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Predicting Cyberbullying Perpetration in Emerging Adults: A Theoretical Test of the Barlett Gentile Cyberbullying Model

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The Barlett and Gentile Cyberbullying Model (BGCM) is a learning-based theory that posits the importance of positive cyberbullying attitudes predicting subsequent cyberbullying perpetration. Furthermore, the tenants of the BGCM state that cyberbullying attitude are likely to form when the online aggressor believes that the online environment allows individuals of all physical sizes to harm others and they are perceived as anonymous. Past work has tested parts of the BGCM; no study has used longitudinal methods to examine this model fully. The current study ($N = 161$) employed a three-wave longitudinal design to test the BGCM. Participants (age range: 18–24) completed measures of the belief that physical strength is irrelevant online and anonymity perceptions at Wave 1, cyberbullying attitudes at Wave 2, and cyberbullying perpetration at Wave 3. Results showed strong support for the BGCM: anonymity perceptions and the belief that physical attributes are irrelevant online at Wave 1 predicted Wave 2 cyberbullying attitudes, which predicted subsequent Wave 3 cyberbullying perpetration. These results support the BGCM and are the first to show empirical support for this model. Aggr. Behav. 43:147–154, 2017.

Keywords: **cyberbullying; cyber-aggression**

INTRODUCTION

The increasing ease of access and usage of the Internet has strong implications for modern communication. According to the Pew Research Center, of US youth aged 13–17, 71% use Facebook, 52% use Instagram, 41% use Snapchat, and 33% use Twitter (Lenhart, 2015). Not all Internet usage is benign in nature, and one negative consequence of online communication is cyberbullying, defined as, "any behavior performed through electronic communication or digital media by individuals or groups that repeatedly communicates hostile or aggressive messages intended to inflict harm or discomfort on others" (Tokunaga, 2010, p. 278). We argue that it is useful to have a theoretical model of how relevant variables operate to elicit cyberbullying. The current study used a three-wave longitudinal design to examine several understudied processes that may predict cyberbullying in an emerging adult sample.

CYBERBULLYING THEORY

Although several variables have been shown to reliably predict or correlate with cyberbullying perpetration (see Kowalski, Giumetti, Schroeder, & Lattanner, 2014 for a recent meta-analysis), a minority of this research has been concerned with theory. Research that has tested cyberbullying predictors within a theoretical context has applied well-established psychological and communication-based theories involved in predicting cyberbullying, including: Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1977), General Aggression Model (GAM; Anderson & Bushman, 2002), and General Strain Theory (GST; Agnew, 2009). Studies applying these theories have found that cyberbullying can be predicted by aspects of each specific theory (see Doane, Pearson, & Kelley, 2014 for TRA; Kowalski et al., 2014 for GAM; and Patchin & Hinduja, 2011 for GST).

One advantage to utilizing these (and other) theories to predict cyberbullying behavior is the vast research supporting these theories; however, one key limitation is that these theories are concerned with aggression in

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general, and only subsequently applied to cyberbullying. This distinction is important. Olweus (2012) argued that cyberbullying is just another form of traditional bullying, and his data show that cyber-victimization is less frequent than traditional victimization. Others have shown significant correlations between traditional and cyberbullying (e.g., Kowalski, Morgan, & Limber, 2012; Wright & Li, 2013) further demonstrating the overlap between these two forms of bullying that are not accounted for in the aforementioned theories. We argue that GAM, TRA, or GST cannot sufficiently add incremental validity to predict cyberbullying to address the claims made by Olweus (and others).

We are only aware of one theory that specifically addresses the psychological processes involved in cyberbullying: the Barlett and Gentile Cyberbullying Model (BGCM; Barlett & Gentile, 2012). Derived from the literature suggesting that cyber and traditional bullying are correlated but psychologically different forms of behaviors (i.e., Dooley, Pyżalski, & Cross, 2009; Vanderbosch & Van Cleemput, 2008), the BGCM takes a learning approach to explain why individuals cyberbully others over time. Specifically, when an individual attacks another online for the first time, that perpetrator learns certain attributes from positively-perceived consequences of the cyber-attack. Barlett and Gentile (2012) posited that an online aggressor perceives himself/herself to be more anonymous online than off-line (e.g., Wright, 2013) and believes that physical strength (e.g., muscle size, height, etc.) is less relevant online (compared to the real world; Barlett, Prot, Anderson, & Gentile, in press). Continued cyber-attacks and subsequent learning of these perceptions and beliefs are additional learning trials that eventually lead to the development of positive cyberbullying attitudes, which are the immediate precursor to cyberbullying behavior. The BGCM is a learning-based theoretical model of cyberbullying that delineates how an initial cyber-attack can eventually lead to later continued cyberbullying behavior via learning processes.

