Original Article

Predicting Cyberbullying Behavior From Attitudes

A 3-Year Longitudinal Cross-Lagged Analysis of Singaporean Youth

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Abstract: There is a paucity of research testing (a) the longitudinal stability in positive cyberbullying attitudes, (b) whether any change in positive cyberbullying attitudes over time predict subsequent cyberbullying perpetration, and (c) the cross-lagged relations between positive attitudes toward cyberbullying attitudes and behavior over time. The current study focused on empirically testing these theoretical gaps and sampled over 3,000 Singaporean youth participants (at Wave 1) who completed measures of cyberbullying behavior and positive attitudes consecutively for 3 years. Correlations and path analyses showed modest stability in positive cyberbullying attitudes and perpetration over time. Also, latent class analysis classified participants into either stable high attitudes, stable low attitudes, increasing attitudes, or decreasing attitudes. Results using this classification showed that changes in positive cyberbullying attitudes across Waves 1 and 2 predicted Wave 3 cyberbullying, such that those who endorsed cyberbullying attitudes were more likely to cyberbully than those who did not advocate such attitudes. Finally, path analysis results showed significant longitudinal cross-lags between positive attitudes toward cyberbullying and behaviors.

Keywords: cyberbully, cyberbullying attitudes

Cyberbullying, defined as, "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), has emerged as an important societal issue and can occur on myriad devices that allow for Internet access or technological communication (e.g., cellular phone, computer, tablet, video game console). Indeed, a world-wide survey of youth (aged 8–17) found that 37% had been victimized online (Microsoft, 2012) – not a trivial percentage. Locating reliable prevalence rates for cyberbullying perpetration in adults is difficult; however, Barlett and Chamberlin (2017) showed that cyberbullying perpetration occurs during adolescence, emerging adulthood, and later – with the highest frequency for 18–35-year-old participants. Overall, cyberbullying perpetration occurs at all ages, possibly fueled by an increase use in the Internet from 2005 to 2014 for all participants independent of age (Lupač, Chrobáková, & Sládek, 2014), and continued empirical work examining what variables predict this form of bullying is needed (e.g., Barlett, 2015). The current study focused on testing the relationship between positive attitudes toward cyberbullying and cyberbullying behavior over time, using a 3-year longitudinal study with over 3,000 Singaporean youth. According to the Microsoft (2012) survey, 58% of Singaporean youth reported being cybervictimized (compared with 37% worldwide) and 46% reported bullying others online (compared with 24% worldwide).

Although many variables predict cyberbullying perpetration (see Kowalski, Giumetti, Schroeder, & Lattanner, 2014, for a meta-analysis), our study focused exclusively on positive attitudes toward cyberbullying for several theoretical reasons. Broad social psychological literature has reliably shown the link between attitudes and subsequent behavior (e.g., Ajzen & Fishbein, 1977). A meta-analysis of 128 effect sizes showed the attitude to behavior relation to be strong ($r = .52$; Glasman & Albarracin, 2006) and has been observed across several antisocial behaviors,

DOI: 10.1027/1864-1105/a000231

such as aggressive behavior (e.g., Anderson, Benjamin, Wood, & Bonacci, 2006), bullying behavior (e.g., Salmivalli & Voeten, 2004), and discriminatory behavior (e.g., McConnell & Leibold, 2001). Whenever attitudes and behavior do not align, negative affect and/or arousal from dissonance is often felt, and research has shown that one way to reduce this dissonance is to cognitively change the behavior or attitude to make them consonant with each other (e.g., Beasley & Joslyn, 2001), which suggests a motivational approach to the attitude to behavior link (see Bohner & Dickel, 2011). Other cognitive – selective forgetting of attitudinal information (Elkin & Leippe, 1986), selective exposure to certain information (confirmation bias; Jonas, Schluz-Hardt, Frey, & Thelen, 2001) – and neural mechanisms (e.g., activation of the dorsal anterior cingulate cortex and anterior insula; van Veen, Krug, Schooler, & Carter, 2009) likely also explain how attitudes and behaviors are related; however, the purpose of the current study was to study the reciprocal relationship between cyberbullying attitudes and cyberbullying perpetration over time.

