HOW DOES INTENSITY OF SOCIAL NETWORK SITES USE MODERATE CYBERVICTIMIZATION? UNDERSTANDING THE FACTORS AND CONDITIONS USING AN R-BASED TOOL FOR PROBING MODERATION EFFECTS

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Abstract

Studies on cyberbullying are replete with questions about whether certain risk or protective factors are likely to predict cyberbullying outcomes such as cybervictimization. Such questions can often be reframed in terms of moderation effects, or hypotheses about how the effect of a predictor variable on an outcome variable depends on the value of a moderator variable. Demonstrating how questions about moderation effects are conventionally tested using the dataset from the Teens and Parents survey conducted by the Pew Research Centre's Internet and American Life Project, the current study found two sets of significant moderation effects that could be interpreted to mean that the predictive relationship between traditional victimization and cybervictimization depend on the teenager's intensity of SNS use and gender. A secondary purpose of this paper is to extend the conventional analytic approach in the form of an R package that provide researchers with methods – based on the pick-a-point technique and the Johnson-Neyman technique – which they can use to probe moderation effects they find significant in their research projects. Empirical illustrations with the cyberbullying dataset are provided throughout to demonstrate the use of this R package.

Keywords: Social network site use, Cybervictimization, Moderation analysis.

1 INTRODUCTION

With the rapid proliferation of social network sites (SNS) like Facebook, there seems to be a growing concern that many of its young users are experiencing cyberbullying on these sites, as witnessed by titles, such as “Cyber-bullying: 5.4m kids in UK are potential victims on Facebook, Twitter and Ask.fm” and “'Growing trend' of cyberbullying on social networks” repeatedly making the headlines in international news media (Butterly 2013; Ellis 2013). Presumably fuelled by these concerns, there has been a recent surge of research interest in the link between social network use and the potential for cybervictimization, particularly among teenagers and young adults (Whittaker & Kowalski 2015).

However, as with other areas of social science research, much of the extant studies on cyberbullying focus on testing hypotheses about the main effects of the phenomenon. Notably, many of the questions in this area relate to which risk or protective factors are the most proximal correlates of cyberbullying or cybervictimization, with scant empirical research attention given to understanding the conditional nature of these effects. For instance, a number of studies have shown a correspondence between traditional bullying and cyberbullying, with many studies reporting that individuals who traditionally bully have a higher tendency to perpetrate cyberbullying, while other studies have also shown that victims of traditional bullying are more likely than non-victims to be targets of cyberbullying online (Olweus 2013). Of specific concern to substantive researchers, merely theorizing and testing the bivariate relationship between traditional bullying and cyberbullying offers very little in terms of understanding the specific circumstances these effects manifest, and whether contextual or individual characteristics can potentially moderate these effects. Furthermore, although most IS researchers recognize the importance of testing for moderation effects, also called interactions, in their research projects, not all the researchers are familiar with the empirical techniques for probing moderation effects or are aware of the statistical tools that are available to conduct this type of analysis.

Thus, one of the aims of this study is to develop a better understanding of the relationships between SNS use, traditional victimization, cybervictimization and potential gender differences. Specifically, in examining the moderation effects of SNS use and gender on the relationship between traditional victimization and cybervictimization, the analyses presented in the current study offers an avenue to advance theorizing and research on cyberbullying. A secondary aim of this paper is to advance a regression-based statistical tool called *probemod* that is written as an R package (R Core Team 2014). This statistical tool is freely available from CRAN (http://cran.R-project.org), and the main focus is to provide researchers with a tool they can easily reach and use to probe significant moderation effects they may find in their research projects. To this end, the rest of this paper is organized as follows. First, a brief overview of the literature on cyberbullying, specifically in regards to its relationships with traditional bullying, social network use and gender differences will be provided. The sections subsequent to this describe the conventional analytic approach to studying moderation effects, with an empirical application of this approach to the cyberbullying dataset. Then, two techniques to probe moderation in further detail will be introduced followed by empirical illustrations with the same dataset. Finally, the paper concludes with a brief discussion of the findings, limitations and suggestions for further development.

