Estimating the Magnitude of the Relation Between Bullying, E-Bullying, and Suicidal Behaviors Among United States Youth, 2015

Kevin S. Kuehn[1], Annelise Wagner[2], and Jennifer Velloza[3]

[1]Department of Psychology, University of Washington, Seattle, WA, USA
[2]Department of Statistics, University of Washington, Seattle, WA, USA
[3]Department of Epidemiology, University of Washington, Seattle, WA, USA

Abstract. *Background:* Suicide is the second leading cause of death among US adolescents aged 12–19 years. Researchers would benefit from a better understanding of the direct effects of bullying and e-bullying on adolescent suicide to inform intervention work. *Aims:* To explore the direct and indirect effects of bullying and e-bullying on adolescent suicide attempts (SAs) and to estimate the magnitude of these effects controlling for significant covariates. *Method:* This study uses data from the 2015 Youth Risk Behavior Surveillance Survey (YRBS), a nationally representative sample of US high school youth. We quantified the association between bullying and the likelihood of SA, after adjusting for covariates (i.e., sexual orientation, obesity, sleep, etc.) identified with the PC algorithm. *Results:* Bullying and e-bullying were significantly associated with SA in logistic regression analyses. Bullying had an estimated average causal effect (ACE) of 2.46%, while e-bullying had an ACE of 4.16%. *Limitations:* Data are cross-sectional and temporal precedence is not known. *Conclusion:* These findings highlight the strong association between bullying, e-bullying, and SA.

Keywords: suicide, suicide prevention, bullying, electronic bullying

Suicide, a public health concern in the United States and globally (Shain, 2016), is the second leading cause of death among US youth aged 12–19 with an estimated rate of 7.49 per 100,000 (Centers for Disease Control and Prevention [CDC], 2016a). Epidemiological estimates indicate 8.6% of US adolescents attempted suicide in 2015, while 17.7% considered attempting (Kann et al., 2016). Rates of US youth suicide have been increasing since 2010 (Curtin, Warner, & Hedegaard, 2016). Given the high rate of youth suicide attempts (SA), it is paramount that researchers identify factors most directly associated with SA, as well as how they interact to confer risk.

Bullying, defined as an imbalance of power in which individuals are repeatedly threatened, teased, or physically hurt (Olweus, 1993; Smith, 2004), is prevalent in the US; an estimated 20.2% of US youth reported being bullied in 2015, while 15.5% of US youth experienced electronic bullying (e-bullying; Kann et al., 2016). Bullying is associated with SA (for a review, see Klomek, Sourander, & Gould, 2010) as bullied youth have been found to be between two and 11 times more likely to attempt suicide than nonbullied peers (Kim & Leventhal, 2008). Even infrequent bullying is associated with SA (Klomek, Marrocco, Kleinman, Schonfeld, & Gould, 2007), and a meta-analysis concluded that e-bullying was also strongly associated with SA (Kowalski, Giumetti, Schroeder, & Lattanner, 2014). Despite evidence that bullying and e-bullying contribute to youth SA, it is difficult to know if they directly impact SA, or if these associations occur via shared risk factors.

Youth identifying as gay, lesbian, bisexual, and questioning (GLBQ) are at higher risk of bullying (Birkett, Espelage, & Koenig, 2009) and SA (D'Augelli et al., 2005). GLBQ youth are two to seven times more likely to attempt suicide (Haas et al., 2011) and higher rates of bullying among GLBQ youth may account for their increased SA (Hatzenbuehler & Keyes, 2013). Because much of the research examining effects of bullying on GLBQ SA has not controlled for confounders, it is not clearly known how these factors interact to increase risk.

Ethical concerns prohibit researchers from using experimental manipulation to establish clear SA and bullying causal links (Nock, 2009). The PC algorithm (*P* for Peter Spirtes and *C* for Clark Glymour, the developers; Spirtes, Glymour, & Scheines, 2000) was constructed to help re-

https://doi.org/10.1027/0227-5910/a000544

searchers infer causal associations from observational data and is a structure learning and causal discovery algorithm. The PC algorithm uses a correlation matrix to test for independencies between variables in a dataset to identify its statistical structure. Results from this matrix produce a Bayesian network-directed acyclic graph (DAG) to graphically model results based on the joint probability distributions (Pearl, 2009). In brief, the PC algorithm uses an exploratory approach to uncover testable hypotheses.

The present study aims to elucidate the mechanisms by which bullying might be associated with SA among US youth aged 13–18 using data from the CDC's 2015 nationally representative Youth Risk Behavior Surveillance Survey (YRBS; Kolbe, Kann, & Collins, 1993). We hypothesized that bullying and e-bullying would be directly related to SA after controlling for covariates. Given the ubiquity of Web-enabled smartphones, we hypothesized that e-bullying would be more strongly associated with SA than in-person bullying. Finally, we hypothesized that the increased rates of SA in GLBQ youth would be explained by bullying.