ANONYMITY PERCEPTIONS AND BELIEF IN THE IRRELEVANCE OF PHYSICAL STATURE

The crux of the Barlett and Gentile (2012) cyberbullying model is the postulate that: (i) anonymity perceptions and (ii) the belief in the irrelevance of physical stature are two related knowledge structures that predict cyberbullying attitudes. Akin to broader aggression models (i.e., GAM; Anderson & Bushman, 2002), we believe that continued positively reinforced learned experiences with cyberbullying will contribute to the formulation of both these cyberbullying-specific learned knowledge structures. Each will be briefly discussed.

Perception of Anonymity

The Center of Disease Control surveyed over 15,000 high school students and found that of those cyber-victimized, 67% reported that cyberbullying occurred via Instant Messaging (IM) programs while 24% occurred via e-mail and 15% via text messages (CDC, 2011). The BGCM posits that individuals are more likely to feel anonymous in IM programs because aggressors can replace their real names and identity with fake names (or handles)—a characteristic of IM that is absent in email and text messaging (mostly). Indeed, Barlett, Gentile, and Chew (2016) found that IM frequency was positively related to the perception that harm can be done online anonymously (anonymity perceptions), which predicted positive attitudes towards cyberbullying and subsequent cyberbullying. In contrast e-mail was negatively related to these anonymity perceptions. These findings and others (e.g., Wright, 2013) suggest that perceiving oneself as anonymous online is a strong predictor of cyberbullying-related outcomes (see also Barlett, 2015).

Belief in the Irrelevance of Physical Stature

A possible reason why cyberbullying may be seen as an attractive method for causing harm is because anyone with a device connected to the Internet (e.g., tablet, computer, cellular phone) can cause harm independent of their physical stature. In the traditional bullying domain, it is often the taller and physically stronger youth who bully their smaller and physically weaker peers (e.g., Unnever & Cornell, 2003). However, as Vanderbosch and Van Cleemput (2008) argue, since cyberbullying is accomplished via technology this assumption may not be as relevant in the online world. Barlett et al. (in press) termed this the belief in the irrelevance of muscularity in online bullying (BI-MOB) and found that these beliefs predicted cyberbullying attitudes and subsequent behavior. The beliefs are not synonymous with computer skills or abilities, which Barlett et al. (in press) found did not account for additional variance in cyberbullying above BI-MOB.

EXPANDING OUR THEORETICAL UNDERSTANDING OF CYBERBULLYING

Despite the recent theoretical developments in our understanding of cyberbullying through the lens of the BGCM, much empirical work is still needed. Indeed, we are unaware of any longitudinal study that has tested the full BGCM. Several studies have longitudinally shown that anonymity perceptions (Barlett, 2015; Barlett et al., 2016) or the belief that muscularity is irrelevant online (Barlett et al., in press) predicts cyberbullying through cyberbullying attitudes. Only correlational research (Barlett & Gentile, 2012) has tested the combined influence of both anonymity perceptions and BI-MOB in the same model. The current study will be the first published longitudinal study testing the postulates of BGCM. Explicitly, we will test the effect that *both* anonymity perceptions and beliefs that the online world is an equalizing arena to harm others independent of physical size have on cyberbullying attitudes and behavior using a short-term longitudinal study with emerging adults. We predict that the BGCM will be valid and that the strength and anonymity constructs will predict subsequent cyberbullying behavior through the development of cyberbullying attitudes. In addition, we will test the relations in the BGCM while statistically controlling for traditional bullying perpetration.

METHOD

Procedure

IRB approval was granted by the corresponding author's ethics committee. Participants were solicited via a posting in the college's Student Digest that purportedly went to the entire college student body (similar methods were used by Barlett et al., 2016) and interested participants completed the online informed consent before the aforementioned questionnaires at Wave 1 (dates of data collection were 9-15-14 to 9-19-14), Wave 2 (dates of data collection were 1-7-15 to 1-16-15), and Wave 3 (dates of data collection were 3-31-15 to 4-7-15). After data collection was complete, participants were compensated, thanked, and fully debriefed.