2 CYBERBULLYING, TRADITIONAL BULLYING, SOCIAL NETWORK SITES USE, AND GENDER DIFFERENCES

Cyberbullying can be broadly defined as aggressive acts that are performed via digital media such as mobile phones or the Internet (Kowalski et al. 2012). Statistics from studies conducted in the United States and other parts of the world indicate that cyberbullying is quite prevalent, especially among children and adolescent. Notably, a recent regional census of US high school student finds that 15.8% of students experienced some form of cyberbullying, with higher victimization rate among girls than among boys (Schneider et al. 2012). Similarly, in a survey of 8,194 Canadian teenagers, Cénat et al. (2014) reported that about 23% had been cyberbullied at least once in the past one year and finding also that girls were more likely to report being victims of cyberbullying compared to boys.

While there is no question that cyberbullying has become one of the most common Internet risks for young people today, much remains to be learned about the factors that puts them at risk of becoming victims of cyberbullying. As noted earlier, most of the studies published so far are in agreement that there is a predictive relationship between traditional bullying and cyberbullying. Some of the earliest studies that brought this issue to light found that individuals who had perpetrated traditional bullying within the previous months were twice as likely to also perpetrate cyberbullying (Hinduja & Patchin 2008; Patchin & Hinduja 2006). Likewise, these early studies also report that individuals who were victims of traditional bullying were also much more likely to be victims of cyberbullying than those who had not been victims of bullying (Hinduja & Patchin 2008; Li 2006). Subsequent research has largely supported this finding (Gradinger et al. 2009; Kowalski et al. 2012; Schneider et al. 2012), including one recent study, which reported that cybervictimization was 10 times higher among traditional middle school victims (Holfeld & Grabe 2012). These findings led Olweus (2013), and Kowalski et al. (2014) in their review of the literature to conclude that cyberbullying may be an extension of traditionally bullying.

Although previous studies have established strong links between traditional bullying and cyberbullying, it should be pointed out that not all researchers have documented a straightforward relationship between the two constructs. For instance, Varjas, Henrich, and Meyers (2009) reported strong correlations between cyberbullying and cybervictimization, but observed that neither of these measures are highly correlated with traditional forms of bullying. Additionally, a couple of studies have also noted that among their sample of youths who experienced traditional victimization or perpetration, a substantial proportion of them do not experience cybervictimization (Olweus 2012; Raskauskas 2010; Raskauskas & Stoltz 2007; Schneider et al. 2012). Such findings suggest that it may be helpful to go beyond straightforward associations and move toward a more fine-grained understanding of the conditional nature of how traditional bullying transmits its effects on cyberbullying. This can be accomplished by integrating existing theoretical understanding of conditional effects associated with how contextual and individual characteristics may alter the association between traditional bullying and cyberbullying to form hypotheses that can be empirically tested using moderation analysis. Indeed, with many of the abovementioned studies reporting that girls are more likely to be victims of cyberbullying, such an analysis can be used to establish the extent to which the influence of traditional bullying on cyberbullying depends on the gender of the teenager.

Furthermore, given the increasing popularity of SNS, and with SNS platforms such as Facebook attracting intensive usage by young users, moderation effects associated with SNS use is of particular interest. While the types of online platforms through which cyberbullying can occur are quite diverse, ranging from instant messaging, e-mail, text messages, to online games, more recent investigations have documented the important role of SNS in cyberbullying (Livingstone et al. 2011; Ybarra & Mitchell 2008). For example, Mesch (2009) in a secondary analysis of the Teens and Parents survey conducted by the Pew and American Life Project reported that having an active profile in a social network site and participating in clip-sharing social networking sites increased the risk for being bullied online, with greater prevalence among girls than for boys. Likewise, Whittaker and Kowalski (2015) found that the most prevalent platforms for experiencing cybervictimization among young users were SNS platforms like Twitter (12.0%) and Facebook (11.4%), while YouTube (4.7%) and chatrooms (2.1%) were rarely reported as platforms for cyberbullying. Recognizing SNS's emergence as the primary platform for victimization, a logical question to ask is to what extent does the intensity of SNS use moderate the association between traditional bullying and cyberbullying. Focusing on victimization in the traditional and online setting (i.e. cybervictimization), the analysis in the current study represents a significant extension of the empirical literature, since there is little empirical work to inform such a question.