Method

Study Population

The YRBS was first conducted in 1990 to measure health behaviors among US youth (CDC, 2016b) and is conducted every 2 years with a stratified random sample of high school students in Grades 9–12 (CDC, 2016b). A total of 180 public, parochial, and private schools were sampled (CDC, 2015a). In all, 125 schools participated (69% response rate). Of 18,165 students at these schools, 15,624 surveys were included in the YRBS 2015 dataset after cleaning (CDC, 2015a). Measures were completed in United States territories, tribal lands, and all states except Minnesota, Oregon, and Washington (CDC, 2015b).

We excluded observations with missing data on any of the 17 variables included in our initial model and this sample consisted of 6,902 (44.18%) observations (Figure 1). Variables without a direct relation to SA were pruned in creating a final DAG. Excluding the missing data for these eight variables resulted in a sample of 10,404 (66.59%) participants. Missing data in the final sample were minimal for questions assessing bullying (1.13% missing data for bullying and 1.02% for e-bullying). Participants who reported GLBQ orientation (5.89%), rape victimization (4.66%), minority race (16.34%), and SA (19.57%) were more likely to have missing data for bullying and e-bullying.

Measures

Outcome Variable

SA: History of SA was assessed via an item asking the number of times youth attempted suicide in the past 12 months (response options of 0 times, 1 time, 2 or 3 times, 4 or 5 times, and 6 or more times). We tested Poisson and binomial models. As results were similar, only the logit model is reported for interpretation; responses were recoded to *yes* or *no* indicating the presence or absence of SA, respectively, in the past 12 months.

Primary Exposure Variables

Bullying: A binary question asking if participants had ever been "bullied on school property" in the past 12 months assessed bullying.

E-bullying: E-bullying was assessed with a binary question asking if participants had ever been "bullied through e-mail, chat rooms, instant messaging, websites, or texting" in the past 12 months.

Covariates

Depressive symptoms (DS): Participants were asked if they felt "sad or hopeless almost every day for two weeks or more in a row." This was considered a proxy for DS. Response items were dichotomous *yes* or *no* answer choices.

Age: Age was assessed by one item with responses limited to a 7-item ordinal scale ranging from (A = *12 years old or younger* to G = *18 years or older*). A mean split was calculated to create groups (M = 16.04). Participants 16 years or younger were in the younger group and those 17 and older were in the older group. The reference group was older.

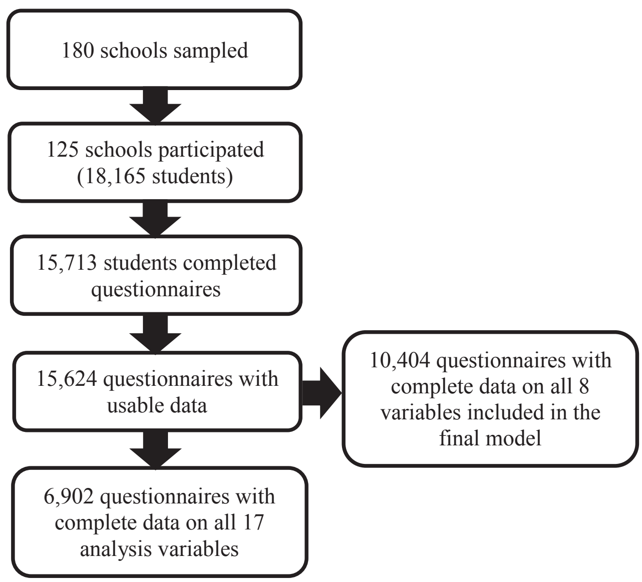

Figure 1. Flow diagram of sample inclusion criteria.

Sex: Biological sex was queried with an item phrased, "What is your sex?" Response items were *female* or *male*. Female sex was the reference category.

Ethnicity: Ethnicity was assessed via a prompt, "Are you Hispanic or Latino?" Response choices were *yes* or *no* and Hispanic/Latino was the reference group.

Race: An item worded, "What is your race?" measured racial identity. Participants selected one or more from five choices. Two racial categories were created: racial minority/non-White and racial majority/White. The minority group (reference) included all non-White participants.

English language proficiency: Proficiency in English was questioned with the item, "How well do you speak English?" Responses ranged from (A = *very well* to D = *not at all*). English language proficiency was operationalized as reporting *very well* or *well* and two groups were created consisting of proficient and not proficient. The proficient group was the reference.

