Psychology of Popular Media Culture
2016, Vol. 5, No. 2, 171–180

2160-4134/16/$12.00 http://dx.doi.org/10.1037/ppm0000055

Predicting Cyberbullying From Anonymity

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Anonymity has been considered one of the constructs that differentiate traditional bullying from cyberbullying; however, few published studies have actually tested how and why anonymity influences cyberbullying behavior longitudinally. We posit that aggressor-perceived anonymity predicts cyberbullying behavior and positive attitudes toward cyberbullying. Additionally, positive cyberbullying attitudes would mediate aggressor-perceived anonymity and cyberbullying behavior. The current study used a 4-wave longitudinal design over the course of one academic year on college-aged participants (N = 146 [at Wave 1]; average age = 19.21). Specifically, participants completed measures of anonymity, cyberbullying attitudes, and cyberbullying behavior 4 times approximately every 2 months. Results using path analysis showed (a) strong stability over time for the variables and (b) several mediated paths between Wave 1 anonymity and Waves 3 and 4 cyberbullying behaviors through Wave 2 cyberbullying attitudes. These results remained using both maximum likelihood estimation and bootstrapping techniques. Overall, the results showed that aggressor-perceived anonymity is an important risk factor for later cyberbullying behavior.

Keywords: aggression, bullying, Internet

The exponential increase in the use of the Internet and mobile phones in the past decade has brought the world into a digital age where communication and social activities are achievable across geographical barriers and time zones. The Internet is now considered a central and important element in the lives of youths and adults (Lenhart, Purcell, Smith, & Zickuhr, 2010). Most youths use various electronic and computer-based communication tools regularly (Mishna, McLuckie, & Saini, 2009) and consider them indispensable to their social lives (Kowalski, Limber, & Agatston, 2008). Indeed, youth can now disseminate ideas, communicate, shop, and carry out myriad other activities online through their computers, tablets, cellular phones, and TV sets. Although we believe that the ease of transferring ideas and knowledge will undoubtedly be beneficial for learning and education, some may use it to harm others.

The ease of Internet accessibility and the increase in Internet and mobile phone usage has generated yet another milieu for bullying to take place, in cyber-space. For youth, bullying has therefore extended from the school environment to the electronic realm (Smith et al., 2008). Cyberbullying has been defined ". . . any behavior performed through electronic 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). Despite the growing concern of cyberbullying frequency by parents, educators, and law-makers alike, the predictors of cyberbullying are understudied. The purpose of the current research was to examine the influence of one such possible predictor: aggressor-perceived anonymity. Several researchers

This article was published Online First August 18, 2014.
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have suggested that anonymity is an important cyberbullying predictor (see Barlett, 2015; Barlett & Gentile, 2012; Vanderbosch & Van Cleemput, 2008; Wright, 2013). However, there is a paucity of research testing whether cyberbullying frequency and anonymity are longitudinally related (cf., Wright, 2013). Thus, the current study used a four-wave short-term longitudinal research design to test whether aggressor-perceived anonymity in the cyber-world is related to subsequent cyberbullying, and if positive cyberbullying attitudes mediated these relations.

Positive Attitudes Toward Cyberbullying and Anonymity in Cyberbullying

Research on the antecedents and predictors of cyberbullying has been growing. Thus far, it has been found that the frequency of use of the Internet (Walrave & Heirman, 2011), level of computer and Internet ability (Vanderbosch & Van Cleemput, 2009), and risky Internet use (Erdur-Baker, 2010) predict cyberbullying perpetration. Also, males (especially in late adolescence and early adulthood; Barlett & Coyne, 2014) and children aged between 12 to 15 years are more likely to cyberbully (Erdur-Baker, 2010). This predictive information is vital in addressing the issue of cyberbullying. To the extent that key predictors can be clustered, populations of potential cyberbullies identified, or conditions of cyberbullying can be manifested have important intervention-focused extensions.