3 CONVENTIONAL ANALYTIC APPROACH TO STUDYING MODERATION EFFECTS

3.1 Fundamentals of Studying Moderation Effects

Before examining the cyberbullying dataset, let us first consider a simple moderation model. The conceptual diagram in Fig. 1a illustrates the simplest form of moderation where a predictor variable X is depicted as having an effect on outcome variable Y that is contingent on moderator variable M, as reflected by the arrow pointing from M to the line from X to Y. In conceptualizing such a model, the researcher's goal is often to determine if a certain contextual or individual characteristic is the specific moderating variable M that affects a known effect of predictor variable X on outcome variable Y. The basic idea is that if M was found to be related to changes in magnitude of the effect of X on Y, then the association between the two variables could be said to be moderated by M.

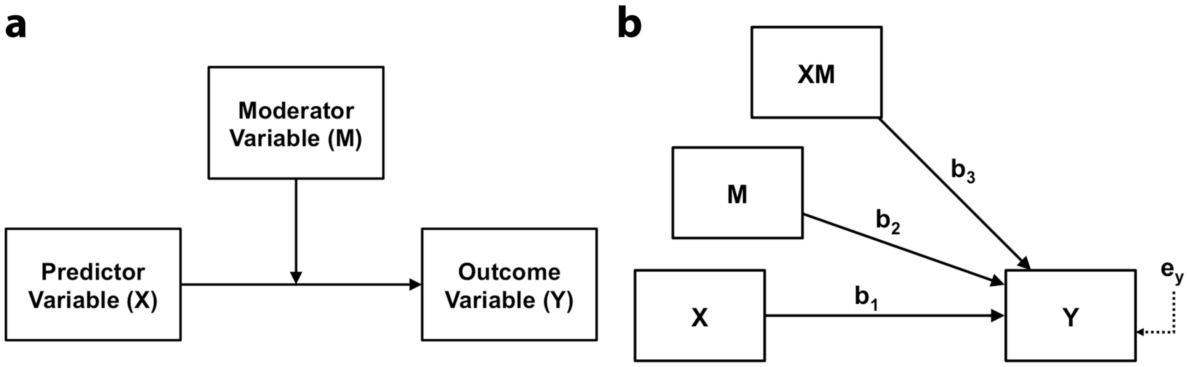

Figure 1. A simple moderation model depicted as a conceptual diagram (panel a) and as a statistical diagram (panel b).

The way that moderation effects are conventionally analysed in the literature is to first set up a regression model in which Y is entered as a dependent variable and regressed on X and M, as illustrated diagrammatically in Fig 1b. In this regression model, the coefficient of X, or b_1, estimates the expected change in Y corresponding to one-unit change in X but equal on M, while b_2 estimates the expected change in Y given one-unit change in M controlling for X's average effect. In other words, b_1 and b_2 both represent unconditional effects on Y that are independent of each other. Thus, to perform moderation analysis, a crucial next step involves the computation of the arithmetic product of X and M and including the arithmetic product, or more commonly known as the interaction term (XM), to the regression model of Y along with X and M. In this expanded model, the coefficient of the interaction term (XM), b_3, measures to what extent a one-unit change in X changes Y given the value of M. Hence, by adding XM, the model now allows the effect of X on Y to be a linear function of M.

