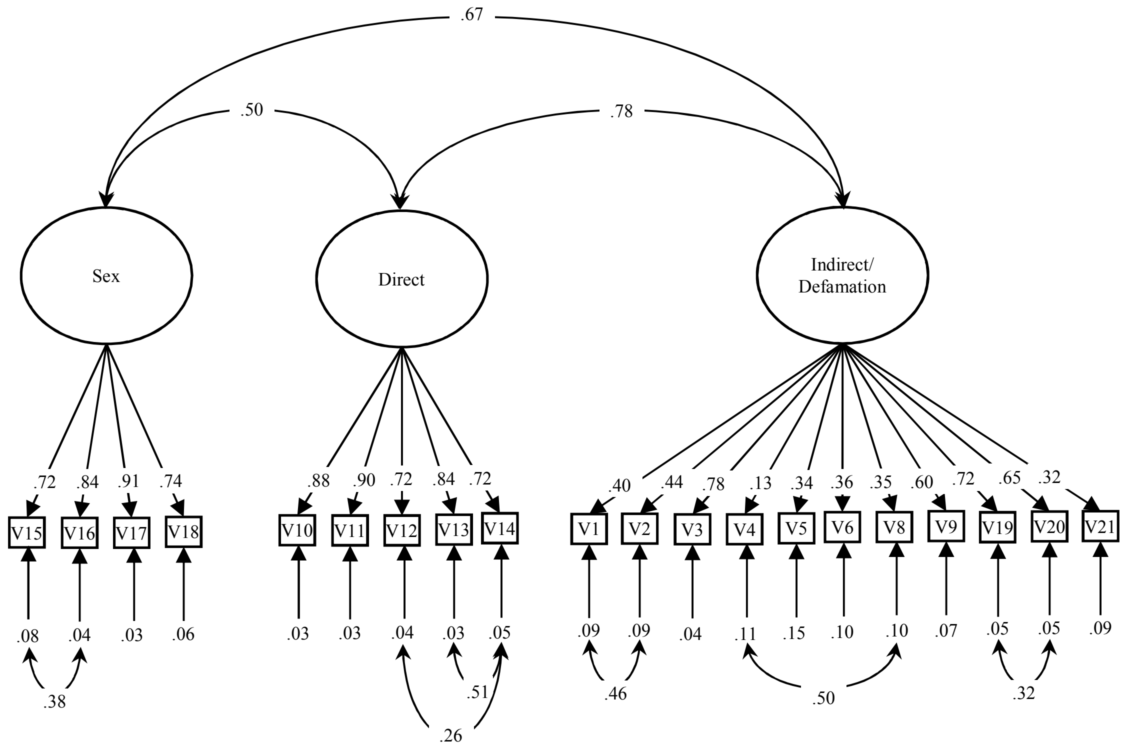

Figure 3.4. Results from the revised CES cybervictimization three-factor solution for high school students. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

between the cyberaggression subscales and measures of peer aggression on the SRASBM and PCS. There was a weak correlation observed between direct cyberaggression and proactive overt aggression subscale on the PCS, however. Weak to moderate correlations were observed between the cyberaggression subscales and the SDQ mental health difficulties subscale in the college sample and the SDQ prosocial behaviors subscale in the high school sample.

3.5.2 CES CYBERVICTIMIZATION SUBSCALE As predicted, moderate correlations were observed between the CES cybervictimization subscales and the RCBI cybervictimization subscale in both samples (*r*s = .30 – .59). Also, as predicted, moderate correlations were observed between the CES cybervictimization subscales and measures

Table 3.4

Standardized Loadings and Item Variance for the 3-Factor Confirmatory Model of Cybervictimization

Item	Sexual Cybervictimization		Defamation		Direct Cybervictimization		Item R^2 Values	
	High School	College	High School	College	High School	College	High School	College
#1	.72	.91	--	--	--	--	.52	.84
#2	.84	.93	--	--	--	--	.70	.86
#3	.91	.84	--	--	--	--	.82	.70
#4	.74	.79	--	--	--	--	.54	.62
#5	--	--	.40	.43	--	--	.16	.19
#6	--	--	.44	.60	--	--	.20	.36
#7	--	--	.78	.62	--	--	.61	.39
#8	--	--	.13	.43	--	--	.02	.18
#9	--	--	.34	.45	--	--	.11	.21
#10	--	--	.36	.48	--	--	.13	.23
#11	--	--	.35	.47	--	--	.12	.22
#12	--	--	.60	.44	--	--	.36	.20
#13	--	--	.72	.53	--	--	.51	.28
#14	--	--	.65	.67	--	--	.43	.45
#15	--	--	.32	.48	--	--	.10	.23
#16	--	--	--	--	.88	.79	.77	.62
#17	--	--	--	--	.90	.85	.81	.72
#18	--	--	--	--	.72	.80	.52	.64
#19	--	--	--	--	.84	.82	.70	.68
#20	--	--	--	--	.72	.76	.52	.58

Note. R^2 represents the variance accounted for in an item by the latent factor for which it serves as an indicator.

of relational victimization (*r*s = .27 – .35) and mental health difficulties (*r*s = .25 – .28) in the college student sample. The CES cybervictimization subscales weakly correlated with a measure of prosocial behavior (*r*s = -.02 – -.17) in the high school sample. These results are also summarized in Tables 3.7 and 3.8. Overall, investigation into the nomological net provided mixed evidence of construct validity for the revised CES scores as most but not all hypotheses were supported.

Table 3.5

Correlations, Reliability, and Descriptive Statistics of the CES Subscales (College)

	Cyberaggression Subscales			Cybervictimization Subscales		
Cyberaggression	Sex	Coercion	Direct	Sex	Defamation	Direct
Sex	1.00	--	--	--	--	--
Coercion	.51**	1.00	--	--	--	--
Direct	.23*	.56**	1.00	--	--	--
Cybervictimization						
Sex	--	--	--	1.00	--	--
Defamation	--	--	--	.60**	1.00	--
Direct	--	--	--	.46**	.71**	1.00
Cronbach's Coefficient α	.54	.61	.88	.92	.76	.91
Factor Mean[a, b]	.32	.81	6.33	3.05	3.66	5.53

Note. $n = 463$. a = possible range of scores for cyberaggression: Sex = 0 – 25; Coercion = 0 – 30; Direct = 0 – 45. b = possible range of scores for cybervictimization: Sex = 0 – 20; Defamation = 0 – 55; Direct = 0 – 25.
$^*p < .05$; $^{**}p < .001$.

3.6 DESCRIPTIVE STATISTICS ACROSS DEMOGRAPHICS

Factor mean scores for all revised CES subscales across demographics are reported in Table 3.9. In college, mean scores indicated that males endorsed higher frequencies of perpetrating cyberaggression as compared to females across all subscales; females reported higher scores on sexual cybervictimization whereas males reported higher scores on direct cybervictimization. In high school, females endorsed higher scores on coercive and direct cyberaggression, as well as sexual cybervictimization and defamation. Males in high school endorsed more direct cybervictimization experiences.

White participants in college endorsed greater involvement in direct cyberaggression and cybervictimization; all other subscale mean scores were similar

Table 3.6

Correlations, Reliability, and Descriptive Statistics of the CES Subscales (High School)

	Cyberaggression Subscales			Cybervictimization Subscales		
Cyberaggression	Sex	Coercion	Direct	Sex	Defamation	Direct
Sex	1.00	--	--	--	--	--
Coercion	.23**	1.00	--	--	--	--
Direct	.27*	.29**	1.00	--	--	--
Cybervictimization						
Sex	--	--	--	1.00	--	--
Defamation	--	--	--	.67**	1.00	--
Direct	--	--	--	.50**	.78**	1.00
Cronbach's Coefficient α	.63	.88	.82	.88	.92	.78
Factor Mean[a, b]	.18	.94	5.92	1.37	2.84	5.46

Note. $n = 200$. a = possible range of scores for cyberaggression: Sex = 0 – 25; Coercion = 0 – 30; Direct = 0 – 45. b = possible range of scores for cybervictimization: Sex = 0 – 20; Defamation = 0 – 55; Direct = 0 – 25.
*$p < .05$; **$p < .001$.

between white and non-white college participants. In high school, non-white participants endorsed higher scores on sexual and coercive cyberaggression, whereas white participants endorsed greater involvement with direct cyberaggression as well as sexual cybervictimization, defamation, and direct cybervictimization. Means indicated similar rates of endorsement across all subscales among military-connected and civilian college participants. In high school, military-connected participants endorsed higher mean levels of sexual cybervictimization and defamation. Civilian high school participants endorsed higher mean-levels of direct cybervictimization and direct cyberaggression.

Table 3.7

Correlations between the CES Subscales and Related Measures (College)

Measure	CES Cyberaggression			CES Cybervictimization		
	Sex	Coercion	Direct	Sex	Defamation	Direct
RCBI						
Cyberbullying	--	--	.31	--	--	--
Cybervictimization	--	--	--	.33	.53	.50
SRASBM						
Relational Aggression						
Reactive	--	--	.32	--	--	--
Proactive	--	--	.45	--	--	--
Cross-Gender	--	--	.33	--	--	--
Relational Victimization	--		--	.35	.37	.27
SDQ						
Total Difficulties	--	--	.27	.25	.28	.26

Note: -- = no prediction hypothesized; RCBI = Revised Cyberbullying Inventory; SRASBM = Self-Report of Aggression and Social Behavior Measure; SDQ = Strengths and Difficulties Questionnaire.