Participants

One hundred and sixty-one (80% female) emerging adults from a small eastern liberal arts college participated in the current study. The average age for the sample was 19.38 ($SD = 1.16$) years (age range 18–24 years). The majority of the sample was Caucasian (80.4%). The age and ethnicity data from our sample is similar to the college population. Participants were paid $10.00 US for completing questionnaires online for each wave. At Wave 2, 148 (82% female) and at Wave 3, 131 (82% female) were retained (77% of the original sample).

Materials

Demographics. A brief demographic questionnaire was used to measure age, sex, ethnicity, and year in school.

Perceived anonymity. The Anonymity questionnaire (Wright, 2013) included four items rated on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). A sample item is: "I am confident that I would not be caught if I engaged in mean online behaviors." We removed one item: "I do not believe that anything you say or write about another person on the internet stay in cyberspace in some form. That is, if someone does something mean to someone else on the Internet it goes away." After several statistical tests, deleting this item increased the reliability of the measure and helped ensure a single factor structure. These items were summed and scored such that higher scores indicate increased perceptions of anonymity.

Belief in the irrelevance of muscularity for online bullying. The BI-MOB subscale of the Attitudes toward Internet Actions Questionnaire (Barlett & Gentile, 2012) was used to assess the belief that one's physical size and related attributes are less influential in the mediated world and, as a result, being online affords an equalizing arena for the physically strong and weak to cause harm. This measure consists of five-items that has participants rate their level of agreement with the items on a 1 (*strongly disagree*) to 5 (*strongly agree*) rating scale. A sample item is: "I can send mean emails or text messages to anybody no matter how big or small they are." These items were summed such that higher scores indicate a greater belief that one's physical stature is irrelevant to online bullying.

Positive attitudes toward cyberbullying. Cyberbullying attitudes were evaluated using the Attitudes toward Cyber-Behavior—Long Form measure (Barlett et al., 2014). This is a 20-item questionnaire that has participants rate their level of agreement with the items on a 1 (*strongly agree*) to 5 (*strongly disagree*) rating scale. A sample item is: "It is OK to bully others online if they deserve it." Items were summed such that higher scores indicate more positive attitudes toward cyberbullying.

Cyberbullying perpetration. Cyberbullying behavior was evaluated using the Malice subscale of the Cyberbullying Experiences Survey (Doane et al., 2014). This six-item subscale has participants rate how frequently they engaged in electronic behaviors on a 1 (*never*) to 6 (*everyday/almost everyday*) rating scale. A sample item is: "Have you sent a rude message to someone electronically." Items were summed such that higher scores indicate higher cyberbullying perpetration.

Traditional bullying. An eight-item Traditional Bullying Questionnaire (Kyriakikdess, Kaloyirou, & Lindsay, 2006) was used to measure how frequently participants engaged in real-world (non-cyber) bullying behavior in the past year. Participants rated how frequently they engaged in traditional bullying behavior on a 1 (*never)* to 6 (*everyday/almost everyday*) rating scale. A sample item is: "I hit, kicked, pushed, and shoved others around." Items were summed such that higher scores represented higher engagement in traditional bullying behavior.

Additional questionnaires were administered, but not analyzed. These include a researcher-created online frequency questionnaire, a researcher-created online medium anonymity measure, the Ang and Goh (2010) cyberbullying measure, the Ybarra, Diener-West, and Leaf (2007) cyberbullying measure, the Barlett and Gentile (2012) cyberbullying attitude scale, the Barlett and Gentile (2012) anonymity scale, a researcher-created online content repeatability and online permanency measure, and an assessment of computer skills (Barlett et al., in press). These measures were not analyzed due to either their exploratory nature or poor psychometric properties.

Data Analysis Plan

Preliminary analyses showed that all measures were significantly skewed (see Table I). Therefore, we present both parametric (Pearson) and non-parametric (Spearman rank ordered) correlations. We examined sex differences in our key variables using parametric (independent *t*-tests) and non-parametric (Z tests associated with the Mann–Whitney *U* test) procedures. MPLUS using maximum likelihood estimation, a method that can statistically handle missing data, was used for our longitudinal path modeling to test the BGCM. This model consisted of Wave 1 anonymity perceptions and BI-MOB as correlated exogenous variables that predicted Wave 2 cyberbullying attitudes, which in turn predicted Wave 3 cyberbullying behavior. We also controlled for Wave 1 cyberbullying behavior by having it: (i) predict Wave 2 cyberbullying attitudes; (ii) predict Wave 3 cyberbullying behavior; and (iii) correlate with Wave 1 anonymity perceptions and BI-MOB (termed Model 1). Second, we test the same model but control for traditional bullying at Wave 1 by having this variable predict Wave 3 cyberbullying (termed Model 2). Bootstrapping procedures were used in both models due to the skewed nature of the cyberbullying measures.