Attitudes and behaviors are likely reciprocally related to each other (c.f., Anderson & Bushman, 2002). Attitudes are, at least in part, formed by continued exposure to stimuli (e.g., Anderson et al., 2010), early direct experiences with certain behaviors (e.g., Fazio & Zanna, 1981) and reinforced learning (e.g., Fazio, Eiser, & Shook, 2004), which ultimately predict behavior. Continued positive experiences with a stimuli–behavior pair should further reinforce and develop the attitude. Despite this theoretical rationale, some studies fail to find such cyclic relations. For instance, Bentler and Speckart (1981) assessed behaviors and attitudes toward dating and exercise using a two-wave longitudinal design, and found that early attitudes positively predicted later behavior, but early behavior did not predict later attitudes; however, the opposite pattern was found when attitudes toward unprotected sex and subsequent behavior were analyzed (Huebner, Neilands, Rebchook, & Kegeles, 2011). Therefore, it is unclear if positive cyberbullying attitudes cause, or are caused by, cyberbullying behavior (or both), and one aim of the current study is to test these possible relationships. Indeed, myriad cyberbullying experiences – as the aggressor, the victim, or both – may be effective early learning experiences used to attack others online later. Research has shown (a) cyberbullying perpetration at Wave 1 predicts cybervictimization at Wave 2 (Jose, Kljakovic, Scheib, & Notter, 2012), (b) cyberbullying victimization at Wave 1 predicts cyberbullying perpetration at Wave 2 (Pabian & Vandebosch, 2016), and (c) cyberbullying perpetration and victimization are significantly correlated at the same time point (e.g., Fanti, Demetriou, & Hawa, 2012), as are cyberbullying victimization and positive cyberbullying attitudes (Barlett & Gentile, 2012).

Positive Cyberbullying Attitudes and Behavior

Multiple theoretical frameworks have been used to explain the attitude to behavior correlation as applied to cyberbullying perpetration. First, both the theory of reasoned action and the theory of planned behavior (Ajzen & Fishbein, 1977) posit the importance of attitudes (along with perceived behavioral control and subjective norms) in predicting future behavior through behavioral intention. Consistent with these theories, Doane, Pearson, and Kelley (2014) found a direct relation between positive cyberbullying attitudes and cyberbullying perpetration and an indirect link through cyberbullying intentions using a cross-sectional design with a college-aged sample. Second, the Barlett and Gentile cyberbullying model (BGCM; Barlett & Gentile, 2012) predicts that positive attitudes toward cyberbullying are a precursor to cyberbullying perpetration and these attitudes are developed through learned experiences of perceived anonymity and the belief that one's physical strength is irrelevant (BI-MOB) in the online world. Results from Barlett, Chamberlin, and Witkower's (2017) research detailed how both perceived anonymity and BI-MOB at Wave 1 predict positive cyberbullying attitudes at Wave 2, which predicted subsequent cyberbullying perpetration at Wave 3. Overall, myriad research shows the positive correlation between positive attitudes towards cyberbullying and cyberbullying behavior (e.g., Barlett, 2015; Barlett & Gentile, 2012; Barlett, Gentile, & Chew, 2016; Barlett et al., 2014; Boulton, Lloyd, Down, & Marx, 2012; Doane et al., 2014; Heirman & Walgrave, 2012). Although these studies are imperative for showing the importance of conceptualizing positive cyberbullying attitudes in predicting cyberbullying perpetration, several theoretical questions remain unanswered.

First, there is a paucity of research examining the longitudinal relationship between early positive attitudes toward cyberbullying and later cyberbullying perpetration. The few published longitudinal studies that exist show the relationship between early positive cyberbullying attitudes and later cyberbullying behavior (Barlett, 2015; Barlett et al., 2016); however, these studies are limited by small time lags between data collection periods (approximately 2–3 months), and path coefficients for attitudes are greater when they are assessed with closer time lags, possibly inflating the relationships between variables (e.g., Staw & Ross, 1985). The current study will address this concern by assessing youth annually (rather than a few months), and we are unaware of any published longitudinal study testing the longitudinal relations between positive cyberbullying attitudes and cyberbullying behavior using such long time lags[1].

Second, we tested the temporal ordering of the longitudinal relations between positive cyberbullying attitudes and cyberbullying behavior. Support for the BGCM (Barlett & Gentile, 2012) will show a reciprocal relationship between positive attitudes and behavior – behavior causes attitude change and attitude change causes the behavior. Previous longitudinal work using multiple waves of data collection with emerging adults did not find these reciprocal relations (Barlett, Gentile, & Chew, 2016); however, the lack of findings may be a function of (a) the age of the sample (attitudes are still forming and changing at younger ages; Baron & Banaji, 2006), (b) the short time lags between data collection, and/or (c) the addition of additional variables in the model (i.e., anonymity perceptions). To address these concerns, we sampled youth who are likely still developing their cyberbullying attitudes, used a 12-month time lag (rather than 2–3 months), and only assessed positive cyberbullying attitudes and cyberbullying behavior. The short time lag concern is imperative to address. Notably, some attitudes necessitate time (and likely other cognitive resources) to develop or change (see Bohner & Dickel, 2011, for review), and our proposed reciprocal attitude to behavior hypothesis for cyberbullying may need ample time to manifest itself – time not afforded in the Barlett et al. (2016) work.

Overview of the Current Study

Youth were asked to complete measures of cyberbullying frequency and positive attitudes toward cyberbullying annually for 3 years. This design allowed us to test: (a) the stability in cyberbullying behavior and attitudes over time, (b) the correlations between positive cyberbullying attitudes and behavior within each wave, and (c) the mediated cross-lagged relations between early attitudes/behaviors and their later counterparts.