Table 3.8

Correlations between the CES Subscales and Related Measures (High School)

Measure	CES Cyberaggression			CES Cybervictimization		
	Sex	Coercion	Direct	Sex	Defamation	Direct
RCBI						
Cyberbullying	--	.31	.27	--	--	--
Cybervictimization	--	--	--	.45	.59	.30
PCS						
Reactive Overt	--	.41	.30	--	--	--
Reactive Relational	--	.37	.36	--	--	--
Proactive Overt	--	.28	.24	--	--	--
Proactive Relational	--	.37	.28	--	--	--
SDQ						
Prosocial	--	-.03	-.31	-.12	-.02	-.17

Note: -- = no prediction hypothesized; RCBI = Revised Cyberbullying Inventory; PCS = Peer Conflict Scale; SDQ = Strengths and Difficulties Questionnaire.

Table 3.9

Subscale Mean Scores across Demographics

Model	CES Cyberaggression			CES Cybervictimization			*n*
College	Sex	Coercion	Direct	Sex	Defamation	Direct	
Sex							
Males	.58	1.05	7.01	1.46	3.41	6.03	80
Females	.26	.76	6.20	3.37	3.70	5.42	378
Race/Ethnicity							
White	.28	.81	6.87	3.04	3.65	5.91	359
Non-white	.42	.84	4.43	3.11	3.67	4.23	103
Military							
Connected	.45	.92	5.63	2.88	3.90	5.61	49
Civilian	.30	.80	6.41	3.07	3.63	5.53	413
High School							
Sex							
Males	.19	.81	5.72	.84	2.69	5.78	94
Females	.17	1.08	6.06	1.83	3.02	5.16	102
Race/Ethnicity							
White	.11	.70	6.34	1.55	2.99	6.03	148
Non-white	.37	1.63	5.18	.84	2.51	3.98	51
Military							
Connected	.13	.93	4.40	2.60	3.60	4.47	15
Civilian	.18	.93	6.18	1.27	2.80	5.59	184

CHAPTER 4

DISCUSSION

The present study had three goals:

1. In light of nationally and internationally recognized issues of rigor and reproducibility (McNutt, 2014), we sought to evaluate evidence for construct validity of the CES using a novel sample of high school and college students.
2. As a result of recent recommendations in cyberaggression research to advance psychometric evaluation in this field (Card, 2013), we also sought to evaluate aspects of measurement invariance of the CES across age as suggested by the CES developers (Doane et al., 2013) and which has yet to be explored more broadly in the cyberaggression literature.
3. Given prior evidence from research suggesting potential differences across demographic indicators such as sex, race/ethnicity, and military-connected status, we sought to investigate the frequency of cyberaggression and cybervictimization among these subgroups, the first of which to explore this among military-connected youth.

4.1 INITIAL MODELS Concerning our first goal, results indicated that the hypothesized four-factor cyberaggression and cybervictimization solutions did not meet cut-off recommendations for both absolute and incremental fit indices. These findings were likely influenced by several issues. First, there were numerous poorly performing cyberaggression and cybervictimization items. Six items on the cyberaggression unwanted contact subscale had 69-95% of the variance not accounted for, all items on the cyberaggression public humiliation subscale had 74-87% of the variance not accounted for, and six items on the cybervictimization public humiliation subscale had 84-98% of the variance not accounted for by their respective latent factors. 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). Regarding the cyberaggression unwanted contact subscale, four of these poorly performing items contained sexual content, were rarely endorsed, and weakly correlated with all other cyberaggression items. This suggests that their integration with non-sexual items may not optimally represent an overarching cyberaggression construct as sexual forms of aggression are distinct from other forms of aggression due to differential personality characteristics of perpetrators and impact on victims (Vega & Malamuth, 2007).

Concerning the public humiliation subscales, several items may not tap into an aggression construct. For example, one item states “Have you posted a picture electronically of someone doing something illegal?” and another reads “Has someone logged into your electronic account and changed your information?” Although the former item might prove problematic for the victim, illegal acts are a vague term and may involve behaviors which many youth participate in such as underage drinking at a party. The latter item assumes both negative intentions by the perpetrator, which may not exist, or the act being accomplished through a social media (e.g., Facebook) account where others may view the altered information. It appears that several poorly performing items measure non-aggressive behaviors which may result in ineffective operationalization and measurement of the cyberaggression and cybervictimization constructs.

Several items also shared variance unrelated to the latent constructs in both solutions likely due to having similar item stems and repetitive content. Although model fit improved after including theoretically supported modification indices, the unwanted contact and deception subscales in the high school cyberaggression model strongly correlated (r = .99) which did not support configural invariance across age for the CES. Evaluation of the items in both of these subscales highlights that many items involve the use of coercive tactics by the perpetrator to either elicit a negative response by or obtain personal information from the victim (e.g., lying to the victim, asking what they are wearing, and asking where they are living). The unwanted contact subscale also contained the sexually related items which all relatively performed poorly. Sexual cyberaggression may operate differently among high school and college students as college is a time of sexual exploration for young adults where sexually related practices are more open and culturally accepted (Chng & Moore, 1994). High school students, however, frequently indicate that coercion or peer pressure led to them sending sexually explicit messages to other students (Dake et al., 2012). Future research should evaluate differential attitudes towards sexual behaviors in the cyber realm between high school and college students which may inform its inclusion in subsequent measures of cyberaggression.

4.1.1 RESIVED MODEL Revisions supported a three-factor solution for the cyberaggression and cybervictimization subscales which was consistent with initial EFA findings in the original CES evaluation (Doane et al., 2013). These revisions were made based on theory regarding item content as well as statistical considerations including inter-item correlations and factor loadings (Appendix D). Although fit indices supported these revisions, several limitations remained including poor internal consistency across three subscales (i.e., sexual cyberaggression, coercion, and sexual cybervictimization) and low variance accounted for in the items by their respective latent factors.

Overall, our findings are in contrast to the results reported in the original CES investigation (Doane et al., 2013). Given the general lack of support for the CES and other measures being used in the literature (Berne et al., 2013), as well as the specific measurement limitations addressed in the current study, there are two overarching insights for future research in this area: 1) the conceptualization and operationalization of cyberaggression appears in need of revision and 2) the development of a screening instrument which would retain fewer items to highlight the most relevant aspects of cyberaggression as informed by research, remove unnecessary model complexity, and have the greatest potential to impact future research, clinical practice, and policy should be considered.

4.2 ISSUES IN CONCEPTUALIZATION AND OPERATIONALIZATION

There are seemingly several issues in the current conceptualization and operationalization of cyberaggression and cybervictimization. As previously mentioned, two issues are a lack of agreement on the definition of cyberaggression as well as the use of inconsistent terminology (e.g., cyberaggression, cyberbullying, cyberharassment). Research has shown that language semantics impact response patterns to cyberaggression instruments and the populations which researchers primarily seek to evaluate these experiences (i.e., K-12 and college) have varying conceptualizations of what aggression or bullying entails (Grigg, 2010; Menesini & Nocentini, 2009). A call for deliberation by field experts to come to a mutual agreement on the construct of interest and its definition is a necessary first step to progress these lines of research as compared to the current practice of developing isolated research, measures, and intervention programs. The current study has suggested the field focus on the construct of *cyberaggression* as this term is broader and more accurately captures the type of behaviors currently assessed by existing instrumentation.

Once cyberaggression is identified as the definitive construct of interest, research should then focus on what aspects of these behaviors are most important in terms of clinical impact and policy directives. Numerous conceptualizations have been posited including organizing cyberaggression experiences based on electronic modality (i.e., cyberaggression via text messages, social media websites, or e-mail), public versus private experiences (e.g., having an embarrassing picture posted online as compared to receiving a mean text message on your personal phone), or possible intentions (e.g., to malaise or deceive) of the perpetrator as observed in the CES (e.g., Doane et al., 2013; Menesini, Nocentini, & Calussi, 2011). It is clear that the field is attempting to determine a severity spectrum of cyberaggression acts to inform research and clinical practice. Focus groups with adolescents and young adults may serve as a useful methodological approach to evaluate and identify which conceptualizations resonate with the populations of interest, given constant technological advancements and that these behaviors may developmentally differ across age groups.

Another commonplace practice is to operationalize cyberaggression in terms of mirrored-item content to simultaneously evaluate both perpetration acts and victimization experiences. Clinicians and policymakers seek to evaluate both perspectives on cyberaggression but possibly for different purposes. Regarding cybervictimization, there are apparent reasons to identify those who have been cybervictimized including the impact on mental health and for the development of effective intervention programs. In terms of how existing measures operationalize these experiences, respondents are typically asked to report how frequently a particular incident has occurred to them over a specified time period. That is, there is usually no attempt to assess the respondent's perceptions of or reactions to these experiences about whether they viewed them as an act of aggression or intention to harm on the behalf of the perpetrator. Mental health providers and even law enforcement officials may therefore find it difficult to intervene in such cases unless there is a serious and substantial threat to a victim's personal safety which may necessarily be difficult to determine given the complexities of the cyber realm (Hinduja & Patchin, 2008; Notar, Padgett, & Roden, 2013). Future instrumentation will need to address both prevalence rates and perceived harm from the cybervictim's perspective to best inform clinical practice and policy.