3.2 Description of the Cyberbullying Dataset

To provide an empirical illustration of how moderation effects are typically analyzed and interpreted, the present analysis rely on the dataset from the 2011 Parents and Teens Digital Citizenship Survey, one of the studies under Pew Research Center's Internet and American Life Project. Data collection was conducted by Princeton Survey Research Associates International using telephone survey. The survey was administered between April 19 and July 14, 2011, and was conducted in either English or Spanish to a sample comprising 799 teenagers who were aged between 12 to 17 years old, along with a parent or guardian. Response rate for the survey was at least 7% and the margin of error was approximately +/- 4.8% at the 95% confidence level.

For the purposes of the present analysis, the dataset included a measure of traditional victimization that was operationalized using one item in which the teens were asked whether they have been bullied in person in the past 12 months. "Yes" on this item was dummy coded as 1 while "No" was coded as 0 (M = .12, SD = .33). Cybervictimization was measured using two items in which the teens were asked to indicate: (a) "In the past 12 months when you have been on a social networking site, has anyone been mean or cruel to you?" (b) "Have you been bullied online in the past 12 months, such as through email, a social networking site or instant messaging?" Responses with "Yes" on the each item was dummy-coded as 1 and responses which are "No", "Don't know" and "Refused" were coded as 0. The responses were summed to derive a composite score for cybervictimization in which higher scores indicate higher self-reports of being cybervictimized (M = .21, SD = .52). Finally, intensity of SNS use was assessed using 7 items in which teens indicated "yes" or "no" to a list of SNS activities. Items on this measure include: (a) "Do you ever post comment to something a friend has posted?" (b) "Do you ever send private messages to a friend within the social networking site?" (c) "Do you ever send instant messages to or chat with a friend through the social networking site?" (d) "Do you ever tag people in posts, photos or videos?" (e) "Do you ever post a status update?" (f) "Do you ever post a photo or video?" and (g) "Do you ever play a game on social networking site?" A "Yes" response for each item was dummy-coded as 1 while "No", "Don't know" and "Refused" responses were coded as 0. These responses were summed to derive a composite score for intensity of SNS use in which higher scores indicate higher intensity of SNS use (M = 4.21, SD = 2.62, r_{KR20} = .98).

Parents provided the gender of the teenager (391 males, 408 females), and two other demographic variables were entered as covariates for the analysis in this study. The two demographic variables included the parent's education level that ranged from 1 (no formal education, or grades 1-8) to 7 (postgraduate/professional school after college). The median for this sample was 5.00 (or "some college, no 4-year degree", SD =1.75). Family income was measured in nine categories from "less than $10,000" to "$150,000 or more." The median for this sample was 6.00 (or "$50,000 to under $75,000," SD = 2.42). Descriptive statistics for this sample of teenagers, broken down by gender can be found in Table 1, which indicates a higher prevalence of cybervictimization among girls than for boys (t = 2.89, p < .01), and no difference was found among the genders for traditional victimization (t = 0.85, n.s.).

	Traditional Victimization		Cybervictimization	
	Mean	SD	Mean	SD
Boys	.1125	.3164	.1535	.4607
Girls	.1323	.3393	.2598	.5748
Overall	.1227	.3282	.2078	.5245

Table 1. Descriptive statistics for the cyberbullying dataset.

3.3 Empirical Application

Modeling cybervictimization as the outcome variable, two sets of moderation hypotheses would be tested (Fig. 2). The first predicts that among teenagers who had experienced bullying in the traditional setting in the past 12 months, they are more likely to report higher instances of cybervictimization if they used SNS intensively. The second hypothesis concerns potential gender differences in cybervictimization if the teenagers had experienced bullying in the traditional setting. In the current cyberbullying dataset, cybervictimization is a count variable with a high proportion of zero outcomes (only about 15% of the teenagers reported at least one instance of cybervictimization). Although Poisson regression models are often used for counts data, a more appropriate approach is to estimate such datasets using zero-inflated