In determining what we consider important predictors of cyberbullying, key statistical, psychological, and theoretical differences between cyberbullying and traditional bullying were examined. These include (a) how repetition is construed in the online versus offline world (see Slonje, Smith, & Frisen, 2012), (b) how cyberbullying does not contain any physical harm to the victim (see Vanderbosch & Van Cleemput, 2008), and (c) anonymity (see Barlett, 2015; Barlett & Gentile, 2012; Vanderbosch & Van Cleemput, 2008; Wright, 2013). Although this is not an exhaustive list, we believe it is important to isolate one of these several factors, and, thus, the current research will focus exclusively on anonymity as a key cyberbullying predictor.

Anonymity can manifest itself myriad ways online. However, it should be noted that anonymity is not a necessary condition for cyberbullying behavior. Indeed, the cybervictim may be able to identify who bullied them. We posit that in the online world, anonymity may be more pronounced because the aggressor may not be as identifiable and the bully does not need to have a previous relationship with the victim. Importantly, the aggressor's perceived anonymity may enhance cyberbullying frequency. This does not preclude that traditional bullying is not anonymous. Indeed, a traditional bully may spread rumors about others or send threatening or degrading information on notes. However, we (and others; Barlett, 2015) argue that the mediated world offers the bully an increased feeling of perceived anonymity that is not as available in the "real world."

Research has elucidated how anonymity can influence antisocial behavior online. For instance one study found that 53% of comments posted anonymously were uncivil compared with 29% of comments posted nonanonymously (Santana, 2014). Another study coded 5,230 online forums for anonymity based on two primary criteria: (a) if the online content was posted by "anonymous" rather than a name or handle, and (b) based on the number of exchanges between person A and person B (higher numbers of exchanges may suggest a relationship between the two individuals; hence not anonymous) and found that the majority of cyberbullying attacks were classified as anonymous (Moore, Nakano, Enomoto, & Suda, 2012). Cross-sectional research showed that anonymity perceptions correlated with cyberbullying behavior (Barlett & Gentile, 2012). Finally, longitudinal work (using two time points approximately six months apart) showed that Wave 1 beliefs in anonymity significantly predicted Wave 2 cyber-aggression (Wright, 2013).

Theory

Although there is literature identifying anonymity as a key trait of cyberbullying, the psychological processes underlying anonymity in cyberbullying has hardly been explored. Broadly, our theory is grounded in the General Learning Model (GLM; Gentile et al., 2009). GLM posits that exposure to a stimulus acts as a learning trial, and continued experiences with that stimulus are related to eventual learned and automatized knowledge structures (e.g., attitudes). The formation of such knowledge structures is then related to the changes in one's personality, which can predict behavior in an immediate situation. Although this theory was originally postulated to explain media effects on behavior (Gentile et al., 2009), Barlett and Gentile (2012) used these theoretical postulates to offer a theoretical rationale for cyberbullying behavior. Barlett and Gentile (2012), in their cyberbullying model, posited that after a cyberbullying attack, the aggressor is likely to learn (at least) two consequences of their behavior: (a) the aggressor is anonymous and (b) the power differential that is pronounced in the traditional bullying domain is removed. Indeed, these two learned behaviors have been described as key differences between traditional and cyberbullying behaviors (Vanderbosch & Van Cleemput, 2008). Theoretically, believing that one is anonymous and cannot get punished for their aggressive online behaviors and understanding that anybody, no matter how physically strong, can attack others online should lead to the development of positive attitudes toward cyberbullying. This postulate has been supported in previous work (Barlett & Gentile, 2012; Barlett, 2015) and is a direct extension of the GLM. Finally, the formation and automatization of positive attitudes toward cyberbullying is hypothesized to predict cyberbullying behavior, which has also received limited empirical support (Barlett & Gentile, 2012).