Concerning cyberaggression perpetration, clinicians are also interested in mental health difficulties experienced by these individuals yet policies surrounding perpetration tend to focus more on discipline, litigation, or even criminal prosecution (Beale & Hall, 2007). Notar, Padgett, and Roden (2013) describe how it is generally not illegal to use electronic communication to mistreat, tease, or even harass others because of First Amendment protection. Although these behaviors may cross the legal line into "harassment" or "stalking," current instruments do not necessarily include items to evaluate harassing or stalking behaviors as traditionally defined. As such, cyberaggression perpetration is potentially more difficult to evaluate from a policy perspective due to current instrumentation not following existing definitions of illegal human interactions. From a measurement perspective, cyberaggression perpetration is likewise more challenging to evaluate as it involves issues such as social desirability response bias and item ambiguity. For example, a CES cyberaggression item states, “Have you cursed at someone electronically?” A perpetrator may respond that they curse at their friends electronically but does not interpret those acts as being aggressive; their friend, on the other hand, may view those interactions in a negative manner unbeknownst to the perpetrator. Language involving the individual’s intent rather than assuming intent to harm is needed in cyberaggression perpetration measures. This example highlights that current practice of using identical or mirrored item stems to evaluate perpetration and victimization may not best capture the construct as they involve different psychological perspectives and policy motives.

4.3 DEVELOPING A CYBERAGGRESSION SCREENING INSTRUMENT

Although the field is quickly growing due to the increasing need to understand and monitor cyberaggression, measurement and instrumentation remain in early development. In order to begin addressing the aforementioned issues, it is recommended that developing a screening instrument be considered. Screeners typically serve three main purposes: 1) cost-effectiveness, 2) decrease burden on the respondent, and 3) case identification in clinical or research contexts (Burnam, Wells, Leake, & Landsverk, 1988). Most, if not all, cyberaggression instruments derive responses from self-report which are both consistent with traditional aggression and bullying measurement strategies (Vivolo-Kantor, Martell, Holland, & Westby, 2014) and contribute to the cost-effectiveness of these instruments. Although limitations in self-reporting are well documented (e.g., Stone, Bachrach, Jobe, Kurtzman, & Cain, 1999), self-report may prove to be the most effective strategy for identifying cyberaggression experiences as the cyber context presents several challenges in monitoring behaviors by other commonly used reporters (e.g., parents and teachers) such as limited technological knowledge and access to the person of interest's electronic accounts.

Screeners also decrease the burden on the respondent by only highlighting core aspects of the construct of interest and removing unnecessary measurement complexity by retaining fewer items which strongly perform in initial evaluation studies. Single-item measures have currently been developed and used in the literature (e.g., Olweus Bully/Victim Questionnaire; Solberg & Olweus, 2003). These single-item measures, however, typically lack precision, are too narrowly defined, and lack construct validation (Berne et al., 2013; Vivolo-Kantor et al., 2014). A screener instrument would serve as a balance between overly complex and single-item measures which are too limited in scope to hold research or clinical utility. Results from this and other evaluation studies can inform what critical items to include in a screener measure as there are no formal "diagnostic criteria" for cyberaggression on which to imitate.

A minimal number of items to establish acceptable internal consistency reliability are recommended. Commonly used screeners such as the Patient Health Questionnaire-4 include as few as four items, for example (Kroenke, Spitzer, Williams, & Löwe, 2009). Maintaining a minimal number of items further expands usage of a screener to other research methodologies. Longitudinal evaluation, for example, is an important methodological approach in clinical and research contexts where measures that are conducive for follow-up are needed. As the cyber realm is complex and constantly changing due to the introduction of new technologies, a quick and precise screener would hold utility for longitudinally evaluating these experiences and subsequent behavioral health impact.

It is likewise important to consider what an effective cyberaggression screener may look like. Other areas in psychology that evaluate behavioral health issues such as mood or trauma-related sequelae (e.g., posttraumatic stress disorder; PTSD) utilize screeners for case identification. For example, the Patient Health Questionnaire-9 (PHQ-9; Kroenke, Spitzer, & Williams, 2001) and PTSD Checklist for DSM-5 (PCL-5; Weather et al., 2013) are the gold standards for briefly assessing depression and PTSD, respectively. These instruments involve answering multiple self-report items (9 items on the PHQ and 20 items on the PCL-5) and summing scores from these items to assign respondents to one of several categories which identify them at a certain risk level for meeting diagnostic criteria for depression or PTSD. The clinician or administrator is then allowed flexibility in following up on the responses to address both intricacies not covered by the screeners and behavioral health impact.

In clinical contexts, a cyberaggression screener may involve a similar approach by identifying whether a cyberaggression experience has occurred or not and saving complexities of the event (e.g., anonymous perpetrator, modality, and mental health impact) for the clinical follow-up interview. As endorsement rates of cyberaggression experiences remains relatively low (Modecki et al., 2014), including broadly worded items (e.g., “via electronic communication” as compared to “on Facebook”) or items asking about the most prevalent forms of cyberaggression (e.g., mean text messages, with intent to harm) is recommended. In research contexts without immediate clinical follow-up capabilities, including a few items in the screener pertaining to the behavioral health impact of these experiences if endorsed (Bauman, 2013) or expanding research into the various severity levels of cyberaggression experiences (Menesini, Nocentini, & Calussi, 2011) may prove useful. The screener may utilize an adaptive item format where if a respondent endorses experiencing cyberaggression, the respondent will subsequently be asked to rate how much of an impact this experience had on their well-being during a certain time period. This item format may also be used to inquire further details about the experience (e.g., modality, frequency) only if an item is endorsed. Examples of these types of item formatting are observed in emerging clinical intake and assessment software programs to inform evaluation and routine outcome monitoring such as OWL Outcome Assessments (Peterson & Fagan, 2017).

To provide a preliminary screener example, a two-factor model derived from the original CES was constructed and evaluated for both cyberaggression and cybervictimization items. The items selected for the cyberaggression model included items 1, 4, 6, and 9 for the "direct cyberaggression" subscale and items 15, 18, 19, and 20 for the "coercion" subscale (Figures 4.1 and 4.2). These items were selected based on inter-item correlations, factor loadings, removal of all sexually related items due to poor performance, and item content to capture broad facets of direct and indirect forms of cyberaggression without repeating unnecessary item content. Results indicated that this two-factor solution met both absolute and incremental fit indices' recommended cut-offs as well as demonstrated acceptable internal consistency reliability in both the college and high school samples (Table 4.1). Results therefore strongly support these revisions.

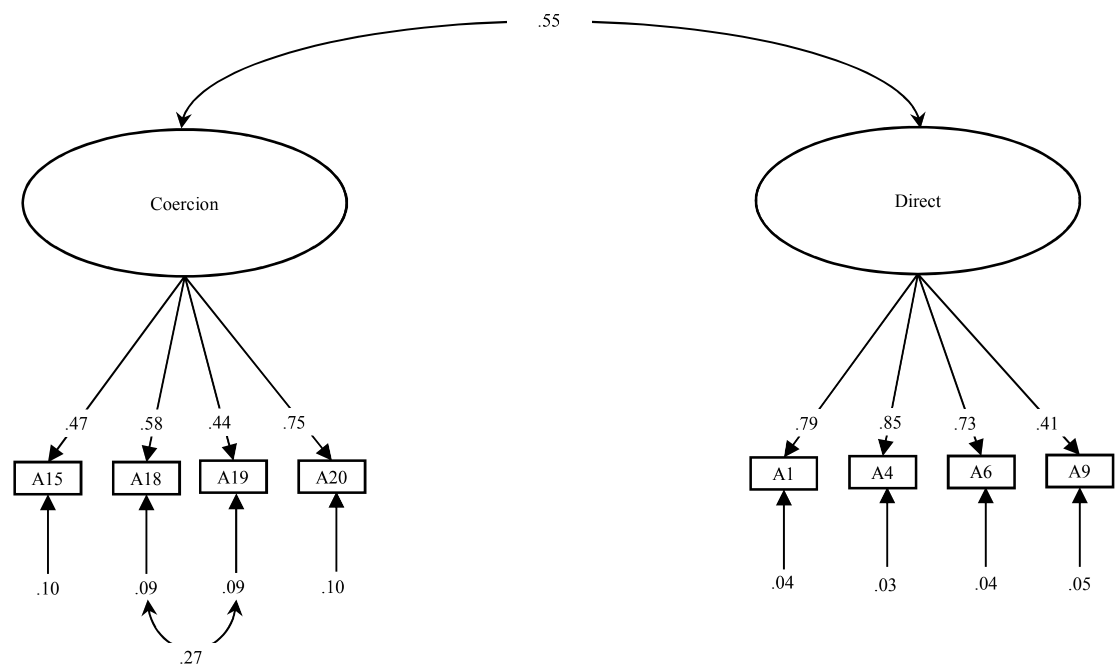

Figure 4.1. Results from the CES cyberaggression two-factor solution for college students. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