RESULTS

Correlations

Table I displays the zero-order correlations using both parametric (Pearson correlation coefficients) and non-parametric (Spearman rank ordered correlation coefficients) procedures. The internal consistency (Cronbach alpha) of each questionnaire is also presented. Of theoretical interest, Wave 1 anonymity perceptions and BI-MOB both correlate significantly with Wave 2 cyberbullying attitudes (rs $> .31$, ps $< .01$). Also, Wave 2 cyberbullying attitudes predict Wave 3 cyberbullying behavior ($r = .51$, $p < .001$).

Sex Differences

Table II displays the results from several independent samples *t*-tests showing sex differences in our measured variables. Of interest, results show that males report significantly higher levels of Waves 1 and 3 cyberbullying, Wave 1 anonymity perceptions, Wave 1 bullying, and Wave 2 cyberbullying attitudes than females. Despite these differences, we caution readers in interpreting these results due to the large proportion of female participants relative to males.

Path Modeling

We test two path models. The first is Model 1, which was our longitudinal test of the full version of the BGCM. Results show that the model fits the data well, $\chi^2 = .13$ (df = 2), $p = .94$, RMSEA = .00 (90% CI:

TABLE I. Zero-Order Correlations Between Relevant Variables

	1	2	3	4	5	6
1: Wave 1 cyberbullying	—	.23**	.45**	.48**	.51**	.59**
2: Wave 1 anonymity	.20**	—	.40**	.29**	.36**	.19*
3: Wave 1 BI-MOB	.53**	.36**	—	.26**	.42**	.22*
4: Wave 1 traditional bullying	.54**	.30**	.38**	—	.51**	.39**
5: Wave 2 cyberbullying attitudes	.50**	.32**	.48**	.52**	—	.46**
6: Wave 3 cyberbullying	.61**	.13	.35**	.40**	.51**	—
Mean	10.25	5.67	9.03	10.14	27.17	9.07
SD	4.70	2.76	3.85	2.61	9.36	4.31
Minimum score	6.00	3.00	5.00	8.00	20.00	6.00
Maximum score	27.00	15.00	21.00	22.00	71.00	27.00
Possible range	6–36	3–15	5–25	8–48	20–100	6–36
Cronbach's alpha	.85	.75	.69	.67	.92	.84
Skew	1.41	.94	.92	1.53	2.44	2.16
SE (skew)	.19	.19	.19	.19	.20	.22

Note: Correlations below the diagonal are Pearson correlations and correlations above the diagonal are Spearman ranked ordered correlations.
$^{**}p < .01$, $^{*}p < .05$.

TABLE II. Descriptive and Inferential Statistics for Sex Differences

	Male		Female				
Outcome	Mean (SD)	*N*	Mean (SD)	*N*	*t*	*d*	*Z* (Mann–Whitney *U*)
Wave 1 cyberbullying	11.84 (5.22)	32	9.83 (4.50)	126	2.18*	.35	2.43*
Wave 1 anonymity	8.06 (3.04)	32	5.06 (2.37)	128	6.04**	.96	5.05**
Wave 1 BI-MOB	10.09 (4.77)	33	8.74 (3.54)	125	1.81	.29	1.16
Wave 1 bullying	11.45 (3.27)	33	9.81 (2.32)	125	3.31**	.53	3.00**
Wave 2 cyberbullying attitudes	34.92 (14.52)	24	25.57 (7.02)	108	4.69**	.82	3.38**
Wave 3 cyberbullying	10.52 (5.13)	23	8.55 (3.72)	97	2.12*	.39	1.82

**$p < .01$, *$p < .05$.

.00–.04), CFI = 1.00, TLI = 1.00, SRMR = .00. Figure 1 shows the unstandardized path coefficients with 95% confidence intervals around the bootstrapped estimates. All relationships are significant, supporting the original BGCM model. Furthermore, the mediation effects found via several indirect effects for the unstandardized relations support BGCM: the relation between Wave 1 anonymity perceptions and Wave 3 cyberbullying behavior is mediated by Wave 2 cyberbullying attitudes ($B = .06$, 95% CI: .01–.15), and the relation between Wave 1 BI-MOB and Wave 3 cyberbullying is significantly mediated by Wave 2 cyberbullying attitudes ($B = .01$ to .14).