Academic troubles: The academic performance item was worded, "During the past 12 months, how would you describe your grades in school?" Response items ranged from A = *mostly A's* to E = *mostly F's*. Participants could choose *none of these grades* and *not sure*. Two groups were created (academic trouble/no academic trouble). The academic trouble (reference) group comprised those selecting *mostly D's* or *mostly F's*. *None of these grades* and *not sure* were considered missing and not included.

Sleep: Sleep was appraised with a question worded, "On an average school night, how many hours of sleep do you get?" Responses ranged from A = *4 or less hours* to G = *10 or more hours*. Sleep was dichotomized by calculating a mean split (M = 6.66 hr). The low sleep group slept 6 hr or less, while the high sleep group (reference) slept 7 hr or more per night.

Computer use: One item phrased, "On an average school day, how many hours do you play video or computer games or use a computer for something that is not school work?" Responses ranged from A = *I do not play video or computer games or use a computer for something that is not school work* to G = *5 or more hours per day*, which was dichotomized by calculating a mean split (M = 2.2 hr). The low computer use group spent 2 hr or less on a computer while the high group (reference) spent 3 hr or more.

Rape victimization: Unwanted sexual intercourse was assessed with a binary question, "Have you even been physically forced to have sexual intercourse when you did not want to?"

Fighting: An item assessed the number of fights youth were involved in over the past 12 months. Choices ranged from A = *0 times* to H = *12 or more times* and was subsequently dichotomized to yes or no.

Sexual assault: Sexual assault was assessed with the item, "During the past 12 months, how many times did anyone force you to do sexual things that you did not want?" Response choices ranged from A = *0 times* to E = *6 or more times* and were dichotomized to indicate the presence or absence of assault.

Obesity: Weight was assessed with the item, "How do you describe your weight?" Response choices ranged from A = *very underweight* to E = *very overweight*. Obesity was operationalized as a response of *very overweight* and was dichotomized into two groups (obese and not obese) with obesity as the reference.

GLBQ: Sexual identity was assessed with the item, "Which of the following best describes you?" Response items were A = *heterosexual (straight)*, B = *gay or lesbian*, C = *bisexual*, and D = *not sure*. GLBQ, the reference category, was collapsed and included answers other than heterosexual.

Data Analysis

All analyses were conducted in R (R Core Team, 2013) using the pcalg package. The PC algorithm identified the structure of the data. The conditional probabilities, given by the PC algorithm, of the exposure variables, covariates, and the outcome were used to construct the DAGs (Kiiveri & Speed, 1982). Variables not directly related to SA were pruned and the PC algorithm was rerun with these eight remaining variables to create a final DAG. A logistic regression estimated the strength of the associations from this final model. Lastly, the backdoor method (Pearl, 2009) calculated the average causal effect (ACE). This is obtained by subtracting the odds of being bullied (or e-bullied) but not attempting suicide from the odds of being both bullied and attempting suicide; it utilizes the following formula:

Equation 1:

$$\Pr(SA)|do\ (Bully = 1) = \textstyle\sum_8 (\Pr(SA)|Bully = 1, X = x)(\Pr(X = x))$$

$^*X$ = factor from final logistic regression.

Results

Description of the Sample

Of the 10,404 complete cases included in the final DAG, 1,978 (19.0%) reported being bullied, 1,171 (11.3%) had GLBQ orientation, 560 (5.4%) reported academic trouble, and 889 (8.5%) attempted suicide in the past 12 months. Characteristics of the samples are presented in Table 1 and Table 2.

Table 1. Sample characteristics by bully status

Characteristics	Bullied	Not bullied	χ^2
GLBQ[a]	375	796	144.15***
DS[a]	1,070	2219	569.73***
Fighting[a]	652	1543	205.66***
Rape[a]	300	416	260.00***
Academic trouble[a]	160	400	34.47***
E-bullied[a]	987	559	2,366.70***
SA[a]	408	481	454.32***
Older age[b]	501	2353	33.54***
Female[b]	900	2618	92.34***
Hispanic ethnicity[b]	245	1187	15.81***
Minority race[b]	325	1562	21.48***
English proficiency[b]	1,429	5409	0.91
More sleep[b]	750	3284	32.27***
High computer use[b]	721	2307	26.35***
Sexual assault[b]	251	287	231.10***
Obese[b]	242	766	6.45*

Note. DS = depressive symptoms. GLBQ = gay, lesbian, bisexual, questioning. SA = suicide attempt. [a]Final model sample (10,404). [b]Initial model sample (6,902). * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2. Sample characteristics by GLBQ orientation