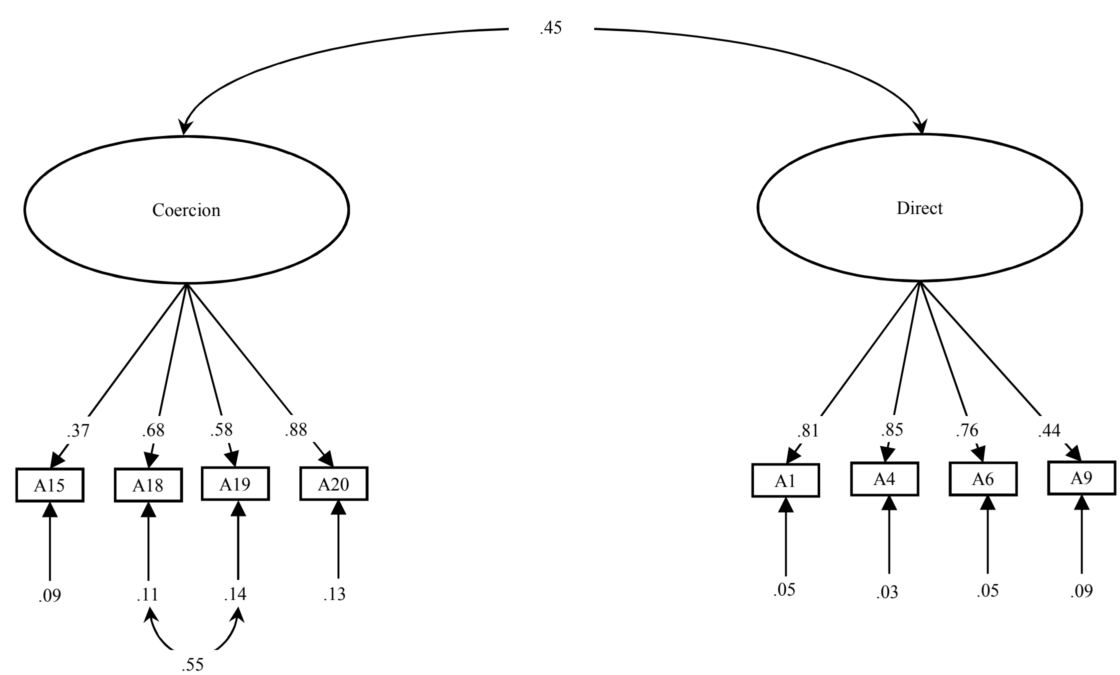

Figure 4.2. Results from the CES cyberaggression two-factor solution for high school students. Standardized factor loadings, error terms, and correlated factor/error terms are presented.

Table 4.1

Goodness-of-Fit Indicators for Proposed 2-Factor Cyberaggression Screener

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR	$\alpha^{\#}$
College	22.41*	18	.02	.99	.03	.78/.70
High School	13.44*	18	.00	1.00	.05	.82/.76

*$p > .05$
[#]Direct cyberaggression/Coercion

The items selected for the 2-factor cybervictimization model included items 9, 11, 12 and 13 for the “direct cybervictimization” subscale and items 1, 19, 20, and 21 for the “deception” subscale (Figures 4.3 and 4.4). These items were selected based on the same rationale as the cyberaggression items. Results indicated that this 2-factor solution met both absolute and incremental fit indices’ recommended cut-offs as well as demonstrated acceptable internal consistency reliability in both student samples (Table 4.2). Results again support these revisions.

The benefits of this example screener include the removal of poorly performing items and improvement of parsimony by simplifying the construct operationalization which has been identified as a major issue in the field (Menesini & Nocentini, 2009). Of course, not all facets or types of cyberaggression are included in such a screener although that is not the primary purpose. As the measurement of this form of cyberaggression appears in its preliminary stages, it is difficult to for research to subsequently inform law and policy surrounding this issue, especially given the complexities of the cyber realm (e.g., public vs. private, item content, intention of perpetrator, and modality).

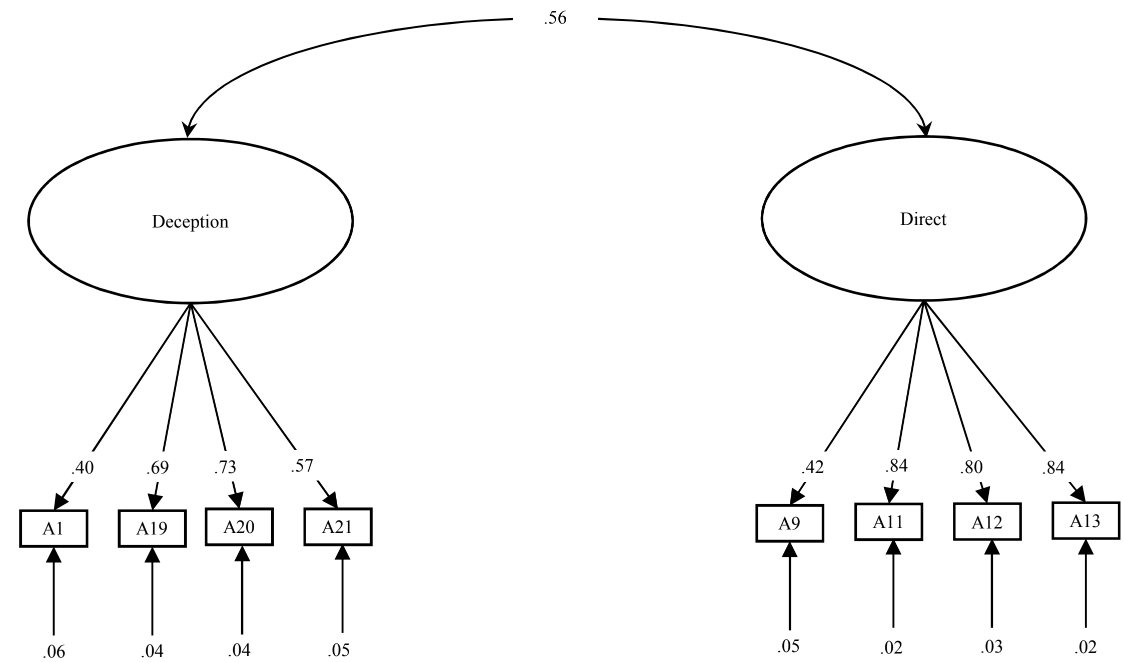

Figure 4.3. Results from the CES cybervictimization two-factor solution for college students. Standardized factor loadings, error terms, and correlated factors are presented.

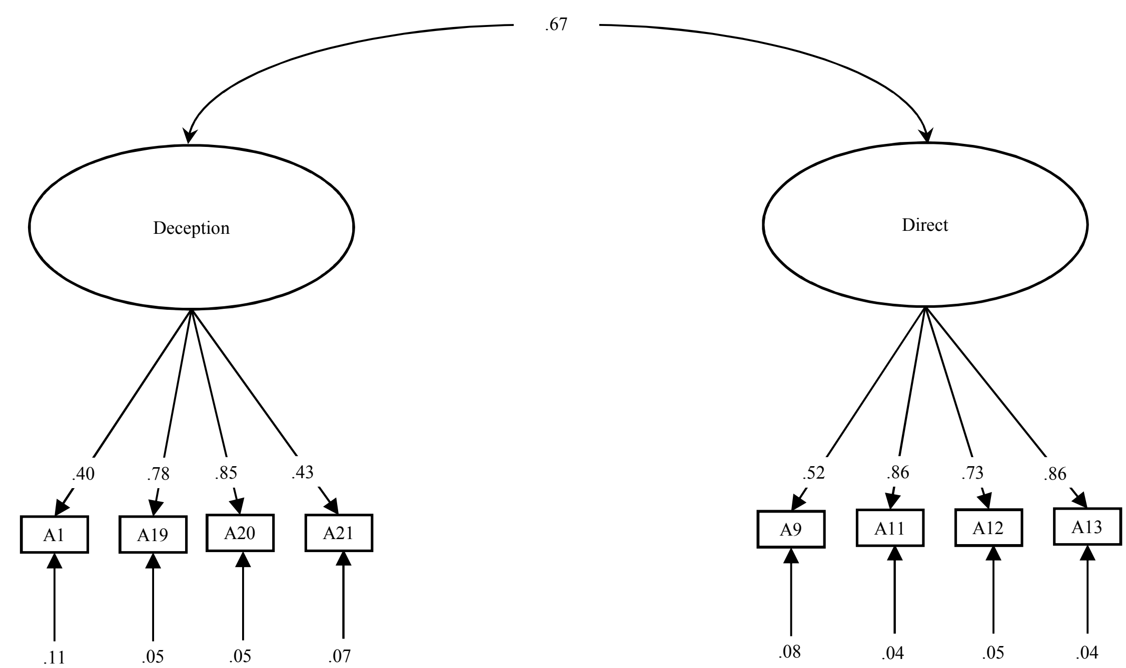

Figure 4.4. Results from the CES cybervictimization two-factor solution for high school students. Standardized factor loadings, error terms, and correlated factors are presented.