The current research is focused exclusively on the anonymity prediction of the Barlett and Gentile (2012) model. Namely, we hypothesize that cyberbullying attitudes will mediate the relation between anonymity and cyberbullying behavior. However, the Barlett and Gentile (2012) model is not the only theoretical model to discuss the importance of anonymity in the online world. Suler (2004) proposed an "online disinhibition effect" to describe the abandonment of social inhibitions that regulate face-to-face interactions when one is on the Internet. Suler (2004) posited six processes that describe why individuals may behave differently online versus face-to-face; however, only one focuses on anonymity: dissociative anonymity, defined as when one separates their actions from the self online due to perceived anonymity. In other words, if one attacks someone online by sending a damning instant message, the anonymity afforded the aggressor online allows the cyberbully to distance their self from their actions. Suler's (2004) dissociative anonymity corresponds with how Barlett and Gentile (2012) conceptualize anonymity. Finally, in accordance with GLM, we believe that with continued cyberbullying actions cyberbullies will learn (a) that they are anonymous, (b) they cannot be identified, and (c) their aggressive actions are dissociated from the self, which should cause the formation and automatization of positive cyberbullying attitudes that likely predict subsequent cyberbullying behavior.

Despite the strong theoretical convergence between the Barlett and Gentile (2012) model and Suler's (2004) postulates (using GLM as a broader theoretical learning backdrop), there is a lack of empirical support for such theoretical integration with longitudinal data. Although Wright (2013) found support for the longitudinal link between anonymity and cyberbullying behaviors, the mediating mechanisms have gone understudied. Barlett and Gentile (2012) and Barlett (2015) found support for these postulates using cross-sectional data, but longitudinal evidence has still eluded the scientific community. Thus, the current research used a four-wave longitudinal study testing the relations between anonymity, cyberbullying attitudes, and cyberbullying behaviors.

Method

Participants

One hundred and forty-six (78% female) undergraduate students from a small liberal arts college participated in the current study for monetary incentives (participants were paid $10 US for each Wave of data collection). The average age of the sample was 19.21 (SD = 1.23) years. The majority of participants were Caucasian (78%). As with many longitudinal studies, there was some attrition over time. At Wave 2, 129 (79% female) of the original sample completed Wave 2 questionnaires (11% attrition from Wave 1). At Wave 3, 99 (81% female) of the original sample completed Wave 3 questionnaires (32% attrition from Wave 1 and 23% from Wave 2). Finally, at Wave 4, 99 (83% female) of the original sample completed Wave 4 questionnaires.

Materials[1]

Anonymity. To measure anonymity, we used the Anonymity subscale of the Attitude and Strength Differential Scale (Barlett & Gentile, 2012). Participants rated their level of agreement to five items using a 1 (*strongly disagree*) to 5 (*strongly agree*) rating scale. A sample item includes, "Sending mean emails or text messages is easy to do because I am not face-to-face with the other person." All items were summed, such that higher scores indicate more anonymity.

Positive attitudes toward cyberbullying. To measure positive attitudes toward cyberbullying, the Positive Attitudes toward Cyberbullying Questionnaire (PACQ; Barlett & Gentile, 2012) was used. This is a 9-item questionnaire that asks participants to rate their level of agreement on a 1 (*strongly disagree*) to 5 (*strongly agree*) rating scale. A sample item includes, "It is acceptable to send mean e-mails to others when they deserve it." Certain items were reverse scored and then summed such that higher scores indicated more positive attitudes toward cyberbullying.

Cyberbullying. The cyberbullying scale of Ang and Goh (2010) was used to assess cyberbullying behavior. This is a 9-item questionnaire that asks participants to indicate how often they cyber-bullied others in the past 12 months on a 1 (*never*) to 5 (*about a few times every week*) rating scale. A sample item includes, "I made fun of someone by sending/posting stories, jokes, or pictures about him/her." These items were summed, such that higher scores indicate more cyberbullying behavior.