Method

Participants

Data were collected as part of a much larger longitudinal study of cyber-wellness issues. At Wave 1, participants (N = 3,079; 50.4% male) with an average age of 13.12 years (SD = 2.44) completed the survey[2]. The majority of these participants were of Chinese descent (71.1%), which is representative of Singaporean society. All participants were followed up for consecutive years. Several cohorts of participants were sampled, which included:

1. Primary 3 (3rd grade in the United States) to 6 (6th grade in the United States),
2. Secondary 1 (7th grade in the United States) to 4 (11th grade in the United States), and
3. Secondary 3 (10th grade in the United States) to 5 (12th grade in the United States).

Table 1. Demographic information of the sample over time

	Wave 1		Wave 2		Wave 3	
	Boys	Girls	Boys	Girls	Boys	Girls
Pri 3	249	237				
Pri 4	116	102	217	222		
Pri 5	134	113	107	93	186	196
Pri 6	132	127	119	102	86	73
Sec 1	353	296				
Sec 2	299	321	311	270		
Sec 3	98	96	249	280	168	133
Sec 4	103	144	89	94	63	76
Sec 5	69	90	11	21	13	22
Total	1,553	1,526	1,103	1,082	516	500

Note. Pri = primary school. Sec = secondary school.

Common for longitudinal studies, there was some participant attrition. Some students graduated from primary or secondary school and were not followed up as it was not possible to track them. Additionally, schools may have opted out of data collection during some years or students may have moved. Of the 2,388 responses in Wave 2, 1,957 (82.0%) completed the survey. In Wave 3, 47.3% (N = 909) participants completed the survey. See Table 1 for sample sizes at each wave. We categorized participants into whether they completed both Waves 1 and 2 or only completed Wave 1. Then we ran two independent t tests: one for cyberbullying behavior and the other for positive cyberbullying attitudes. Results showed no difference between the two groups for Wave 1 cyberbullying behavior, $t(3077) = .75$, $p = .45$, but there was a significant difference for Wave 1 cyberbullying attitudes, $t(3077) = 3.49$, $p < .05$, such that those who completed both waves of data collection ($M = 19.13$, $SD = 6.44$) had more positive attitudes

[1] Although Barlett and colleagues' longitudinal work is theoretically important, we are explicitly arguing that the use of short time lags is an important limitation that the current work addresses by using longer time lags. It is likely that the short time lags used in the Barlett work are a function of funding issues and/or the inability to sample youth in schools for longer. Indeed, Barlett (2015) stated in their four-wave longitudinal work with youth that "...time lags were established in conjunction with school officials and their scheduling" (p. 92), which suggests scheduling restrictions necessitated the shorter-than-optimal time lags.

[2] Results from several independent t tests showed that males scored significantly higher on all cyberbullying perpetration and attitude measures; however, sex effects were not of theoretical interest. Thus, all of our analyses controlled for participant sex.

than those who only did the first wave ($M = 18.16$, $SD = 6.45$). It is important to explicitly note the larger attrition in Wave 3 compared with earlier waves. We believe that the lack of participation in Wave 3 was mostly due to the timing of the survey, which coincided with the secondary students' school exams and they most likely opted to spend more time studying than completing the survey.

Materials

Cyberbullying

The 3-item cyberbullying subscale of Ybarra, Diener-West, and Leaf (2007) asks participants to indicate how often they engaged in several behaviors in the past 12 months on a rating scale from 1 (*never*) to 6 (*everyday/almost everyday*)[3]. A sample item includes, "Made rude comments or mean comments to anyone online." The three items were summed such that higher scores indicated higher reported frequency of cyberbullying. This questionnaire makes clear that the behaviors represented by the items occurred while on the Internet.

Positive Attitudes Toward Cyberbullying

In order to measure positive attitudes toward cyberbullying, a modified version of the 9-item Barlett and Gentile (2012) positive attitudes toward cyberbullying measure was used. This questionnaire asks participants to rate their level of agreement with the items on a rating scale of 1 (= *strongly disagree*) to 5 (= *strongly agree*). This scale was modified slightly to make the wording more understandable to Singaporean youth (although Singapore is a native English-speaking country, several items were changed for clarity). A sample item includes, "Teasing others on the Internet by using Facebook, emails, or text messages is fun." Appropriate items were reverse-scored and then summed such that higher scores indicated more positive attitudes toward cyberbullying.

Demographic Questionnaire

A demographic questionnaire measured sex, school grade, ethnicity, and other relevant information.

Procedure

Data collection for this study was obtained via a large longitudinal project entitled "Singapore Youths in the Cyber-world." In order to explore what Internet activities Singaporean youths are engaged in, 30 randomly selected Singaporean schools (15 primary and 15 secondary schools) were invited to participate in the study. Two schools later dropped out from the first year of study. The total sample thus includes 28 schools. Informed consent was sought from the parents through the schools. A liaison teacher from each school collated the information and excluded from the study any students whose parents refused consent. Assent was obtained from the students through informing them that participation in the survey was voluntary and that they could withdraw at any time. The online questionnaires were administered by teachers to participants during school sessions with a set of standardized instructions[4]. Participants made their responses on school computers and the privacy of their responses was assured by the confidential nature of the online response format. All of the ethical procedures and policies of the Ministry of Education and the participating schools were followed.