Table 4.2

Goodness-of-Fit Indicators for Proposed 2-Factor Cybervictimization Screener

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR	$\alpha^{\#}$
College	26.86*	19	.03	.99	.03	.81/.72
High School	27.83*	19	.05	.97	.05	.83/.70

*$p > .05$
[#]Direct cybervictimization/Deception

The development and scoring of screener items may therefore prove challenging as the process will need to consider numerous measurement issues and deciding how best to inform research, clinical practice, and policy. As mentioned, policy directives primarily care about establishing prevalence rates and determining harm. Accurate measurement and scoring of cyberaggression items is thus an important issue in screener development to assess prevalence rates. Many cyberaggression instruments attempt to measure the frequency of these experiences using a continuous variable Likert scale format. In some instances, such as in the present study however, substantial floor effects are observed in the data as there is little variability among rated frequencies of cyberaggression. In their evaluation of the Cyberbullying Scale, Menesini, Nocentini, and Calussi (2011) dichotomized participants' responses to accommodate substantial floor effect observed in their data. As policy is driven by prevalence rates that are frequently determined on a "yes/no" basis, it is important for future measurement research to consider whether cyberaggression is most effectively measured on a dichotomous "yes/no" or continuous variable format. Lastly, in assessing harm, screener development will have to consider whether and how to simultaneously evaluate both perpetration and victimization perspectives. Research suggests that individuals who are identified as a combination of perpetrator and victim experience the poorest behavioral health outcomes (e.g., Cassidy, Faucher, & Jackson, 2013). Thus, it may prove essential to evaluate both cyberaggression perpetration and victimization, with the consideration that operationalizing both aspects may require attention to item wording to lessen ambiguity and social response biases as compared to utilizing mirrored-item content across scales.

4.4 IMPLICATIONS OF NOMOLOGICAL NET ANALYSES

Investigation into convergent validity evidence for the CES yielded support for the majority of hypotheses. Of note, moderate correlations were observed between the cyberaggression and cybervictimization subscales and mental health difficulties in the college sample. Our results reflect prior research that has also indicated that both cyberaggressors and cybervictims experience mental health issues such as depression, anxiety, and suicidal ideation (Landoll et al., 2015; Schenk et al., 2013). There was a weak correlation observed between the direct cyberaggression subscale and proactive overt aggression subscale on the PCS in the high school sample. Cyberaggression research has remained inconclusive as to whether this act is a proactive or reactive form of aggression, although qualitative research has revealed that cyberaggressors attribute their negative online behaviors to extract revenge as compared to causing harm proactively (Hinduja & Patchin, 2008; Law, Shapka, Domene, & Gagné, 2012). These qualitative findings may inform the development of cyberaggression items in that language related to revenge or reactive behaviors should be integrated in item content.

As previously mentioned, several subscale correlations (e.g., sexual cyberaggression) were not estimated as they did not meet acceptable internal consistency reliability standards. Future research should expand upon the nomological net in the present study once additional evidence is provided for the underlying factor structure and internal consistency reliability of all CES subscales. Likewise, as further evidence is provided for the conceptualization and operationalization of these constructs, exploration into discriminative validity evidence is also needed as the present investigation only evaluated evidence for convergent validity.

4.5 IMPLICATIONS OF DESCRIPTIVE ANALYSES

Several mean differences were observed between demographic groups across cyberaggression and cybervictimization subscales. Males endorsed higher frequencies of perpetrating cyberaggression in college whereas females generally endorsed higher frequencies of cyberaggression in high school. Females in both college and high school, however, reported more experiences of sexual cybervictimization where males in college and high school reported more experiences of direct cybervictimization. This difference may also be attributed to sex differences that are observed in face-to-face aggression where females typically endorse experiencing greater rates of sexual victimization and males participating in more direct or overt forms of aggressive behavior such as berating or cursing (Dooley, Pyżalski, & Cross, 2009).

Concerning race/ethnicity, white participants were generally more involved in both cyberaggression and cybervictimization as compared to non-white participants in both college and high school samples. Our results contribute to the already mixed evidence as to whether prevalence rates of cyberaggression differ across various racial and ethnic populations (e.g., Bauman, Toomey, & Walker, 2013). Along with conducting additional prevalence studies, future research may consider whether experiences of cyberaggression and cybervictimization have a differential psychological impact on racial and ethnic populations and whether the types of cyberaggression experienced vary across these groups.

Means indicated similar endorsement in cyberaggression and cybervictimization among military-connected and civilian college participants; military-connected participants in high school reported higher mean levels of sexual cybervictimization and defamation, whereas civilian participants endorsed higher mean levels of direct cybervictimization. Although traditional aggression research has indicated higher frequencies of victimization among military-connected youth (Atuel et al., 2014), additional research on experiences of cyberaggression with a more representative military youth sample is needed. These initial results also highlight the need for additional research utilizing more advanced statistical techniques to evaluate cyberaggression and cybervictimization across demographic groups. Valid instrumentation is a necessary prerequisite, however, to progress the field in this direction.

4.6 STRENGTHS AND LIMITATIONS

There are several strengths to the present study. First, our study was one of the first investigations to fully examine a novel measure of cyberaggression and cybervictimization utilizing comprehensive, psychometric methodologies. Second, this is one of the first studies to address both cyberaggression and cybervictimization across age groups using a high school and college student sample. Considering limited research on college students (Schenk et al., 2013) and need for a measure which can be used over developmental time periods, we attempted to capture information to advance these lines of research. Third, our study is one of the first to suggest and provide preliminary evaluation for a cyberaggression/cybervictimization screener as a call for brief and effective measurement in this field.

The generalizability of our high school and college samples may be limited. High school participants attended a private school which may differentiate these participants based on sociodemographic and other indicators from the high school student population at-large. Our college student sample was also largely homogenous (i.e., predominantly female and white) which may impact score distributions and observed factor or intra-measure correlations. Lastly, a third limitation is that the present study did not directly investigate discriminative validity evidence for the CES. With the novel state of measurement in this field, future research should seek to concurrently assess both convergent and divergent validity evidence for the CES and other developed measures.

4.7 CONCLUSION

Measurement in the field of cyberaggression and cybervictimization has become a recent focus of research yet is limited in both its scope and evaluation. The CES is one of the few measures of cyberaggression and cybervictimization to be thoroughly analyzed through validated statistical methodologies. However, evaluation of the CES highlighted several areas for improvement which reflected the lack of uniformity, unnecessary complexity, and ultimately the overall ineffective measurement strategies discerned in current cyberaggression instrumentation. Given the cultural embeddedness of technology and electronic communication, it will be challenging to develop valid instrumentation to inform policies that consider a balance between recognizing the social desire to connect and communicate in the modern era as well as consequences associated with negative online/electronic behaviors. It is recommended that the development of a cyberaggression screening instrument to address the notable measurement issues observed in the field and to effectively inform policy directives be considered.

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APPENDIX A: INTER-ITEM CORRELATIONS FOR THE CES ITEMS

Table A.1

Inter-item Correlations for CES Cyberaggression Items (College)

	CES1	CES2	CES3	CES4	CES5
CES1	1.000				
CES2	0.138	1.000			
CES3	0.099	0.283	1.000		
CES4	0.149	0.167	0.415	1.000	
CES5	-0.029	-0.002	0.136	0.112	1.000
CES6	0.032	0.151	0.200	0.200	0.242
CES7	0.172	0.273	0.058	0.154	0.022
CES8	0.144	0.203	0.146	0.098	-0.012
CES9	0.124	0.129	0.136	0.155	0.093
CES10	0.018	0.078	0.200	0.116	0.111
CES11	0.030	0.063	0.130	0.124	0.139
CES12	0.029	0.052	0.099	0.106	0.112
CES13	0.077	0.071	0.191	0.158	0.103
CES14	0.105	0.122	0.132	0.050	0.055
CES15	0.041	0.103	0.106	0.188	0.090
CES16	0.072	0.181	0.129	0.104	0.138
CES17	0.002	0.213	0.092	0.130	0.020
CES18	-0.015	0.068	0.090	0.027	0.022
CES19	0.012	0.017	0.028	-0.005	-0.020
CES20	-0.018	0.068	0.134	0.067	0.071

	CES6	CES7	CES8	CES9	CES10
CES6	1.000				
CES7	0.170	1.000			
CES8	0.070	0.197	1.000		
CES9	0.220	0.214	0.178	1.000	
CES10	0.285	0.103	0.176	0.538	1.000
CES11	0.183	0.083	0.113	0.674	0.580
CES12	0.172	0.072	0.115	0.625	0.590
CES13	0.183	0.119	0.192	0.545	0.690
CES14	0.156	0.108	0.168	0.592	0.461
CES15	0.313	0.055	0.096	0.194	0.229
CES16	0.291	-0.010	0.126	0.161	0.147

CES17	0.321	0.159	0.196	0.342	0.390
CES18	0.116	-0.019	0.134	0.300	0.360
CES19	0.123	0.020	0.100	0.214	0.275
CES20	0.079	0.048	0.098	0.310	0.281

	CES11	CES12	CES13	CES14	CES15
CES11	1.000				
CES12	0.844	1.000			
CES13	0.727	0.758	1.000		
CES14	0.619	0.649	0.519	1.000	
CES15	0.264	0.246	0.231	0.109	1.000
CES16	0.201	0.193	0.171	0.191	0.451
CES17	0.395	0.386	0.397	0.303	0.444
CES18	0.333	0.307	0.325	0.330	0.166
CES18	0.266	0.292	0.278	0.260	0.209
CES20	0.311	0.311	0.310	0.377	0.194

	CES16	CES17	CES18	CES19	CES20
CES16	1.000				
CES17	0.302	1.000			
CES18	0.183	0.243	1.000		
CES19	0.205	0.294	0.551	1.000	
CES20	0.226	0.251	0.435	0.405	1.000

Table A.2

Inter-item Correlations for CES Cybervictimization Items (College)