Characteristics	GLBQ	Not GLBQ	χ^2
DS[a]	694	2,295	465.28***
Fighting[a]	320	1,875	30.34***
Rape[a]	199	517	208.77***
Academic trouble[a]	103	457	29.44***
Bullied[a]	375	1,603	144.15***
E-bullied[a]	318	1,228	156.61***
SA[a]	278	611	387.70***
Older age[b]	291	2,563	4.76*
Female[b]	580	2,938	200.59***
Hispanic ethnicity[b]	165	1,267	0.15
Minority race[b]	219	1,668	0.38
English proficiency[b]	761	6,077	2.98
More sleep[b]	333	3,701	83.94***
High computer use[b]	437	2,591	56.10***
Sexual assault[b]	114	424	57.47***
Obese[b]	137	871	6.51*

Note. DS = depressive symptoms. GLBQ = gay, lesbian, bisexual, questioning. SA = suicide attempt. [a]Final model sample (10,404). [b]Initial model sample (6,902). * $p < .05$. ** $p < .01$. *** $p < .001$.

DAG Estimation and Model Formulation

The PC algorithm determined variables that marginally confound the relationship between bullying, e-bullying, and SA. On the basis of previous literature, 14 covariates were considered potentially linked to SA. Owing to the amount of missing data and the number of covariates, only variables directly related to SA in the initial PC algorithm were used for the final DAG and logistic regression.

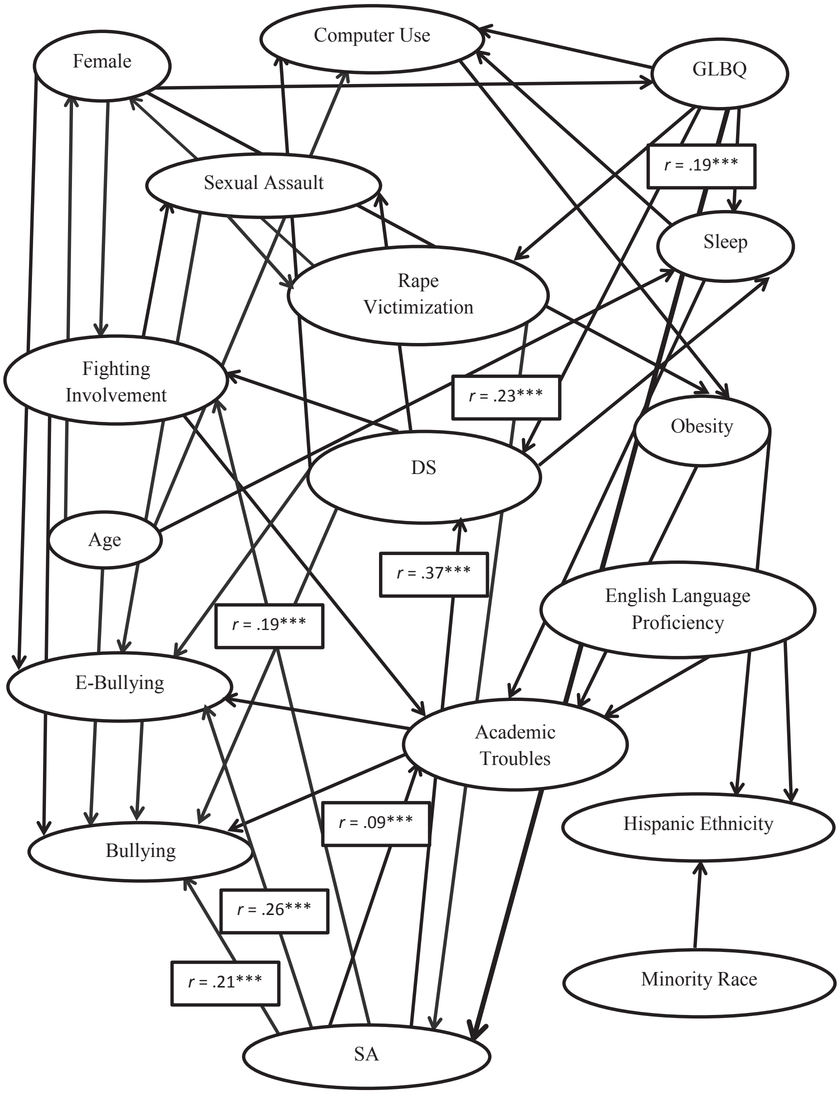

Figure 2. Working DAG from the initial PC algorithm. DAG = directed acyclic graph. DS = depressive symptoms. PC = Peter Spirtes and Clark Glymour. GLBQ = gay, lesbian, bisexual, questioning. SA = suicide attempt. ***$p < .001$.