Demographics. A demographic questionnaire was used to assess age, sex, ethnicity, the date that the participant completed the study, and other demographic information.

Procedure

The current data are a part of a much larger emerging adulthood/media habits research project.[2] Only the relevant cyberbullying analyses were presented. The current study was approved by the Institutional Review Board at Gettysburg College. In September (of 2013), participants completed the online informed consent document along with the anonymity, positive attitudes toward cyberbullying, cyberbullying, and demographic questionnaires.

Approximately two months later, participants completed a modified version of the aforementioned measures. We modified the instructions to ask about the behaviors in the past two months (rather than past 12 months). Also the rating scale was changed to reflect this shortened time frame. For instance, if the original scale had "Once or twice this year" as response option 2, it was changed to read "Once or twice in the past 2 months." Wave 3 was collected approximately two months after Wave 2 using identical measures as in Wave 2. Finally, Wave 4 was collected approximately two months after Wave 3. The internal consistency measures of the scales are included in the correlation matrix presented in Table 1.

Results

Data Analysis Plan

Because we are assessing antisocial behaviors and attitudes using self-reported measures, it is important to first test the distributional properties of the key variables. Specifically, we assessed the degree of predicted skew in the measured constructs. Next, we tested the zero-order correlations between all variables. To test our main hypotheses, we conducted a path model using MPLUS. Missing data were handled using maximum likelihood estimation techniques. Because the major-

[1] Additional cyberbullying-related questionnaires were included in the current study. However, these scales were not included in the analyses for either theoretical reasons or low reliability made the scale unusable. These scale included the strength differential scale (Barlett & Gentile, 2012), cyberbullying reinforcement scale (Barlett & Gentile, 2012), the Ybarra, Diener-West, and Leaf (2007) cyberbullying questionnaire, a modified media habits questionnaire (Gentile, Lynch, Linder, & Walsh, 2004; Barlett, 2015), and two research-created computer self-efficacy measures.

[2] Because these data also are related to an independent project testing emerging adulthood changes over time and the variables that predict that change, the following questionnaires were also included but are not relevant to the current study's theoretical developments: social competence (Robinson, Fetterman, Hopkins, & Krishnakumar, 2013), subjective well-being (Diener, Emmons, Larsen, & Griffin, 1985), independence (Quick, Joplin, Nelson, & Quick, 1992), emerging adulthood facets (Reifman, Arnett, & Colwell, 2007), and research-created helicopter parenting and worry scales.

Table 1
Bivariate Correlations and Descriptive Statistics

	1	2	3	4	5	6	7	8	9	10	11	12
1	—	.55**	.58**	.33**	.36**	.28**	.39**	.41**	.24**	.25**	.24*	.29**
2	.56**	—	.65**	.54**	.37**	.41**	.37**	.52**	.33**	.27**	.31**	.26*
3	.71**	.68**	—	.51**	.17	.28**	.29**	.32**	.39**	.28**	.33**	.26*
4	.31**	.40**	.68**	—	.13	.23*	.25*	.36**	.31**	.18†	.34**	.33**
5	.30**	.35**	.10	.01	—	.65**	.62**	.70**	.26**	.36**	.38**	.22*
6	.21*	.40**	.19†	.11	.65**	—	.64**	.75**	.41**	.48**	.37**	.32**
7	.29**	.38**	.23*	.15	.63**	.65**	—	.67**	.25*	.42**	.44**	.39**
8	.35**	.39**	.27*	.28**	.67**	.72**	.68**	—	.48**	.44**	.46**	.40**
9	.29**	.33**	.30**	.27**	.29**	.42**	.30**	.49**	—	.44**	.52**	.54**
10	.18†	.34**	.21†	.08	.36**	.51**	.50**	.50**	.46**	—	.67**	.50**
11	.21*	.31**	.31**	.21†	.40**	.46**	.52**	.54**	.55**	.68**	—	.65**
12	.23*	.22*	.27*	.31**	.23*	.33**	.42**	.44**	.56**	.56**	.71**	—
Mean	10.76	10.11	10.22	10.34	9.20	9.28	8.82	8.96	14.89	14.90	13.78	14.24
StDev	2.16	1.61	2.23	2.38	3.28	3.60	3.41	3.33	4.22	4.58	4.25	4.56
Skew	2.32	2.79	3.22	3.44	0.30	0.54	0.57	0.47	0.35	0.53	0.82	0.63
SE (Skew)	0.20	0.22	0.25	0.25	0.20	0.22	0.24	0.26	0.21	0.22	0.25	0.25
Minimum	9.00	9.00	9.00	9.00	5.00	5.00	5.00	5.00	9.00	9.00	9.00	9.00
Maximum	23.00	19.00	23.00	23.00	18.00	19.00	18.00	18.00	24.00	28.00	26.00	27.00
Possible range	9–45	9–45	9–45	9–45	5–25	5–25	5–25	5–25	9–45	9–45	9–45	9–45
Cronbach's Alpha	0.58	0.55	0.70	0.75	0.58	0.70	0.69	0.64	0.53	0.63	0.61	0.67