	CES1	CES2	CES3	CES4	CES5
CES1	1.000				
CES2	0.324	1.000			
CES3	0.184	0.472	1.000		
CES4	0.212	0.375	0.288	1.000	
CES5	0.189	0.355	0.291	0.322	1.000
CES6	0.173	0.361	0.334	0.285	0.374
CES7	0.144	0.208	0.149	0.195	0.142
CES8	0.363	0.263	0.237	0.408	0.194
CES9	0.175	0.319	0.281	0.131	0.126
CES10	0.189	0.298	0.496	0.201	0.211
CES11	0.179	0.344	0.508	0.191	0.247
CES12	0.169	0.328	0.419	0.282	0.201
CES13	0.190	0.345	0.396	0.191	0.197
CES14	0.174	0.351	0.398	0.190	0.187
CES15	0.210	0.233	0.351	0.222	0.286
CES16	0.177	0.165	0.280	0.141	0.163
CES17	0.202	0.180	0.270	0.205	0.150
CES18	0.192	0.223	0.274	0.152	0.191
CES19	0.336	0.246	0.274	0.198	0.176
CES20	0.304	0.301	0.359	0.167	0.229
CES21	0.244	0.215	0.205	0.171	0.251

	CES6	CES7	CES8	CES9	CES10
CES6	1.000				
CES7	0.151	1.000			
CES8	0.243	0.127	1.000		
CES9	0.185	0.134	0.259	1.000	
CES10	0.175	0.093	0.228	0.329	1.000
CES11	0.213	0.071	0.268	0.305	0.851
CES12	0.185	0.027	0.267	0.308	0.623
CES13	0.222	0.046	0.264	0.408	0.649
CES14	0.217	0.075	0.255	0.414	0.574
CES15	0.190	0.126	0.232	0.293	0.382
CES16	0.167	0.115	0.223	0.243	0.337
CES17	0.182	0.118	0.229	0.267	0.317
CES18	0.217	0.160	0.182	0.251	0.384
CES19	0.182	0.267	0.288	0.183	0.319
CES20	0.348	0.192	0.301	0.268	0.431
CES21	0.147	0.333	0.236	0.081	0.267

	CES11	CES12	CES13	CES14	CES15
CES11	1.000				
CES12	0.677	1.000			
CES13	0.701	0.663	1.000		
CES14	0.634	0.616	0.820	1.000	
CES15	0.388	0.368	0.316	0.355	1.000
CES16	0.328	0.308	0.274	0.327	0.851
CES17	0.354	0.334	0.282	0.335	0.760
CES18	0.360	0.361	0.345	0.308	0.707
CES19	0.299	0.252	0.258	0.304	0.391
CES20	0.414	0.410	0.417	0.411	0.483
CES21	0.245	0.204	0.205	0.204	0.357

	CES16	CES17	CES18	CES19	CES20	CES21
CES16	1.000					
CES17	0.781	1.000				
CES18	0.735	0.662	1.000			
CES19	0.384	0.372	0.417	1.000		
CES20	0.476	0.526	0.526	0.566	1.000	
CES21	0.341	0.316	0.331	0.428	0.473	1.000

Table A.3

Inter-item Correlations for CES Cyberaggression Items (High School)

	CES1	CES2	CES3	CES4	CES5
CES1	1.000				
CES2	0.189	1.000			
CES3	0.156	0.372	1.000		
CES4	0.101	0.115	0.893	1.000	
CES5	0.015	0.102	0.045	0.028	1.000
CES6	-0.010	0.163	0.296	0.307	0.377
CES7	0.116	0.205	0.235	0.155	0.059
CES8	-0.011	0.124	0.051	0.001	0.424
CES9	0.106	0.146	0.245	0.182	0.145
CES10	0.087	0.114	0.194	0.144	0.170
CES11	0.096	0.177	0.234	0.160	0.167
CES12	0.068	0.155	0.203	0.138	0.073
CES13	0.048	0.156	0.147	0.101	0.157
CES14	0.085	0.051	0.126	0.081	0.147
CES15	0.057	0.172	0.233	0.233	0.559
CES16	0.026	0.158	0.339	0.329	0.652
CES17	0.145	0.104	0.236	0.212	0.507
CES18	0.033	0.134	0.075	-0.004	0.050
CES19	0.033	0.204	0.162	0.058	0.087
CES20	0.046	0.096	0.076	0.008	0.080

	CES6	CES7	CES8	CES9	CES10
CES6	1.000				
CES7	0.284	1.000			
CES8	0.073	0.069	1.000		
CES9	0.287	0.108	0.235	1.000	
CES10	0.171	0.124	0.173	0.720	1.000
CES11	0.246	0.035	0.196	0.701	0.619
CES12	0.228	0.198	0.106	0.634	0.664
CES13	0.192	0.156	0.204	0.628	0.674
CES14	0.179	0.056	0.207	0.614	0.596
CES15	0.239	0.093	0.531	0.236	0.227
CES16	0.238	0.093	0.447	0.119	0.120
CES17	0.314	-0.028	0.307	0.343	0.299
CES18	0.053	0.026	0.185	0.334	0.446
CES19	0.034	0.119	0.206	0.223	0.131
CES20	0.014	0.074	0.098	0.339	0.265

	CES11	CES12	CES13	CES14	CES15
CES11	1.000				
CES12	0.802	1.000			
CES13	0.753	0.847	1.000		
CES14	0.656	0.666	0.643	1.000	
CES15	0.245	0.203	0.311	0.201	1.000
CES16	0.121	0.036	0.154	0.129	0.724
CES17	0.326	0.211	0.276	0.264	0.603
CES18	0.344	0.422	0.512	0.400	0.236
CES19	0.346	0.300	0.338	0.235	0.234
CES20	0.337	0.410	0.438	0.419	0.192

	CES16	CES17	CES18	CES19	CES20
CES16	1.000				
CES17	0.521	1.000			
CES18	0.135	0.272	1.000		
CES19	0.171	0.180	0.388	1.000	
CES20	0.118	0.116	0.341	0.398	1.000

Table A.4

Inter-item Correlations for CES Cybervictimization Items (High School)

	CES1	CES2	CES3	CES4	CES5
CES1	1.000				
CES2	0.553	1.000			
CES3	0.236	0.294	1.000		
CES4	0.271	0.082	0.074	1.000	
CES5	0.205	0.292	0.266	0.051	1.000
CES6	0.327	0.324	0.291	0.092	0.218
CES7	0.171	0.204	0.046	0.001	-0.029
CES8	0.277	0.175	0.153	0.513	0.265
CES9	0.347	0.375	0.385	0.228	0.253
CES10	0.154	0.347	0.553	0.053	0.110
CES11	0.182	0.243	0.651	0.082	0.115
CES12	0.189	0.229	0.421	0.085	0.052
CES13	0.240	0.300	0.565	0.126	0.139
CES14	0.265	0.256	0.384	0.142	0.105
CES15	0.274	0.206	0.401	0.070	0.286
CES16	0.214	0.273	0.400	-0.014	0.364
CES17	0.218	0.205	0.455	-0.085	0.264
CES18	0.105	0.167	0.476	-0.070	0.203
CES19	0.310	0.258	0.646	0.141	0.173
CES20	0.347	0.299	0.475	0.016	0.145
CES21	0.106	0.145	0.186	-0.054	0.152

	CES6	CES7	CES8	CES9	CES10
CES6	1.000				
CES7	0.179	1.000			
CES8	0.089	0.182	1.000		
CES9	0.260	0.047	0.469	1.000	
CES10	0.219	0.003	0.165	0.399	1.000
CES11	0.188	-0.005	0.209	0.428	0.802
CES12	0.201	0.022	0.241	0.410	0.646
CES13	0.164	0.026	0.305	0.427	0.729
CES14	0.199	-0.011	0.313	0.413	0.642
CES15	0.224	0.158	0.192	0.437	0.284
CES16	0.166	-0.040	0.067	0.400	0.309
CES17	0.209	0.046	0.053	0.386	0.354
CES18	0.183	0.095	0.121	0.343	0.359
CES19	0.233	0.114	0.320	0.340	0.434
CES20	0.208	0.064	0.262	0.335	0.432
CES21	-0.016	0.131	0.061	0.163	0.099

	CES11	CES12	CES13	CES14	CES15
CES11	1.000				
CES12	0.620	1.000			
CES13	0.742	0.638	1.000		
CES14	0.613	0.665	0.800	1.000	
CES15	0.303	0.383	0.280	0.286	1.000
CES16	0.361	0.301	0.294	0.216	0.749
CES17	0.446	0.412	0.337	0.290	0.662
CES18	0.425	0.262	0.353	0.310	0.492
CES19	0.507	0.310	0.495	0.431	0.261
CES20	0.498	0.420	0.437	0.461	0.342
CES21	0.187	0.187	0.119	0.150	0.333

	CES16	CES17	CES18	CES19	CES20	CES21
CES16	1.000					
CES17	0.767	1.000				
CES18	0.602	0.662	1.000			
CES19	0.307	0.375	0.442	1.000		
CES20	0.303	0.417	0.492	0.650	1.000	
CES21	0.314	0.377	0.309	0.308	0.418	1.000

APPENDIX B: DESCRIPTIVE STATISTICS FOR THE CES ITEMS

Table B.1

Item Means, Standard Deviations, Skewness, and Kurtosis for the CES Items (College)