The results from the PC algorithm are shown in Figure 2. Since the PC algorithm runs many tests and our initial model contained a large number of variables, we set a stringent significance criterion for the initial and final PC algorithms ($p < .0005$). Ignoring the directions (which may be influenced by the order of the data input into the algorithm), we used the results to design our working DAG. The PC algorithm was run treating data both as Gaussian (keeping count variables in tact as assessed) and binomial producing seemingly identical DAGs.

According to the results of the PC algorithm (Figure 2), demographics such as age ($r = -.03$, $p > .0005$), obesity ($r = .03$, $p > .0005$), minority race ($r = .04$, $p > .0005$), and ethnicity ($r = .05$, $p > .0005$) were not associated with SA. Thus, these variables were pruned for the final model. Female gender was moderately correlated with SA ($r = .13$, $p < .0005$); however, the DAG depicted in Figure 2 suggests that female gender is indirectly related to SA. Further analysis indicated that females are more likely to be GLBQ (71% of GLBQ individuals are female) and experience higher rates of e-bullying (70.0% of females report e-bullying). Female gender was thus indirectly related to SA (through GLBQ and e-bullying) and was not included in the final model.

The only other variable pruned from the final model with a higher r than .05 was sexual assault ($r = .18$, $p < .0005$), but it was excluded from the final analysis because the initial DAG suggested an indirect relationship with suicide through rape. GLBQ was directly related to SA ($r = .19$, $p < .0005$) as was bullying ($r = .21$, $p < .0005$), e-bullying ($r = .26$, $p < .0005$), academic trouble ($r = .09$, $p < .0005$), physical fights ($r = .19$, $p < .0005$), rape ($r = .23$, $p < .0005$), and DS ($r = .37$, $p < .0005$). DS played a key role in the structure of the DAG, accounting for indirect relationships between four other variables and suicide. Rape was the most isolated variable, although it mediated the GLBQ–SA relation.

The final DAG (Figure 3) combined information provided by the PC algorithm with the initial model depicted in

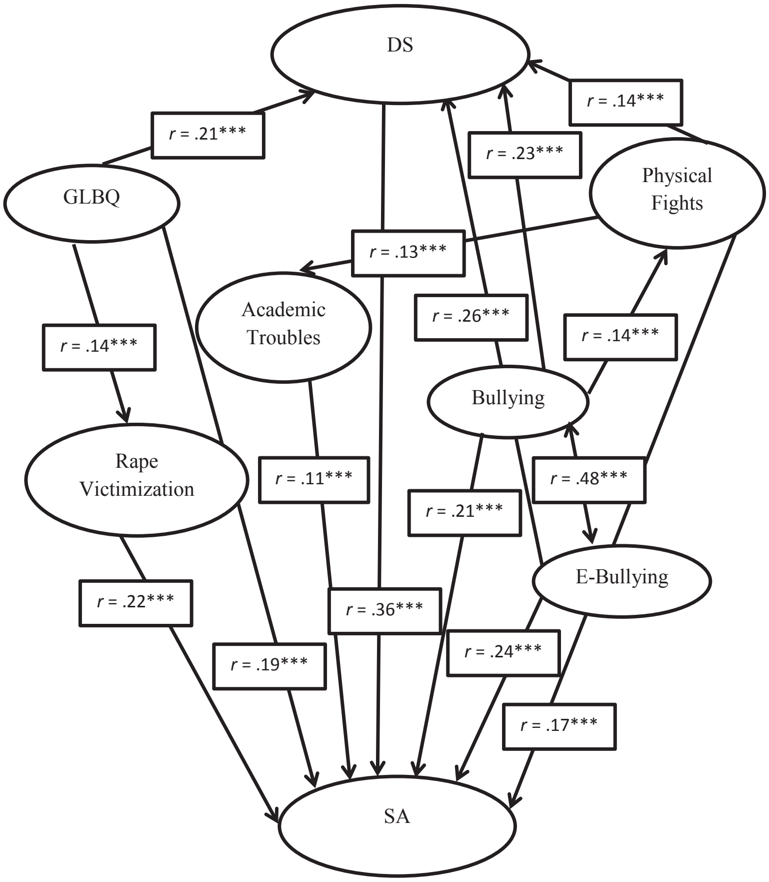

Figure 3. Final DAG. DAG = directed acyclic graph. DS = depressive symptoms. GLBQ = gay, lesbian, bisexual, questioning. SA = suicide attempt. ***$p < .001$.

Figure 2. The decision to prune does neglect some relationships not related to SA. For example, the variables physical fights and rape were both correlated with DS through sexual assault. Despite this, by reducing our model to the variables shown in Figure 3 we were able to capture the structure of the DAG as it immediately concerns SA.