Model 2 was identical to Model 1, but we controlled for Wave 1 traditional bullying by: (i) correlating it with Wave 1 cyberbullying, anonymity perceptions, and BI-MOB and (ii) having it predict Wave 3 cyberbullying and Wave 2 cyberbullying attitudes. Results show that the model fits the data well, $\chi^2 = .12$ (df = 2), $p = .94$, RMSEA = .00 (90% CI: .00–.03), CFI = 1.00, TLI = 1.00, SRMR = .00. Figure 2 shows the unstandardized path coefficients and 95% confidence intervals around the bootstrapped estimates. All direct relations found in Model 1 were retained except for the non-significant relation between Wave 1 cyberbullying and Wave 2 cyberbullying attitudes. Wave 1 bullying predicts Wave 2 cyberbullying attitudes and correlates with the other Wave 1 exogenous predictors.

DISCUSSION

We sought to examine several remaining theoretical gaps in the Barlett Gentile Cyberbullying Model (BGCM). First, we tested the longitudinal relations between anonymity perceptions, the belief that physical attributes are irrelevant online, cyberbullying attitudes, and cyberbullying perpetration to seek to replicate the original postulates of the BGCM longitudinally. Examination of the correlation coefficients show support for the BGCM postulates (independent of whether one is viewing Pearson or Spearman Rank Ordered correlations). Furthermore, consistent with this model, results from our path modeling showed that both anonymity perceptions and BI-MOB at Wave 1 predicted Wave 2 cyberbullying attitudes, which predicted subsequent cyberbullying perpetration at Wave 3. When we controlled for Wave 1 traditional bullying, results were largely replicated.

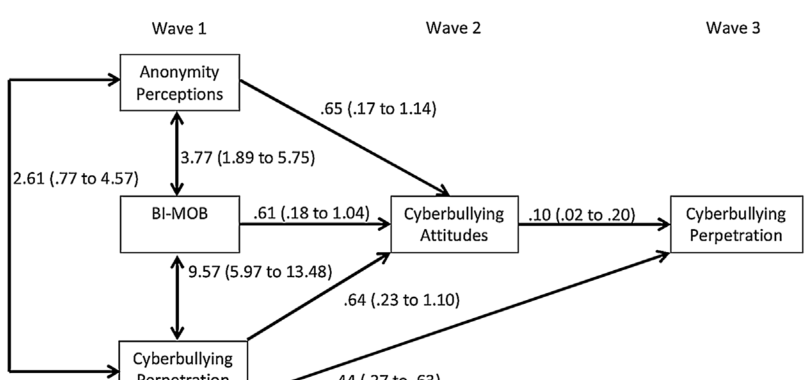

Fig. 1. Model 1: Testing the original Barlett Gentile Cyberbullying Model. *Note*: Values are unstandardized path coefficients with 95% confidence intervals from our bootstrapping procedure. BI-MOB, Belief in the irrelevance of muscularity in online bullying.

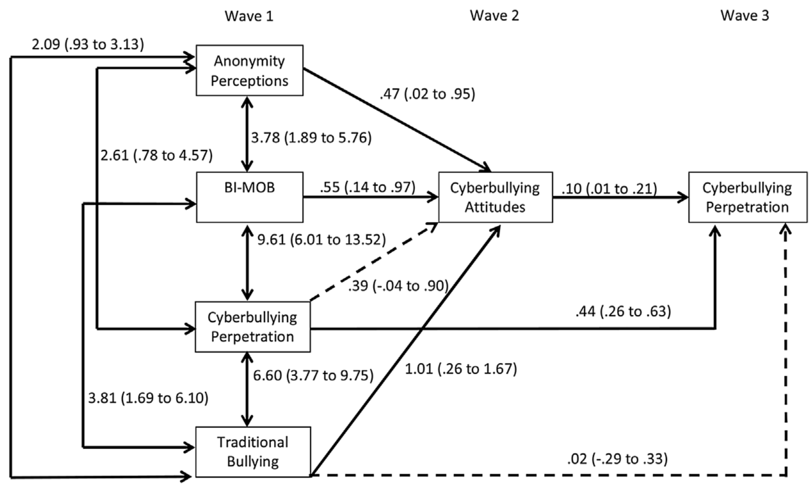

Fig. 2. Model 2: Testing the original Barlett Gentile Cyberbullying Model while controlling for bullying. *Note*: Values are unstandardized path coefficients with 95% confidence intervals from our bootstrapping procedure. BI-MOB, Belief in the irrelevance of muscularity in online bullying; Dashed lines indicate a non-significant relation.