Item	Mean	SD	Skewness	Kurtosis
#1	0.06	.32	6.39	45.55
#2	0.10	.32	3.51	12.53
#3	0.05	.26	6.68	53.60
#4	0.06	.30	5.76	38.09
#5	0.02	.14	6.25	37.02
#6	0.12	.40	3.97	18.18
#7	0.05	.26	5.29	29.73
#8	0.12	.41	4.59	27.66
#9	0.87	.97	1.08	0.74
#10	0.79	1.07	1.58	2.28
#11	0.77	.97	1.32	1.37
#12	0.73	1.01	1.52	1.97
#13	0.74	1.08	1.68	2.58
#14	1.39	1.48	0.99	-0.03
#15	0.13	.40	3.51	14.91
#16	0.05	.24	5.22	29.27
#17	0.36	.73	2.32	5.74
#18	0.43	.79	2.11	4.57
#19	0.15	.48	3.94	18.78
#20	0.45	.81	2.09	4.72
#21	0.16	.45	3.16	11.06
#22	0.16	.45	3.17	11.01
#23	0.48	.69	1.38	1.70
#24	0.22	.49	2.59	9.26
#25	0.04	.26	7.41	62.41
#26	0.26	.63	2.79	8.14
#27	0.06	.30	6.43	50.18
#28	0.28	.56	2.09	4.49
#29	0.75	.92	1.22	1.16
#30	0.91	.99	1.11	1.09
#31	1.03	.97	0.98	1.04
#32	1.52	1.40	0.93	0.12

#33	1.05	1.07	1.26	1.75
#34	1.03	1.10	1.30	1.76
#35	0.79	.97	1.07	0.28
#36	0.69	.92	1.22	0.78
#37	0.97	1.00	0.90	0.36
#38	0.60	.87	1.56	2.48
#39	0.34	.61	1.80	2.79
#40	0.75	.92	1.29	1.87
#41	0.21	.54	3.45	17.45

Note: n = 463. Items 1-20 = Cyberaggression, Items 21-41 = Cybervictimization

Table B.2

Item Means, Standard Deviations, Skewness, and Kurtosis for the CES Items (High School)

Item	Mean	SD	Skewness	Kurtosis
#1	0.06	.40	10.16	118.62
#2	0.02	.39	7.94	61.02
#3	0.04	.20	6.56	46.70
#4	0.04	.30	10.58	124.44
#5	0.05	.35	8.95	90.62
#6	0.11	.42	4.24	18.76
#7	0.03	.20	8.18	72.08
#8	0.12	.55	5.46	31.44
#9	0.78	1.03	1.44	1.57
#10	0.89	1.21	1.55	1.92
#11	0.70	1.14	1.81	2.70
#12	0.78	1.25	1.74	2.26
#13	0.78	1.23	1.95	3.31
#14	1.31	1.68	1.04	-0.33
#15	0.20	.57	4.22	24.88
#16	0.09	.45	7.62	71.56
#17	0.36	.76	2.62	8.28
#18	0.27	.67	3.32	14.34
#19	0.09	.35	4.82	28.29
#20	0.32	.88	3.26	11.01
#21	0.16	.51	3.52	12.74
#22	0.18	.49	9.16	2.44
#23	0.44	.39	6.28	3.71
#24	0.15	.45	16.70	7.94
#25	0.02	.41	61.02	2.79
#26	0.17	.26	6.95	4.72
#27	0.07	.44	23.48	3.29
#28	0.19	.54	11.68	1.54
#29	0.46	.75	1.46	1.42
#30	0.91	1.23	1.20	1.70
#31	0.87	1.21	2.55	2.55
#32	1.60	1.73	0.90	-0.57
#33	0.93	1.25	1.38	0.95
#34	1.15	1.40	1.27	0.68
#35	0.35	.71	2.18	4.72
#36	0.26	.59	2.45	5.67
#37	0.39	.75	2.10	4.20
#38	0.36	.80	2.49	5.98
#39	0.34	.71	2.60	7.71

#40	0.59	.92	1.48	1.42
#41	0.14	.44	3.66	14.70

Note: n = 200. Items 1-20 = Cyberaggression, Items 21-41 = Cybervictimization

APPENDIX C: ITEM CONFIGURATIONS FOR CES AND REVISED 3-FACTOR MODEL

Table C.1

CES Cyberaggression and Cybervictimization Items

Item	Cyberaggression	Cybervictimization
#1	Have you posted an embarrassing picture of someone electronically where other people could see it?[PH]	Has someone distributed information electronically while pretending to be you?[PH]
#2	Have you posted a picture of someone electronically that they did not want others to see?[PH]	Has someone changed a picture of you in a negative way and posted it electronically?[PH]
#3	Have you posted a picture electronically of someone doing something illegal?[PH]	Has someone written mean messages about you publically electronically?[PH]
#4	Have you sent a rude message to someone electronically?[M]	Has someone logged into your electronic account and changed your information?[PH]
#5	Have you teased someone electronically?[M]	Has someone posted a nude picture of you electronically?[PH]
#6	Have you been mean to someone electronically?[M]	Has someone printed out an electronic conversation you had and then showed it to others?[PH]
#7	Have you called someone mean names electronically?[M]	Have you completed an electronic survey that was supposed to remain private but the answers were sent to someone else?[PH]
#8	Have you made fun of someone electronically?[M]	Has someone logged into your electronic account and pretended to be you?[PH]

CES Cyberaggression and Cybervictimization Items - Continued

Item	Cyberaggression Subscale	Cybervictimization Subscale
#9	Have you cursed at someone electronically?[M]	Has someone posted an embarrassing picture of you electronically where other people could see it?[PH]
#10	Have you sent an unwanted pornographic picture to someone electronically?[UW]	Has someone called you mean names electronically?[M]
#11	Have you tried to meet someone in person that you talked to electronically who did not want to meet you in person?[UW]	Has someone been mean to you electronically?[M]
#12	Have you sent an unwanted sexual message to someone electronically?[UW]	Has someone cursed at you electronically?[M]
#13	Have you sent an unwanted nude or partially nude picture to someone electronically?[UW]	Has someone made fun of you electronically?[M]
#14	Have you sent a message to a person electronically that claimed you would try to find out where they live?[UW]	Has someone teased you electronically?[M]
#15	Have you tried to get information from someone you talked to electronically that they did not want to give?[UW]	Have you received a nude or partially nude picture that you did not want from someone you were talking to electronically?[UW]
#16	Have you sent a message electronically to a stranger requesting sex?[UW]	Have you received a pornographic picture that you did not want from someone electronically that was not spam?[UW]
#17	Have you asked a stranger electronically about what they were wearing?[UW]	Have you received an unwanted sexual message from someone electronically?[UW]

CES Cyberaggression and Cybervictimization Items – Continued

Item	Cyberaggression Subscale	Cybervictimization Subscale
#18	Have you pretended to be someone else while talking to someone electronically?[D]	Have you received an offensive picture electronically that was not spam?[UW]
#19	Has someone shared personal information with you electronically when you pretended to be someone else?[D]	Has someone pretended to be someone else while talking to you electronically?[D]
#20	Have you lied about yourself to someone electronically?[D]	Has someone lied about themselves to you electronically?[D]
#21	---	Have you shared personal information with someone electronically and then later found the person was not who you thought it was?[D]

Note. [PH] = Public Humiliation subscale, [M] = Malice subscale, [UC] = Unwanted Contact subscale, [D] = Deception subscale.

Revised 3-factor Cyberaggression Model Item Reconfigurations

Sexual Cyberaggression

1. Have you sent an unwanted pornographic picture to someone electronically?
2. Have you tried to meet someone in person that you talked to electronically who did not want to meet you in person?
3. Have you sent an unwanted sexual message to someone electronically?
4. Have you sent an unwanted nude or partially nude picture to someone electronically?
5. Have you sent a message electronically to a stranger requesting sex?

Coercion

1. Have you sent a message to a person electronically that claimed you would try to find out where they live?
2. Have you tried to get information from someone you talked to electronically that they did not want to give?
3. Have you asked a stranger electronically about what they are wearing?
4. Have you pretended to be someone else while talking to someone electronically?
5. Has someone shared personal information with you electronically when you pretended to be someone else?
6. Have you lied about yourself to someone electronically?

Direct Cyberaggression

1. Have you sent a rude message to someone electronically?
2. Have you teased someone electronically?
3. Have you been mean to someone electronically?
4. Have you called someone mean names electronically?
5. Have you made fun of someone electronically?
6. Have you cursed at someone electronically?
7. Have you posted an embarrassing picture of someone electronically where other people could see it?
8. Have you posted a picture of someone electronically that they did not want others to see?
9. Have you posted a picture electronically of someone doing something illegal?

Revised 3-factor Cybervictimization Model Item Reconfigurations

Sexual Cybervictimization

1. Have you received a nude or partially nude picture that you did not want from someone you were talking to electronically?
2. Have you received a pornographic picture that you did not want from someone electronically that was not spam?
3. Have you received an unwanted sexual message from someone electronically?
4. Have you received an offensive picture electronically that was not spam?

Direct Cybervictimization

1. Has someone called you mean names electronically?
2. Has someone been mean to you electronically?
3. Has someone cursed at you electronically?
4. Has someone made fun of you electronically?
5. Has someone teased you electronically?