Note. Numbers range from 73–142 due to missing data and attrition across Waves. Numbers below the diagonal are Pearson correlation and numbers above the diagonal are Spearman correlations (non-parametric tests). Variables 1–4 are for cyberbullying frequency in Waves 1–4, respectively; Variables 5–8 are for anonymity in Waves 1–4, respectively; and Variables 9–12 are for cyberbullying attitudes in Waves 1–4, respectively.
† $p < .10$. * $p < .05$. ** $p < .01$.

ity of the data were skewed (see results), we tested the same path model with bootstrapping techniques (with 5000 samples). Finally, to show triangulation within one study, we tested whether cyberbullying attitudes mediated the relation between anonymity and cyberbullying behavior using data from only Wave 1. This analysis was construed as a strictly cross-sectional analysis that may compliment the longitudinal analysis. Bootstrapping procedures were also used for this analysis.

Distributional Properties of Key Variables

Results showed that cyberbullying (*Z*s > 13. 76, *p*s < .05) at all waves, cyberbullying attitudes at Waves 2, 3, and 4 (*Z*s > 2.41, *p*s < .05), and anonymity at Waves 2 and 3 (*Z*s > 2.45, *p*s < .05) had significant skew. Thus, we conducted our primary analysis (the path analysis) using both bootstrapping and maximum likelihood estimations.

Correlations

Zero-order correlations (below the diagonal) and relevant descriptive statistics are presented in Table 1. Also, because the majority of data are skewed, we also presented the Spearman Rank Ordered correlations in Table 1 (above the diagonal).

Path Analysis

Our path model consisted of having anonymity, cyberbullying attitudes, and cyberbullying behavior correlated within their respective Wave. Next, all Wave 1 variables were correlated with their respective Waves 3 and 4 counterparts. Third, all Wave 1 variables were allowed to correlate with the other Wave 4 variables. For instance, Wave 1 cyberbullying was correlated with Wave 4 cyberbullying attitudes and anonymity. Finally, Wave 1 variables predicted all Wave 2 variables, which, in turn, predicted all Wave 3 variables, which predicted all Wave 4 variables.

Results showed that the model fit the data well, $\chi^2 = 21.24$ ($df = 15$), $p = .13$, RMSEA = 0.05 (90% CI: 0.00–0.10), CFI = 0.99, TLI = 0.96, SRMR = 0.03. The standardized regression paths are presented in

Figure 1. Of theoretical interest, results showed (a) strong stability in the constructs over time, (b) several significant cross-lags, including the significant relation between Wave 1 anonymity to Wave 2 cyberbullying attitudes and the significant relation between Wave 2 cyberbullying attitudes and Wave 3 cyberbullying frequency, and (c) the only significant predictors of Wave 4 outcomes were their Wave 3 counterparts.