Results

Correlations

Zero-order correlations along with descriptive information for each questionnaire (skew, Cronbach's α, mean, *SD*, minimum score, and maximum score) are presented in Table 2[5]. The data show that Waves 1–3 positive cyberbullying attitudes and behavior were significantly skewed (all Shapiro–Wilk tests > .30, all p values < .001), and, thus, we present both parametric and nonparametric tests (where appropriate) and use bootstrapped confidence interval estimates for our path models. Results from the correlation tests (both Pearson and Spearman rank ordered) show that early cyberbullying behavior was correlated with later cyberbullying behavior (a result also found for positive cyberbullying attitudes). In addition, cyberbullying frequency at each wave was significantly correlated with positive attitudes toward cyberbullying at each wave.

Latent Class Analysis

Longitudinal latent class analysis was conducted using the growth mixture model analysis in Mplus 7.2. Missing data

[3] At Waves 1 and 2, participants were first asked a dichotomous, "Have you said nasty and hurtful things to others online?" question. If a participant answered *no*, they did not complete the Ybarra et al. (2007) cyberbullying scale. For these participants a score of 3 (the lowest possible score indicating no cyberbullying) was inserted. For Wave 3, this criterion was removed, and the participants completed the Ybarra et al. (2007) scale.

[4] Additional questionnaires were measured but not used in the current study. These scales measured a wide range of variables, and included media violence exposure, perceptions of family life, physical and mental health issues, attitudes toward Internet usage, risky online behavior, cybervictimization, and others. For a complete list of variables, please contact the second author.

[5] When partial correlations were conducted, controlling for sex, all relationships displayed in Table 2 remained significant.

Table 2. Correlations between relevant variables

	1	2	3	4	5	6
1: Wave 1 Cyberbullying	–	.23**	.15**	.31**	.22**	.16**
2: Wave 2 Cyberbullying	.25**	–	.33**	.25**	.33**	.29**
3: Wave 3 Cyberbullying	.17**	.29**	–	.21**	.25**	.42**
4: Wave 1 Cyberbullying Attitudes	.31**	.25**	.22**	–	.45**	.38**
5: Wave 2 Cyberbullying Attitudes	.20**	.36**	.25**	.45**	–	.49**
6: Wave 3 Cyberbullying Attitudes	.17**	.26**	.46**	.38**	.49**	–
M	3.44	3.56	3.82	18.91	18.25	17.65
SD	1.62	1.62	1.73	6.46	6.33	6.52
Min	3.00	3.00	3.00	9.00	9.00	9.00
Max	15.00	15.00	15.00	45.00	45.00	44.00
Shapiro-Wilk	.97**	.95**	.94**	.30**	.38**	.53**
α	.88	.86	.81	.78	.79	.79

Notes. Numbers range from 652 to 3,079 due to missing data and attrition across waves. Numbers below the diagonal are Pearson correlations and numbers above the diagonal are Spearman rank ordered correlations. *p < .05. **p < .01.

were estimated using Mplus maximum likelihood estimation procedures. This analyzes each child's changes across time and groups children together who change similarly on positive cyberbullying attitudes. In total, 12 classes were found that fit with theoretical predictions, which could be grouped together based on similar trajectories to make four groups, as displayed in Figure 1.[6] One group of children showed a stable low positive attitude about cyberbullying pattern (which we title the *Stable Low group*). One group had stable high positive attitudes about cyberbullying (which we title the *Stable High group*). One group started with more positive attitudes in Wave 1 but changed to have lower positive attitudes by Wave 2 (which we title the *Drop group*). Finally, one group changed to have more positive attitudes about cyberbullying by Wave 2 (which we title the *Modest Increase group*). Figure 1 shows the trajectories of these four groups. The four latent classes allow us to estimate the stability of attitudes across 2 years. As has been shown theoretically and empirically, attitudes tend to be stable. The majority of students had low positive stable attitudes (55.9%, N = 1,721), and the next most common was high positive stable attitudes (32.9%, N = 1,013). Almost 8% had increases in positive attitudes about cyberbullying (7.7%, N = 238), and very few who started with positive attitudes decreased across a 1-year time lag (3.5%, N = 107).