Defamation

1. Has someone distributed information electronically while pretending to be you?
2. Has someone changed a picture of you in a negative way and posted it electronically?
3. Has someone written mean messages about you publicly electronically?
4. Has someone logged into your electronic account and changed your information?
5. Has someone posted a nude picture of you electronically?
6. Has someone printed out an electronic conversation you had and then showed it to others?
7. Has someone logged into your electronic account and pretended to be you?
8. Has someone posted an embarrassing picture of you electronically where other people could see it?
9. Has someone pretended to be someone else while talking to you electronically?
10. Has someone lied about themselves to you electronically?
11. Have you shared personal information with someone electronically and then later found the person was not who you thought it was?

APPENDIX D: ANALYTICAL METHOD FOR CES MODEL REVISIONS

D.1. CYBERAGGRESSION MODEL REVISIONS

We used the following analytic method to investigate a revised model solution for the CES cyberaggression model:

Step 1: Conducted an exploratory factor analysis (EFA) for the high school sample to uncover the underlying structure of the CES cyberaggression items.

Step 2: Integrated EFA results with theoretical considerations and item intercorrelations to conduct an EFA with target rotation for the high school sample. The Target EFA places additional restrictions on model parameters compared to a traditional EFA where items are partially specified to serve as indicators for the proposed latent variable structure.

Step 3: Performed a CFA for both college and high school samples with the revised model solution as informed by the previous two steps. A CFA is more restrictive compared to the Target EFA where items are now fully specified to serve as indicators for the proposed latent variable structure.

Step 1 Results: Findings from the 1-, 2-, 3-, and 4-factor EFA solutions for the high school sample are presented in Table D.1. Results indicated that a three-factor model best fit the CES cyberaggression items for high school students which likely reflects the strong correlation (r = .99) between the “unwanted contact” and “deception” cyberaggression subscales in the originally hypothesized four-factor CFA solution.

Table D.1

Goodness-of-Fit Indicators of Models for CES Cyberaggression Items

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR
Exploratory Analyses: Step 1					
EFA High School					
1-Factor	700.71	170	.13	.52	.14
2-Factor	459.34	151	.10	.72	.08
3-Factor	**240.97**	**133**	**.06**	**.90**	**.06**
4-Factor	355.46	116	.10	.78	.05
Exploratory Analyses: Step 2					
Target EFA High School 3-Factor##	238.72*	131	.06	.90	.05

**p* < .001
##"Sexual cyberaggression," "direct cyberaggression," and "coercion" subscales.

Step 2 Results: We examined item content and inter-item correlations in an attempt to identify new item configurations based on the proposed three-factor solution. Upon examining item content, several items included on the "unwanted contact" subscale contained sexually related content (e.g., "Have you sent an unwanted sexual message to someone electronically?" and "Have you sent a message electronically to a stranger requesting sex?"). Research on aggression has identified sexual aggression to be a construct unique from other commonly identified forms of aggression such as physical and relational aggression. This is likely a result of both theoretical considerations surrounding personalities and attitudes of sexual aggressors compared to aggressors more generally as well as real-world legal implications of committing a sexually-related crime (Vega & Malamuth, 2007). Research has also identified a growing trend of communicating sexually-related material in the cyber realm, commonly referred to as "sexting" (Dake, Price, Maziarz, & Ward, 2012). Although sexting behaviors were initially theorized as voluntary acts, sexting can transition into cyberaggressive behavior if an individual utilizes peer pressure, sends unwanted sexual messages/pictures to another, or intentionally forwards sexual messages/pictures to unintended parties (Dake et al., 2012). Lastly, observed inter-item correlations among sexually related items in our high school and college samples indicated mostly moderate to strong correlations (*r*s = .12 – .89), although items 10 and 16 weakly correlated with all CES cyberaggression items. Considering both theory proposed in the traditional aggression and cyberaggression literature and the observed inter-item correlations in our sample, it may make conceptual sense to interpret sexually-related forms of aggression in the cyber realm as a distinct construct.

EFA factor loadings also suggested that the items originally included on the "malice" subscale strongly covaried with each other and the "public humiliation" items. The content of these items reflect more direct forms of cyberaggression (e.g., "Have you sent a rude message to someone electronically?" and "Have you posted an embarrassing picture of someone electronically where other people could see it?"). The remaining CES cyberaggression items included three items on the original "unwanted contact" subscale (i.e., "Have you sent a message to a person electronically that claimed you would try to find out where they live?," "Have you tried to get information from someone you talked to electronically that they did not want to give?," and "Have you asked a stranger electronically about what they are wearing?") and the "deception" subscale items. These items all generally appear to utilize coercive tactics to obtain information that the recipient did not want to originally provide via electronic communication.

Utilizing these revised item configurations to form “sexual cyberaggression,” “direct cyberaggression,” and “coercion” subscales, results from the three-factor Target EFA solution for the high school sample supported this latent construct conceptualization as incremental fit indices met or approached cut-off recommendations (Table D.1).

D.2. CYBERVICTIMIZATION MODEL REVISIONS

We used the following analytic method to investigate a revised model solution for the CES cybervictimization model:

Step 1: Conducted an exploratory factor analysis (EFA) for the high school sample to uncover the unrestricted, underlying structure of the CES cybervictimization items.

Step 2: Integrated EFA results with theoretical considerations and item intercorrelations to conduct an EFA with target rotation for the high school sample.

Step 3: Performed a CFA for both college and high school samples with the revised model solution as informed by the previous two analytical steps.

Step 1 Results: Findings from the 1-, 2-, 3-, and 4-factor EFA solutions for the high school sample are presented in Table D.2. Results suggested that a four-factor model would best fit the CES cybervictimization items for high school students. Upon examining all item factor loadings, item 7 (“Have you completed an electronic survey that was supposed to remain private but the answers were sent to someone else?”) did not load on any factor in any of the potential solutions. This is likely due to low endorsement in the high school sample (M = .07, SD = .29) as well as item content unrelated to a

Table D.2

Goodness-of-Fit Indicators of Models for CES Cybervictimization Items

Model	MLM χ^2	*df*	RMSEA	CFI	SRMR
Exploratory Analyses: Step 1					
EFA High School					
1-Factor	738.42	189	.12	.58	.11
2-Factor	482.70	169	.10	.76	.08
3-Factor	450.96	150	.10	.77	.06
4-Factor	**350.94**	**132**	**.09**	**.83**	**.05**
Exploratory Analyses: Step 2					
Target EFA High School 4-Factor[#]	213.59*	112	.06	.92	.04
Exploratory Analyses: Step 3					
CFA 4-Factor Solution High School[##]	269.12*	160	.06	.91	.07
Exploratory Analyses: Step 4					
Target EFA High School 3-Factor[###]	234.42*	126	.06	.92	.04

*$p < .001$
[#]Removed CES cybervictimization item #7.
[##]"Public Humiliation" and "Deception" subscales correlated $r = .87$.
[###]"Sexual cybervictimization," "direct cybervictimization," and "defamation" subscales.

cyberaggressive act (e.g., intention of the survey answers being sent to someone else may not be interpreted as aggression). As such, this item was removed in subsequent models.

Step 2 Results: We examined item content and inter-item correlations in an attempt to identify potential item configurations based on the proposed 4-factor solution. Theoretical considerations were made to be consistent with how latent constructs were conceptualized to represent cyberaggression. That is, all cybervictimization items that included sexually-related content were theorized to represent a sexual cybervictimization latent variable; this involved specifying one item from the "public humiliation" factor

(“Has someone posted a nude picture of you electronically?”) on the “unwanted contact” subscale. All other items as well as item factor loadings supported the originally hypothesized four-factor model. Thus, we ran the reconfigured model along with item #7 removed from the solution. The results from the Target EFA lent further support for the four-factor model as indicated by incremental fit indices meeting recommended cut-off values (Table D.2).

Step 3 Results: Given evidentiary support from our EFA and Target EFA solutions, we performed a revised four-factor CFA solution for the high school sample. Although the Satorra-Bentler chi-square was significant, incremental fit indices met or approached recommended cut-off values. Of note, however, the “public humiliation” and “deception” subscales correlated at $r = .87$ and the “public humiliation” and “malice” subscales correlated at $r = .82$. As previously mentioned, strong correlations between factors may potentially result in multicollinearity in a solution due to poor discriminative validity between latent variables (Kenny, 2012). Considering these strong correlations between factors, and to propose a cybervictimization model solution consistent with the revised cyberaggression factor solution, we additionally explored a potential three-factor model for the cybervictimization items.

Step 4 Results: We conducted a Target EFA based on the proposed three-factor solution. Items were partially specified to load on three factors (i.e., “sexual cybervictimization,” “direct cybervictimization,” and “defamation” subscales). Items originally on the “unwanted contact” subscale were all included on the renamed “sexual cybervictimization” subscale to better represent their item content. Items on the original “malice” subscale remained in the renamed “direct cybervictimization” subscale. Items on the “public humiliation” and “deception” subscales were combined to form the novel “defamation” subscale based on the observed strong correlation between factors in Step 3. To further support this revision, our EFA analyses indicated that the “defamation” items all loaded on the same factor. That is, all items concerned false pretenses being claimed about the cybervictim (e.g., “Has someone changed a picture of you in a negative way and posted it electronically?”) or the cyberaggressor (e.g., “Has someone lied about themselves to you electronically?”). The three-factor Target EFA supported these revisions for our high school sample (Table D.2).