Poisson regression models which take into account the excess of zero outcomes in the data (Lambert 1992). In zero-inflated Poisson regression models, two separate models are generated and then combined. Specifically, a logit model, or zero-inflated model, is first generated for the "certain zero" cases, predicting whether or not a teenager would be in this group which had not experienced cybervictimization. Then, a Poisson count model is generated to predict the counts for those teenagers who are not certain zeros (i.e. at least one instance of cybervictimization). And finally, the two models are combined. As can be seen in Fig. 2b, this model is similar to the prior simple moderation model, except it now includes two interaction terms, XM_1 and XM_2, which model the moderation effects of intensity of SNS use and gender on the relationship between traditional victimization and cybervictimization in the count model, respectively. The syntax for running zero-inflated Poisson regression using the R package *pscl* (Jackman 2015) can be found in the Appendix. Before turning to the results, it should be pointed out that although R was used for the present analysis (R Core Team 2014), the analysis of this particular moderation model can be accomplished using any statistical software that supports zero-inflated Poisson regression (e.g. STATA, SAS).

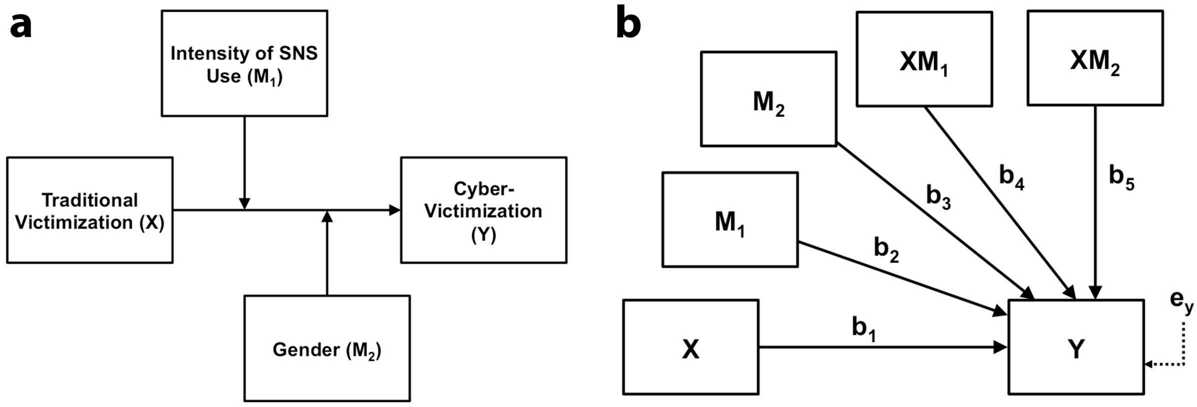

Figure 2. *Moderation model with intensity of SNS use and gender as the moderator variables depicted as a conceptual diagram (panel a) and as a statistical diagram (panel b).*

Table 2 contains the exponentiated coefficients from the zero-inflated Poisson regression along with their standard errors, z and p-values, with the upper half of Table 2 showing the coefficients for the zero-inflation model. Since traditional victimization was coded such that they differ by a single unit (1 if they have experienced traditional bullying versus 0 if they have not) on X, we can derive from b_1 that compared to non-victims, teenagers who had been victims of traditional bullying in the last 12 months ($X = 1$, $b_1 = .03$, $p <.001$) are very unlikely to fall under the zero group (i.e. not having experienced cybervictimization; note the odds of 0.03 is very close to 0). Moreover, the coefficient for intensity of SNS use (M_1) is also statistically significant ($b_2 = .48$, $z = 3.47$, $p < .001$). This can be interpreted to mean that among teenagers who have not been victims of traditional bullying in the last 12 months ($X = 0$), if they were to increase their SNS use by one unit, the odds that they had not experienced victimization online would decrease by a factor of .48. Also, since gender was coded such that boys and girls differ by a single unit (1 versus 0) on X, the significant effects of gender (M_2; $b_3 = 7.23$, $z = 2.38$, $p < .05$) can be interpreted as the difference between the two genders. Thus, given that b_3 is greater than one, the claim can be made that among those who have not been victims of traditional bullying in the last 12 months ($X = 0$), boys are much more likely than girls to not have experienced victimization online.