Cyberbullying Theory

The application of pre-existing theories to cyberbullying is useful but may not provide incremental validity to predicting cyberbullying beyond traditional bullying. Olweus (2012) argued that cyberbullying is a specialized form of traditional bullying; however, we argue that even though the correlation between traditional and cyberbullying is strong (e.g., Barlett & Gentile, 2012), there are important psychological differences between these two forms of bullying that warrant study. Therefore, theory that specifies the psychological mechanisms involved in cyberbullying while also showing incremental validity evidence above traditional bullying is needed. The BGCM is the only theory that we are aware of that accomplishes these goals, and the current study is the first longitudinal attempt to assess this model fully. Data from the current study show support for the longitudinal relation between: (i) BI-MOB and cyberbullying attitudes and (ii) cyberbullying attitudes and cyberbullying perpetration while controlling for traditional bullying perpetration. These relations are predicted in the Barlett and Gentile Cyberbullying Model and support past work (see Barlett & Gentile, 2012; Barlett et al., in press; Barlett, 2015).

Findings from the current study also can be used to help inform or change interventions. If a predictor of cyberbullying behavior can be reliably found using well-established theory across multiple samples, measures, and study designs (i.e., correlational and longitudinal), then interventions can and should be adapted to incorporate such findings. Several researchers have shown that cyberbullying intervention programs can be successful at reducing cyberbullying behavior (Salmivalli, Karna, & Poskiparta, 2011; Kowalski & Agatston, 2008 2009); however, to our knowledge none of them incorporate several key tenants of the BGCM that could be easily taught to youth.

Limitations and Future Work

Limitations exist in the current research that should be addressed with future research. First, there was a disproportionate number of female, relative to male, participants. Research by Barlett and Coyne (2014) showed that for college-aged participants males are more likely to cyberbully than females, a finding supported here. Although we report *t*-tests comparing males and females on our variables, caution must be warranted due to the heavily biased female sample. Future work should test the longitudinal postulates of the current study with a more balanced sex comparison. Related to this issue, the majority of our sample was Caucasian females, which limits the generalizability of our findings; however, we have no theoretical reason to expect differences in the relations of our variables with a more diverse sample. This is speculative, however, and future work should either sample a more heterogeneous population or offer comparisons between those of different ages and ethnic backgrounds.

Second, the time lag between waves of data collection was approximately three months. Ideally, lengthier lags would allow for tests to determine how long these longitudinal effects last. Our decision to use such short time lags between scale administration periods was made for practical reasons: we wanted three data points to appropriately test for mediated effects within one academic year. Fear of losing participants who graduated after Wave 3 prevented us from expanding the time frame any longer. Future work should attempt to replicate the current findings while allowing for longer time lags between data collection periods.

Third, the BI-MOB and bullying measures had questionable internal validity. Table 1 displays the Cronbach's alpha for each scale, which clearly shows this limitation. Further examination of the measures themselves showed that the Cronbach's alpha would not have increased for either scale had any single item been removed. We retained these measures due to their theoretical importance; however, this is one limitation when researching an ever-changing technology-based behavior (and related constructs). Future work should continue to create or modify measures to keep current with technological advances and changing attitudes/ beliefs regarding said technology.

Finally, in addition to carefully selecting measures to assess cyberbullying (and related constructs), future work should continue to add to the BGCM by testing additional variables that may either be learned and aid in the formation of positive cyberbullying attitudes or directly predict cyberbullying behavior. Barlett et al. (in press) found evidence to suggest that harmful online technological abilities (e.g., create a computer virus, send a computer virus) does not predict cyberbullying attitudes; however, other variables may. Online disinhibition and the belief that online content is permanent are likely candidates that warrant continued study. Further, research by Barlett and Gentile (2012) found a high correlation between cyberbullying perpetration and cyber-victimization. Future research should assess cyber-victimization to add as a covariate.

Final Remarks

With growing support for the theoretical underpinnings of cyberbullying perpetration, scholars are closer to understanding the processes by which cyberbullying develops, and with the expansion of these models, we can continue to identify additional methods for addressing this societal issue. Clearly, cyberbullying is complicated, and future research should continue to delve into variables that may influence both how cyberbullying develops and how it is retained over time. Hopefully, with continued advances in our understanding of cyberbullying, data and theory can be used to inform interventions to reduce cyberbullying behavior.

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