These longitudinal data also allow us to begin to answer questions about whether attitude stability or changes predict behaviors 1 year later. Analyses of variance (ANOVAs) were conducted with group classification as the independent variable and positive cyberbullying attitudes and behavior at Wave 3 as the outcome[7]. First, as expected, the results showed a significant main effect of classification group with Wave 3 positive cyberbullying attitudes as the outcome, $F(3, 1072) = 98.44$, $p < .001$, $\eta^2p = .22$. Bonferroni corrected pairwise comparisons showed that all groups significantly ($p < .05$) differed from

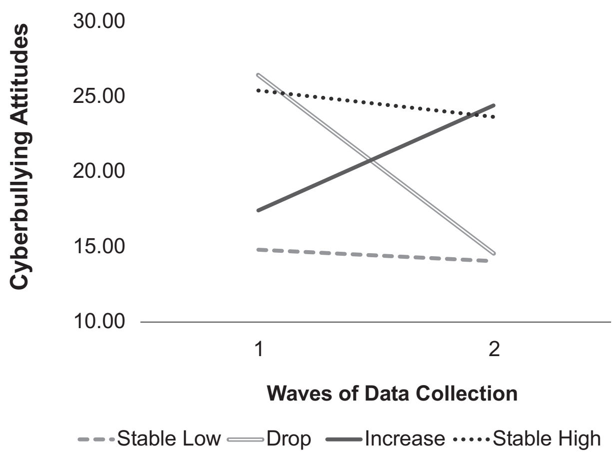

Figure 1. Four group classifications derived from the latent class analysis.

[6] Multiple criteria were used to choose the 12-class model as the best fit. Most importantly, the classes need to fit with one's theoretical predictions, and each of the 12 classes was theoretically sensible. Second, classification quality is assessed by entropy, which is a standardized summary measures with higher values indicating more accurate classification. Entropy continued improving with additional classes up until 12 classes. Third, the Bayesian information criterion (BIC) statistic gets smaller with improved fit, and 12 classes were better than 11. Fourth, the bootstrap Lo, Mendell, and Rubin test compares the fit with k classes to the fit with $k - 1$ classes, providing a p value to determine if there is a statistically significant improvement in fit with more classes. The BLRT was nonsignificant at 11, 12 and 13 classes.

[7] When sex was added as a covariate, the main effect of group classification remained significant for both cyberbullying perpetration and attitudes.

Table 3. Descriptive and inferential statistics for the class analysis

	Wave 3 cyberbullying attitudes			Wave 3 cyberbullying perpetration		
Group	*M*	*SD*	*N*	*M*	*SD*	*N*
Drop	16.30_a	5.85	60	3.53_a	1.29	60
Stable Low	15.11_a	5.13	590	3.47_a	1.13	585
Modest Increase	20.18_b	6.20	84	4.00_{ab}	1.96	84
Stable High	21.63_b	6.65	342	4.43_b	2.34	337

Note. Means with differing subscripted letters denote a significant ($p < .05$) difference using a Bonferroni corrected pairwise comparison.

each other, except for the nonsignificant difference between the Drop and Stable Low groups and the Stable High and Modest Increase groups (see Table 3).

Results from the ANOVA with cyberbullying perpetration at Wave 3 as the outcome showed a significant main effect of classification group, $F(3, 1062) = 23.91$, $p < .001$, $\eta^2 p = .05$. Bonferroni corrected pairwise comparisons revealed that the Stable High group significantly ($p < .05$) differed from the Drop and Stable Low groups, but not the Modest Increase group ($p = .22$). The Modest Increase group differed from the Stable Low group significantly ($p < .05$). That is, children with attitudes that were either stable high or increasingly positive were more likely to engage in cyberbullying behavior. No other differences were significant (see Table 3). These effects remained when we used Kruskal-Wallis tests owing to the skewed nature of the data. Although these data are not particularly surprising (i.e., earlier attitudes predict later attitudes and behaviors), it is valuable to test this hypothesis as it demonstrates some validity for the measures used as well as for the underlying theory.

Path Models

We used Mplus to examine the cross-lagged reciprocal relations between positive cyberbullying attitudes and behavior over time. Again, missing data were estimated using maximum likelihood estimation techniques in Mplus. Our three-wave path analysis had cyberbullying and positive attitudes toward cyberbullying at each wave correlated. Each wave directly predicted the subsequent wave (e.g., Wave 1 cyberbullying predicted Wave 2 cyberbullying, which predicted Wave 3 cyberbullying) for both cyberbullying behavior and attitudes, demonstrating stability of both attitudes and behaviors. Third, the previous wave predictor also predicted the subsequent wave of the other variable. For example, Wave 1 cyberbullying predicted Wave 2 positive attitudes toward cyberbullying, and Wave 1 positive attitudes toward cyberbullying would predict Wave 2 cyberbullying. This was done across the entire three waves. Fourth, we estimated the correlation between Wave 1 variables with their Wave 3 counterpart (for instance, Wave 1 cyberbullying was allowed to correlate with Wave 3 cyberbullying).