Due to the skewed nature of some of the variables in the model, we reran the model using bootstrapping procedures (with 5,000 bootstraps) and the results were largely unchanged. The one change that did occur was that the relation between Wave 1 cyberbullying attitudes and Wave 2 cyberbullying became significant using the bootstrapping method, whereas it was marginally significant using the maximum likelihood estimation technique (see Table 2).

Finally, we conducted several mediation tests using INDIRECT model statements in MPLUS while utilizing the bootstrapping approach. Results from the significant and marginal effects are presented in Table 3. Of theoretical interest, results showed that Wave 1 anonymity marginally predicted Wave 3 cyberbullying due to Wave 2 cyberbullying attitudes (the lower bound of the confidence interval included 0).

Table 2
95% Confidence Intervals Around Significant Paths in Figure 1 for Bootstrap Analysis

Significant path	Estimate	95% CI
Wave 3 CB → Wave 4 CB	0.71	0.36–0.93
Wave 3 PAC → Wave 4 PAC	0.68	0.44–0.88
Wave 3 AN → Wave 4 AN	0.44	0.23–0.66
Wave 2 CB → Wave 3 CB	0.82	0.39–1.25
Wave 2 PAC → Wave 3 CB	0.11	0.01–.19
Wave 2 PAC → Wave 3 PAC	0.52	0.32–0.70
Wave 2 PAC → Wave 3 AN	0.15	0.02–0.27
Wave 2 AN → Wave 3 AN	0.35	0.14–0.55
Wave 1 CB → Wave 2 CB	0.36	0.23–0.54
Wave 1 PAC → Wave 2 CB	0.05	0.01–0.11
Wave 1 AN → Wave 2 CB	0.09	0.01–0.18
Wave 1 PAC → Wave 2 AN	0.20	0.09–0.30
Wave 1 AN → Wave 2 AN	0.64	0.48–0.80
Wave 1 PAC → Wave 2 PAC	0.43	0.23–0.62
Wave 1 AN → Wave 2 PAC	0.31	0.08–0.55

Note. CB = cyberbullying; PAC = positive attitudes toward cyberbullying; AN = anonymity.

Wave 1 Analysis: Cross-Sectional Support

To show consistency in our results using both longitudinal and cross-sectional results, we conducted an INDIRECT model test using MPLUS only on Wave 1 data. Wave 1 data were the only appropriate data to use for several reasons. First, the questionnaires were in their original form, rather than Waves 2–4 that used modified in-

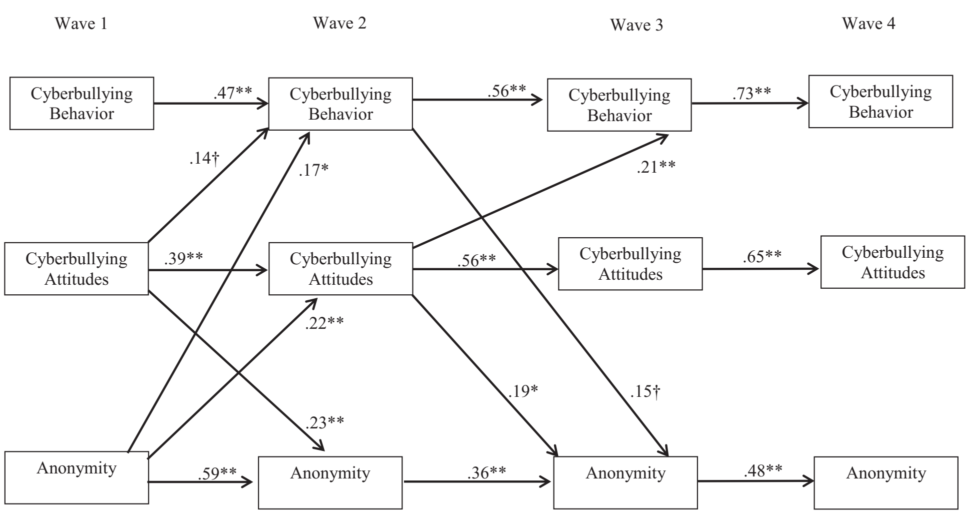

Figure 1. Indirect Path Model. Correlations between variables are not depicted for ease of readability. *Note.* Nonsignificant paths are not drawn. † $p < .10$. * $p < .05$. ** $p < .01$.