Logistic Regression Results

We used the results of the PC algorithm to calculate the odds ratios and relative risks of bullying, e-bullying, and SA, after accounting for confounds using a logit model with a binomial SA variable. These results are presented in Table 3. There was a significant association of bullying (*OR* = 1.47, 95% CI = 1.22–1.78) and e-bullying (*OR* = 1.86, 95% CI = 1.53–2.25) with SA. Additional results from the logistic regression indicate that DS was strongly associated with SA, increasing the odds of SA by 10 times (*OR* = 10.5, 95% CI = 8.50–12.80). Rape (*OR* = 2.35, 95% CI = 1.91–2.89), GLBQ (*OR* = 2.05, 95% CI = 1.71–2.47), fighting (*OR* = 2.16, 95% CI = 1.84–2.55), and academic trouble (*OR* = 1.93, 95% CI = 1.49–1.78) were all significant covariates.

These results indicate that bullying increases the log odds of SA by .39, suggesting that bullying increases the odds of SA by 47% for someone who does not endorse any of the six other covariates. For an individual who possesses all other relevant traits, bullying increases the odds by 6.6%. E-bullying increases the log odds of SA by .62, suggesting that e-bullying increases the log odds of suicide by 86% for someone with negative responses on the six other covariates. For someone who reports a positive response on all covariates, e-bullying increases the odds of SA by 10.4%. The majority of the relationships between all variables were maintained between the logistic regression and the DAG.

Point estimates necessary to calculate the ACE of bullying and e-bullying on suicide were obtained with the logistic regression results. Eight binary variables were included in the final model (8 × 8 = 64); hence, there were 64 distinct scenarios to consider. We examined the ACE of bullying and e-bullying using the backdoor method (Pearl, 2009) and calculated an ACE of 2.46% for bullying, while e-bullying was higher at 4.16%.

Table 3. Logistic regression estimates in association with SA

Parameter	Estimate	*OR* estimate	*OR* 95% CI		*p*
Intercept	−4.55	0.01	0.01	0.01	< .001
GLBQ	0.72	2.05	1.71	2.47	< .001
DS	2.35	10.5	8.50	12.8	< .001
Fighting	0.77	2.16	1.84	2.55	< .001
Rape	0.85	2.35	1.91	2.89	< .001
Academic trouble	0.66	1.93	1.49	2.50	< .001
Bully	0.39	1.47	1.22	1.78	< .001
E-bully	0.62	1.86	1.53	2.25	< .001

Note. DS = depressive symptoms. GLBQ = gay, lesbian, bisexual, questioning. SA = suicide attempts.

Discussion

E-bullying may be more strongly associated with SA than bullying owing to the pervasiveness of the Internet and youths' inability to escape from toxic social environments. Because in-person bullying occurs most often while on school grounds, administrators can more easily manage social dynamics in school; however, e-bullying can happen anywhere and anytime youth are using Internet-enabled devices, thus extending beyond the school day. School administrators may benefit by alerting parents about the ubiquity and aversive consequences associated with e-bullying and/or by suggesting parents enforce limits on devices. Additionally, school counselors may profit by talking to students about the dangers of both bullying and e-bullying and by enacting policies that treat e-bullying similar to bullying.

One of the more surprising findings from our study implies different risk factors for SA between GLBQ and non-GLBQ adolescents. For GLBQ youth, rape, not bullying, seems to mediate the relation between GLBQ and SA. Contrary to our hypothesis, these results suggest that neither bullying nor e-bullying account for the increased frequency of GLBQ SA. Rape victimization may manifest into posttraumatic stress disorder, a disorder with high rates of suicide (Smith, Armelie, Boarts, Brazil, & Delahanty, 2016). Unfortunately, gender minority, transgender, and/or gender nonconforming status was not assessed in the version of the YRBS used. Given that 40% of transgendered individuals in the United States have attempted suicide (Haas, Rodgers, & Herman, 2014), it would have been desirable to examine whether these individuals have similar risk factors as GLBQ youth. Future research should look into this important question.

Strengths and Limitations

A significant limitation of our study concerns the measurement of our variables, which were either binary self-report items or continuous items that were later dichotomized. Although we tested different models treating our continuous responses as such, our primary exposure variables were binary items prohibiting us from investigating the chronicity and severity (e.g., physical) of bullying experiences. Bullying and e-bullying occur on a continuum with chronic and severe forms of bullying most likely conferring the greatest consequences. These factors could not be explored and should be an emphasis of future research. Additionally, prior SA research has concluded that reliance on single-item measures increases the risk of misclassification as some adolescents report attempts not fitting objective definitional criteria of SA (Millner et al., 2015). The assessment of suicide in a school setting may also account for the large amount of missing data (55.82%) since students may have been unwilling to report SA for privacy concerns or fear of consequences (e.g., hospitalization, school counselor intervention, mental health treatment, etc.).