Results showed that this model fit the data well, $\chi^2 = 16.08$ ($df = 2$), $p < .001$, RMSEA = .05 (90% CI = .03–.07), CFI = .99, TLI = .94, SRMR = .03. Bootstrapped confidence intervals around the unstandardized estimates are presented in Figure 2. Overall, none of the 95% confidence intervals around the estimated regression coefficients and correlations included 0, suggesting statistically significant relations. Figure 2 shows: (a) strong stability over time for both positive attitudes toward cyberbullying and cyberbullying frequency; (b) strong correlations between variables within each wave; and (c) strong cross-lagged relations, such that cyberbullying predicted positive attitudes 1 year later and positive attitudes predicted cyberbullying 1 year later[8].

Mediation was tested by adding INDIRECT model statements using Mplus to test all possible mediated pathways from Wave 1 to Wave 3 variables through Wave 2 data. Results are presented in Table 4 and show that none of the 95% confidence intervals around the standardized bootstrapped estimates included 0, suggesting significant mediation. Of theoretical interest, results showed that the relationship between Waves 1 and 3 cyberbullying perpetrations was mediated by Wave 2 positive attitudes toward cyberbullying (indirect $B = .011$; 95% CI = .002–.02), and the relationship between Waves 1 and 3 cyberbullying attitudes was mediated by Wave 2 cyberbullying perpetration (indirect $B = .017$; 95% CI = .003–.031). These data suggest that the reason why Wave 1 exogenous variables (cyberbullying perpetration and pro-cyberbullying attitudes) predicted Wave 3 cyberbullying attitudes and perpetration was because of increases in Wave 2 cyberbullying attitudes and behavior.

Discussion

The current longitudinal study was conducted in order to test several theoretical gaps in the cyberbullying literature. First, we examined the reciprocal relationship between positive cyberbullying attitudes and cyberbullying behavior. Drawing upon the theoretical postulates of the BGCM (Barlett & Gentile, 2012) and past longitudinal work (Barlett, 2015; Barlett et al., 2016), we hypothesized that early cyberbullying behaviors will cause later positive

[8] When sex was added to the model (predicting all observed variables), results showed a good model fit and all the relations depicted in Figure 2 remained significant.

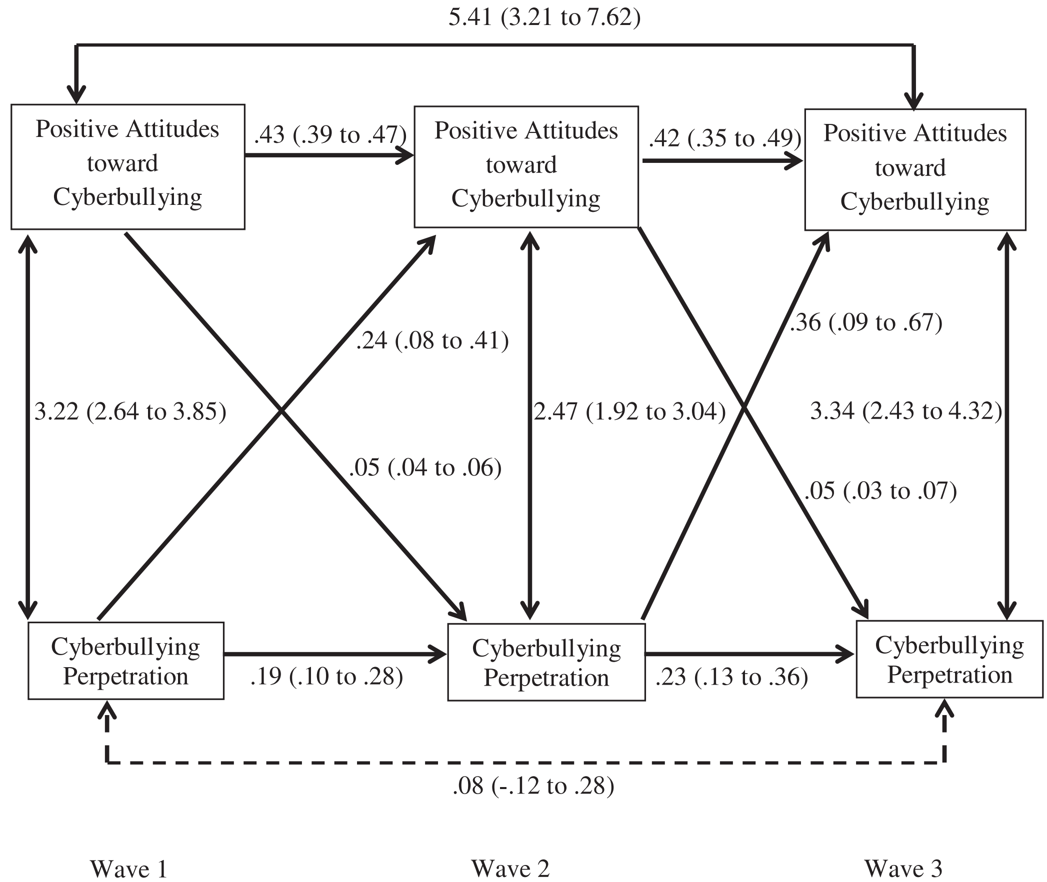

Figure 2. Longitudinal path model with unstandardized coefficients and 95% bootstrapped confidence intervals. Solid lines are significant relations while dashed lines are nonsignificant.