Table 3
Significant and Marginal Indirect Paths Using Bootstrapping Methods

Wave 1	Wave 2	Wave 3	Wave 4	Indirect *B*	95% CI
Anonymity	PAC	CB		.05	[.00–.09]
CB	CB	CB		.26	[.10–.43]
PAC	PAC	CB		.08	[.01–.15]
CB	CB	CB	CB	.19	[.04–.35]
Anonymity	PAC	CB	CB	.03	[.00–.07]
PAC	PAC	CB	CB	.06	[.00–.12]

Note. CB = cyberbullying behavior; PAC = positive attitudes toward cyberbullying.

structions. Second, Wave 1 had the largest sample size. Finally, data from Waves 2–4 are related to changes in Wave 1 predictors (as evidenced in Figure 1). In this model, cyberbullying attitudes mediated the relation between anonymity and cyberbullying attitudes. Because all paths are estimated, there are no degrees of freedom to estimate model fit, and, thus, the model is a perfect fit for the data. Results showed that cyberbullying behaviors were predicted by both anonymity ($\beta = .24$, $p < .01$) and attitudes ($\beta = .22$, $p < .01$). Also, anonymity predicted cyberbullying attitudes ($\beta = .29$, $p < .01$). The INDIRECT model tests confirmed the mediated effect (Indirect B = .06, $SE = .03$, $t = 2.18$, $p < .03$). When we used the bootstrapping procedures, the results were similar (see Table 4).

Discussion

Aggressor-perceived anonymity was related to cyberbullying behavior. Specifically, the more people feel that they are anonymous online, the more they are likely to cyberbully others. Consistent with theory, this was mediated by positive attitudes toward cyberbullying. In other words, one reason why anonymity was related to cyberbullying longitudinally was because of the positive correlation between anonymity and positive attitudes toward cyberbullying. This suggests that anonymity supports positive feelings regarding cyberbullying behavior, leading to the manifestation of those attitudes in behaviors. Although other variables may also mediate this relationship (i.e., normative aggressive beliefs, Werner, Bumpus, & Rock, 2010; empathy, Ang & Goh, 2010), our results suggest that anonymity is one of likely many risk factors for cyberbullying behavior using cross-sectional and longitudinal analyses.

One interesting finding was that the Wave 4 predictors were only significantly predicted by their Wave 3 counterpart rather than any other cross-lagged predictor. One possible explanation for this effect is that over time cyberbullying attitudes and behaviors tend to become more stable. Indeed, examination of the stability path coefficients for cyberbullying attitudes and behaviors show that the strongest degree of stability occurs in the path between Waves 3 and 4 relative to the Waves of data collection. This high degree of stability may be accounting for so much variance that the other cross-lagged predictors are not significant. Indeed, examination of the rank order correlations in Table 1 show that Wave 3 cyberbullying attitudes is correlated with Wave 4 cyberbullying behaviors (Spearman's $\rho = .34$, $p < .01$). Another possible explanation is practice effects involved in completing the same questionnaires over time. Recall that the time lag between data collection waves approximately two months, and it could be argued that participants recalled their answers from earlier waves or did not have much variation as in earlier waves. Although we cannot rule out this hypothesis, we believe that our temporal distance between waves of data col-

Table 4
95% Confidence Intervals Around Significant Paths and Mediation for Wave 1 for Bootstrap Analysis

Significant path	Estimate	95% CI
AN → CB	.16	[.06–.26]
AN → PAC	.38	[.18–.57]
PAC → CB	.11	[.01–.22]
AN → PAC → CB	.06	[.002–.13]

Note. CB = cyberbullying; PAC = positive attitudes toward cyberbullying; AN = anonymity.

lection was sufficient and the results are best explained by the former, rather than the latter, postulate.