Our data were cross-sectional and observational, limiting our ability to make temporal claims. The statistical method used, the PC algorithm, also makes some strong assumptions, one of which is that all variance is accounted for through measurement. This assumption, as is the case in most causal modeling approaches (Kalisch & Buhlman, 2007), was certainly violated in our analysis. It could be the case that factors not assessed by the YRBS are associated with SA and unaccounted for by our analysis. It is promising, however, that our models identified most of the commonly studied suicide risk factors as directly related to SA, suggesting that the most pertinent factors are included in our analysis. Finally, SA are highly clustered within schools. Variables allowing our analysis to account for these types of data are suppressed in the YRBS data prohibiting us from employing analytic tools appropriate for these types of data (e.g., generalized linear mixed models). Ignoring the correlated nature may affect the accuracy of our odds ratios. For all these reasons, our results should be interpreted with caution and future longitudinal studies with reliable measures of SA are needed to confirm (or refute) these findings.

The strengths of this study include the large, nationally representative dataset, allowing for a more accurate estimation of the prevalence of bullying, physical fights, GLBQ status, and SA. Secondly, the analytic approach employed facilitates a comparison of the different risk factors associated with SA. This study also used a data-driven approach to identify potential confounding, moderating, and mediating variables rather than restricting power by testing for a priori effects (e.g., sex, gender, sexual orientation, etc.).

Conclusion

This study suggests that most demographic variables are indirectly related to SA and that the processes by which these covariates affect SA do not appear to differ based on gender. Our analysis provides some testable findings for future research (mainly divergent suicide pathways between GLBQ and non-GLBQ youth and a larger effect for e-bullying than in-person bullying). More studies replicating these findings are needed.

Acknowledgments

The authors thank the CDC for use of YRBS data as well as Drs. Thomas Richardson, PhD, and Kevin King, PhD, for statistical consultation.

References

Birkett, M., Espelage, D. L., & Koenig, B. (2009). LGB and questioning students in schools: The moderating effects of homophobic bullying and school climate on negative outcomes. *Journal of Youth and Adolescence*, *38*(7), 989–1000. http://doi.org/10.1007/s10964-008-9389-1

Centers for Disease Control and Prevention. (2015a). *2015 YRBS data user's guide*. Atlanta, GA: Author. Retrieved from https://www.cdc.gov/healthyyouth/data/yrbs/pdf/2015/2015_yrbs-data-users-guide.pdf

Centers for Disease Control and Prevention. (2015b). *YRBS participation maps & history*. Retrieved from www.cdc.gov/healthyyouth/data/yrbs/participation.htm

Centers for Disease Control and Prevention, National Center for Injury Prevention and Control. (2016a). *Web-based Injury Statistics Query and Reporting System (WISQARS)* [online]. Retrieved from www.cdc.gov/injury/wisqars)

Centers for Disease Control and Prevention. (2016b). *Youth Risk Behavior Surveillance System (YRBS) overview.* Retrieved from https://www.cdc.gov/healthyyouth/data/yrbs/overview.htm

Curtin, S. C., Warner, M., & Hedegaard, H. (2016). Increase in suicide in the United States, 1999-2014. *NCHS Data Brief*, *241*, 1–8.

D'Augelli, A. R., Grossman, A. H., Salter, N. P., Vasey, J. J., Starks, M. T., & Sinclair, K. O. (2005). Predicting the suicide attempts of lesbian, gay, and bisexual youth. *Suicide and Life-Threatening Behavior, 35*(6), 646–660.

Haas, A. P., Eliason, M., Mays, V. M., Mathy, R. M., Cochran, S. D., D'Augelli, A. R., ... Clayton, P. J. (2011). Suicide and suicide risk in lesbian, gay, bisexual, and transgender populations: Review and recommendations. *Journal of Homosexuality*, *58*(1), 10–51. http://doi.org/10.1080/00918369.2011.534038

Haas, A. P., Rodgers, P. L., & Herman, J. L. (2014, January). *Suicide attempts among transgender and gender non-conforming adults: Findings from the national transgender discrimination survey*. Report to the National Action Alliance for Suicide Prevention Task Force, The Williams Institute, Los Angeles, CA.

Hatzenbuehler, M. L., & Keyes, K. M. (2013). Inclusive anti-bullying policies and reduced risk of suicide attempts in lesbian and gay youth. *Journal of Adolescent Health, 53*(1), S21–S26. https://doi.org/10.1016/j.jadohealth.2012.08.010

Kalisch, M., & Buhlmann, P. (2007). Estimating high-dimensional directed acyclic graphs with the PC-algorithm. *Journal of Machine Learning Research, 8,* 613–636.