Table 4. Significant indirect pathways from Wave 1 predictors to Wave 3 outcomes

		95% CI	
Path	Indirect *B*	Lower limit	Upper limit
CB → CB → CB	.040	.013	.068
CB → PATC → CB	.011	.002	.020
CB → CB → PATC	.017	.001	.032
CB → PATC → PATC	.025	.007	.043
PATC → CB → CB	.041	.019	.064
PATC → PATC → CB	.077	.046	.109
PATC → CB → PATC	.017	.003	.031
PATC → PATC → PATC	.177	.145	.208

Note. CB = cyberbullying. PATC = positive attitudes toward cyberbullying.

attitudes toward cyberbullying and early positive cyberbullying attitudes will cause later cyberbullying behavior. Our data support the reciprocal longitudinal relationship between positive cyberbullying attitudes and behavior. Across all waves of data collection, positive attitudes formed behaviors and behavioral experiences formed positive attitudes. The BGCM explicitly states such relations by outlining the imperative learning trials with behaviors that help form and automatize easily accessible attitudes (see also Anderson & Bushman, 2002). In short, after a positively reinforced behavior is enacted, individuals likely begin to develop positive attitudes, which predict later behavior (see Ajzen & Fishbein, 1977). The important test for these reciprocal relations was the longitudinal mediated path analyses. Examination of the indirect effects showed that the relation between Waves 1 and 3 cyberbullying behavior was mediated by Wave 2 positive cyberbullying attitudes and the relation between Waves 1 and 3 positive cyberbullying attitudes was mediated by Wave 2 cyberbullying behavior. Recent longitudinal work (Barlett et al., 2016) failed to find these reciprocal effects; however, the current study used longer time lags between data collection administrations, and research has suggested that attitude formation and change requires (at least) time and experience (Bohner & Dickel, 2011). Therefore, perhaps the 2–3-month time lag used by Barlett et al. (2016; Barlett, 2015) was insufficient to detect such relationships. Further, Barlett et al. (2016) used a sample of emerging adults, and previous work has shown that attitude change and formation changes with age (Baron & Banaji, 2006). Thus, perhaps assessing the attitude–behavior relationship in youth, rather than emerging adults, allowed for a more sensitive population to discover such relations. Independent of the exact reason(s) driving differences between the current and past work, the theoretical support of the learning mechanism of the BGCM are very important to (a) further validating the theoretical postulates of the model and to (b) detailing the learning-based hypotheses surrounding the cyberbullying attitude to behavior link that have eluded researchers.

Second, the three-wave longitudinal design allowed us to examine the psychological and behavioral consequences of early positive cyberbullying attitude change. We noted that the magnitude of the stability coefficients suggests that this stability is not ubiquitous – some individuals are likely to change (increase or decrease) over time while others remain stable. Indeed, using latent class analysis we found 12 unique classifications that we were able to theoretically collapse into four distinct groups of participants: stable low positive cyberbullying attitudes, stable high positive cyberbullying attitudes, decrease in positive cyberbullying attitudes over time, and modest increase in positive cyberbullying attitudes over time. Results from this latent class analysis showed that the majority (88.8%) were in the two stable groups, with 11.2% of the sample showing change in a 1-year period. This supports the hypothesis that positive cyberbullying attitudes likely remain stable over time; however, a nontrivial number of participants changed their cyberbullying attitudes over time. Analyses using group classification as a predictor showed that cyberbullying behavior at Wave 3 was highest for the Stable High group and lowest for the Stable Low group, as would be predicted by attitude theories. Furthermore, those who had a modest increase in their positive cyberbullying attitudes at Wave 2 had high cyberbullying perpetration scores at Wave 3 compared with those who had a decrease. Overall, the results from these analyses suggest that group classification based on positive attitudes toward cyberbullying change from Wave 1 to Wave 2 predicted Wave 3 cyberbullying perpetration.

Limitations and Future Directions

The current study has some limitations that future research should address. First, akin to most longitudinal studies, participant attrition was an issue. Several participants who started the study did not complete all three waves of data collection. The latent class analysis and path analysis were able to impute missing data and any analyses involving Mplus estimated values using maximum likelihood estimation. However, the correlation and ANOVA analyses excluded participants who were missing data (SPSS was used). There were several possible reasons for why not all participants completed the study, most of which were not due to students refusing to continue. The main cause of attrition was students finishing or changing schools. When students graduated after completing their primary or secondary education, they were not followed up for subsequent years. Students were also not followed up when they changed schools for any reason. While most schools were cooperative, some schools opted out of data collection in some of the years, especially in Wave 3. This was mostly due to the timing of the survey, which coincided with the secondary school exams. Although some students also opted not to complete the survey because it was voluntary, this was a very small number of students. However, even with the high attrition rate, we still had enough statistical power to adequately test the hypotheses of the current study.