Implications of "Online Disinhibition Effect"

The results of this study confirm the presence of an "online disinhibition effect" (Suler, 2004), and lend support to the dissociative anonymity process. According to Suler, dissociative anonymity taps onto the compartmentalization of selves. The "online self" is but one compartment of many selves. When online, whatever individuals say or do is dissociated from who they are in "real life" and the moral cognitive processes acquired in real life that guide their behavior "off-line" would be suspended while online. Findings from the current research confirm this by showing that anonymity was positively correlated with cyberbullying. This finding alone has implications for interventions. If we can inform Internet users that they are not anonymous and show them evidence of IP address tracking and how History folders operate, then perhaps cyberbullying will decrease. On the other hand, new cellular phone and tablet applications to guarantee anonymous posting (e.g., YikYak) may only serve to increase cyberbullying over time as a function of anonymity, according to our findings and Suler's (2004) theoretical stance.

Implications for Barlett and Gentile (2012) Model

In addition to supporting Suler's (2004) theoretical postulates, our study also makes a unique contribution to the Barlett and Gentile (2012) model. Recall that this model states that one reason why anonymity is related to cyberbullying behavior is through the development of positive cyberbullying attitudes. Findings from the current research show that cyberbullying attitudes mediate the relation between anonymity and later cyberbullying behavior. In other words, as one learns how anonymous their cyberbullying behaviors are, this likely leads to the development and eventual internalization of positive attitudes toward cyberbullying, which predict subsequent cyberbullying behavior. This also has implications for intervention. In addition to targeting anonymity, intervention specialists can also target cyberbullying attitudes and try to downplay the positives of cyberbullying. We are not exactly sure how this would manifest itself in an intervention, but, logically, if such interventions can target the mediator of an effect, the overall effect should decrease.

Limitations

This study provides novel contributions to understanding the role of anonymity in cyberbullying research. However, limitations do exist that require future work. First, our longitudinal study is limited by a short time lag between scale administration times. Although the data are longitudinal, making causal claims warranted, future research should test these longitudinal effects with much greater time lags (e.g., years rather than months). Alternatively, causal claims can also be made using controlled experimental studies where anonymity is directly manipulated and cyberbullying is the primary outcome. This is an excellent area of future work (thanks to a reviewer for this suggestion) that may further elucidate the theoretical role of perceived anonymity in predicting cyberbullying.

Second, measurement issues were important for the overall study. First, all the measures used in this study had lower than optimal reliabilities. As seen in Table 1, the Cronbach's alpha is not low enough to discredit the results; however, measurement of variables is an issue in this field. Researchers need to use reliable measures to validly assess their constructs. However, in the ever-changing media world, cyberbullying techniques, behaviors, and platforms are often changing, which makes developing new or using already published measures difficult.

Third, the majority of participants in the study were female. This made conducting statistical tests comparing men and women on the measured variables unwarranted. Future work should attempt to sample a similar number of males and females and conduct multigroup path analyses to test for invariance in the path coefficients across the two sexes.

Final Remarks

Overall, understanding the predictors of cyberbullying behavior is important to inform interventions aimed at reducing this "new" form of bullying. We were specifically interested in testing how perceived anonymity predicted cyberbullying frequency. The results suggest that anonymity is related to positive attitudes toward cyberbullying and cyberbullying frequency. Thus, anonymity is one important risk factor for future cyberbullying behavior.

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Received December 6, 2013
Revision received June 25, 2014
Accepted July 2, 2014 ■