Kann, L., McManus, T., Harris, W. A., Shanklin, S. L., Flint, K. H., Hawkins, J., ... Zaza, S. (2016). Youth risk behavior surveillance – United States, 2015. *MMWR Supplements*, *65*(6), 1–50. https://doi.org/10.15585/mmwr.ss6506a1

Kiiveri, H., & Speed, T. P. (1982). Structural analysis of multivariate data: A review. *Sociological Methodology*, *13*, 209. https://doi.org/10.2307/270722

Kim, Y. S., & Leventhal, B. (2008). Bullying and suicide: A review. *International Journal of Adolescent Mental Health, 20*(2), 133–154.

Klomek, A. B., Marrocco, F., Kleinman, M., Schonfeld, I. S., & Gould, M. S. (2007). Bullying, depression, and suicidality in adolescents. *Journal of the American Academy of Child and Adolescent Psychiatry, 46*(1), 40–49. https://doi.org/10.1097/01.chi.0000242237.84925.18

Klomek, A. B., Sourander, A., & Gould, M. (2010). The association of suicide and bullying in childhood to young adulthood: A review of cross-sectional and longitudinal research finding. *The Canadian Journal of Psychiatry, 55*(5), 282–288. https://doi.org/10.1177/070674371005500503

Kolbe, L. J., Kann, L., & Collins, J. L. (1993). The youth risk behavior surveillance system: Overview of the Youth Risk Behavior Surveillance System. *Public Health Reports*, *108*(Suppl 1), 2–10.

Kowalski, R., Giumetti, G. W., Schroeder, A. N., & Lattanner, M. R. (2014). Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth. *Psychological Bulletin, 140*(4), 1073–1137. https://doi.org/10.1037/a0035618

Millner, A. J., Lee, M. D., Nock, M. K., Wang, P., Kessler, R., & Jenkins, R. (2015). Single-item measurement of suicidal behaviors: Validity and consequences of misclassification. *PLoS ONE*, *10*(10), e0141606. http://doi.org/10.1371/journal.pone.0141606

Nock, M. K. (2009). Suicidal behavior among adolescents: Correlates, confounds, and (the search for) causal mechanisms. *Journal of the American Academy of Child & Adolescent Psychiatry, 48*(3), 237–239. http://doi.org/10.1097/CHI.0b013e318196b944

Olweus, D. (1993). *Bullying at school: What we know and what we can do*. Oxford, UK: Blackwell Publishing.

Pearl, J. (2009). *Causality: Models, reasoning, and inference* (2nd ed.). Cambridge, UK: Cambridge University Press. Retrieved from http://bayes.cs.ucla.edu/BOOK-2K/neuberg-review.pdf

R Core Team. (2013). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.r-project.org/

Shain, B. (2016). Suicide and suicide attempts in adolescents. *Pediatrics*, *138*(1), e1–e11. http://doi.org/10.1542/peds.2016-1420

Smith, P. K. (2004). Bullying: Recent developments. *Child and Adolescent Mental Health*, *9*(3), 98–103. https://doi.org/10.1111/j.1475-3588.2004.00089.x

Smith, B. C., Armelie, A. P., Boarts, J. M., Brazil, M., & Delahanty, D. L. (2016). PTSD, depression, and substance use in relation to suicidality risk among traumatized minority lesbian, gay, and bisexual youth. *Archives of Suicide Research*, *20*(1), 80–93. https://doi.org/10.1080/13811118.2015.1004484

Spirtes, P., Glymour, C., & Scheines, R. (2000). *Causation, prediction, and search*. Retrieved from https://www.cs.cmu.edu/afs/cs.cmu.edu/project/learn-43/lib/photoz/.g/scottd/fullbook.pdf

Received September 28, 2017
Revision received February 21, 2018
Accepted February 24, 2018
Published online September 14, 2018

Mr. Kuehn, BS, is a doctoral student in the clinical psychology program at the University of Washington, WA. His research focuses on predicting and preventing adolescent suicidal behaviors. In his future work he plans to use advanced quantitative methods to explore relations of self-regulation, coping styles, and impulsivity among youth at high risk for suicide.

Ms. Wagner is a doctoral student in the Statistics Department at the University of Washington. Presently, she is working on extracting marginal distribution information from partially ordered permutation data in the context of Recursive Inversion Models.

Ms. Velloza is a doctoral student in the Department of Epidemiology at the University of Washington, WA. Her research focuses on mental health, HIV prevention, and reproductive health among adolescents and young women. She has experience in qualitative and quantitative analysis techniques, including causal modeling and longitudinal and multilevel data analysis.

Kevin S. Kuehn
Department of Psychology
University of Washington
University Way NE
Seattle, WA 98195
USA
kskuehn@uw.edu