Second, at Wave 1 positive cyberbullying attitudes and behaviors were strongly correlated. From a theoretical point of view, it would be interesting to find a younger sample where their attitudes and behavior are uncorrelated to test the learning postulates of the BGCM (Barlett & Gentile, 2012). This would allow us to determine how early attitude development derives from different types of learned experiences, such as direct involvement (as the BGCM claims), parental or peer (un)encouragement, or other factors. It is unclear if such a sample of youth who meet this criterion can be found, but future work should look into further elucidating the temporal ordering of how positive cyberbullying attitudes are formed due to their stability over time and predictive power.

Third, since all the measures were self-report assessments of antisocial behaviors and attitudes, social desirability may be influencing the overall results. For instance, some participants may be reluctant to indicate how often they engage in cyberbullying behaviors because it may excite cognitive dissonance and corresponding negative psychological reactions and/or the fear of the negative consequences from parents, teachers, friends, or law officials if their responses are linked to their name (although participants were told their responses were anonymous, which some have argued helps combat social desirability; Ang & Goh, 2010). Results from the current study showed that cyberbullying behaviors and attitudes were significantly positively skewed, and the mean score on the Ybarra et al. (2007) cyberbullying measure across waves was near the bottom value of possible scores. Despite this issue, we corrected for the skewed nature of the data in our path analyses by using bootstrapping procedures and our study was focused on individual-level change over time. Therefore, we believe that social desirability, although important, did not exert too much noise in our data, but future research should address this issue.

Fourth, although we have argued that the year-long time lag between scale administrations is advantageous to allow for more observable attitude and behavioral changes in antisocial behaviors, such a long gap in waves introduces the possibility that other macro-level changes may have influenced any change over time. For instance, if (a) the school adopted cyberbullying intervention curricula, (b) there were any cyberbullying-related suicides, and/or (c) new technology or online outlets became available, cyberbullying behavior may have changed. These, and likely other, events that are beyond our control may have influenced the measured variables in-between waves of data collection, which could harm the internal validity of the results. Future longitudinal research needs to carefully review the strengths and limitations of using various time lags and possibly code for these societal changes to statistically control for their influence.

Fifth, we did not incorporate cybervictimization frequency in our modeling. Being the target of a cyberattack may also be a learning experience that could help develop subsequent positive cyberbullying attitudes. For instance, a cybervictim may learn that their aggressor is anonymous and has little repercussions for their actions, which may spurn the victim to aggress against others using cyberbullying tactics. However, even though past work has shown that cybervictimization and cyberbullying perpetration is correlated (e.g., Barlett & Gentile, 2012), the reciprocal relations between early and later cyberbullying and cybervictimization are mixed. Jose et al. (2012) showed that early cyberbullying perpetration predicts later cybervictimization, but the reverse is not statistically valid (see also Del Rey, Elipe, & Ortega-Ruiz, 2012); however, Pabian and Vandebosch (2016) did show that early cybervictimization predicted Wave 2 cyberbullying perpetration. Overall, these contradictory findings do not allow for a priori theoretical hypotheses to be accurately derived. Although our larger data set included a measure of cybervictimization, we did not analyze such relations for these theoretical reasons; however, future research should examine such effects.

Finally, the current study is limited by not measuring variables that allow for a test of a specific theory. Although the theory of planned behavior, theory of reasoned action, BGCM, and other theories highlight the importance of predicting cyberbullying perpetration from earlier attitudes, other key predictors are crucial to fully test these theories. For instance, the theory of reasoned action includes perceived behavioral control, subjective norms, and behavioral intentions (Ajzen & Fishbein, 1977), and the BGCM posits that perceived anonymity and the belief that one's physical strength is irrelevant in the online world are important learned processes to the development of positive cyberbullying attitudes. Although we view this as a limitation from a holistic perspective, we first wanted to further explore the attitude to behavior correlation longitudinally to fill important theoretical gaps in the literature. Future work should build on the current study and include additional predictors important to theory so as to further elucidate the psychological processes involved in cyberbullying perpetration.

Conclusion

As countries become more technologically sophisticated and children gain access to technologies, cyberbullying rates are likely to increase. Researchers need to continue to examine the theoretical predictors of cyberbullying in order to inform interventions. Indeed, if research can identify a predictor of cyberbullying, replicate the effect, and develop theoretical relations regarding why these effects occur, interventions can be modified to reduce cyberbullying. We believe that the findings from the current study are an important first step in this regard and demonstrate the powerful influence that positive cyberbullying attitudes have on subsequent behavior. Interventions should incorporate these, and other, findings by targeting the development of these attitudes to hopefully reduce cyberbullying in our society.

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Received August 3, 2016
Revision received April 24, 2017
Accepted May 2, 2017
Published online October 18, 2017

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