Of key interest are the exponentiated interaction coefficients in the count model in the upper half of Table 2, which indicates that the interaction between traditional victimization and intensity of SNS use (XM_1) is statistically significant ($b_4 = 1.39$, $z = 2.21$, $p < .05$). The significant interaction can be interpreted to mean that the relationship between traditional victimization and cybervictimization is moderated by the teenager's intensity of SNS use and that the expected self-reports of cybervictimization would increase by a factor of 1.39 if the teenager had experienced traditional victimization and increased his/her SNS use by one unit. In addition, because the interaction between traditional victimization and gender is significant (XM_2; $b_5 = 0.32$, $z = 2.55$, $p < .05$), the inference can be made that the relationship between traditional victimization and cybervictimization depends on the gender of the teenager. However, one issue remains. Even though these results demonstrate that there is evidence of moderation effects by SNS use and gender, they do not establish that, for instance, traditional victimization has an effect on cybervictimization for teenagers with high SNS use but not for teenagers are low SNS users. All that b_4 and b_5 establish is that the effect of traditional victimization on cybervictimization depends on SNS use and gender. To overcome this and enable easier interpretation, a common practice in the literature is to plot the moderation effects so that readers can interpret it visually. Hence, in the context of our cyberbullying data, this would be accomplished by calculating predicted values of cybervictimization under different conditions (victims versus non-victims of traditional bullying, and high and low values of SNS use) and plotting the predicted relationship, also known as "simple slopes'' between the traditional victimization and cyberbullying at different levels of SNS use.

	Coefficient	SE	z	p
Zero-inflation model coefficients (Binomial with logit link)				
b_1: Traditional victimization (X)	.029	.030	3.468	.000
b_2: Intensity of SNS Use (M_1)	.482	.218	3.568	.000
b_3: Gender (M_2)	7.226	6.587	2.380	.017
Count model coefficients (Poisson with log link)				
b_1: Traditional victimization (X)	.587	0.580	.546	.585
b_2: Intensity of SNS Use (M_1)	.892	0.330	.841	.400
b_3: Gender (M_2)	2.398	1.484	2.285	.022
b_4: XM_1	1.394	0.540	2.211	.027
b_5: XM_2	.318	0.213	2.552	.011

Table 2. *Zero-inflated Poisson regression estimating cybervictimization from traditional victimization, intensity of SNS use, gender and their interaction terms. Notes: coefficients have been exponentiated to transform the estimates to the original metric of the outcome variable.*

Figure 3 depicts the simple slopes between traditional victimization and cybervictimization plotted as a function of intensity of SNS use, where the left panel shows the plot for boys and the right panel shows the plot for girls. Across both genders, the plots demonstrate that the association between traditional victimization and cybervictimization differs according to the intensity of SNS use. As illustrated by the slopes for the two lines, the plots depict not only a positive relationship between SNS use and cybervictimization but also indicate a much larger effect among teenagers who have experienced traditional victimization than for teenagers who are non-victim, mirroring the results from the regression model. This visual representation of the regression model certainly makes it clearer if the direction and slope of the moderation effects are consistent with one's prediction rather than relying on just numerical values of the regression coefficient for the interaction term. But while this aid in the interpretation of moderation effects, there is often a need to extend the conventional analytic approach in terms of probing how the conditional effect of X on Y vary at different values of M in order to fully explicate the nature of the moderation effects. Concerning this, a secondary aim of this paper is to facilitate these extensions in the form of an R package that provide researchers with techniques they could use to probe moderation effects they find significant in their research projects. Empirical illustrations with the cyberbullying dataset will be provided to demonstrate the use of this R package.

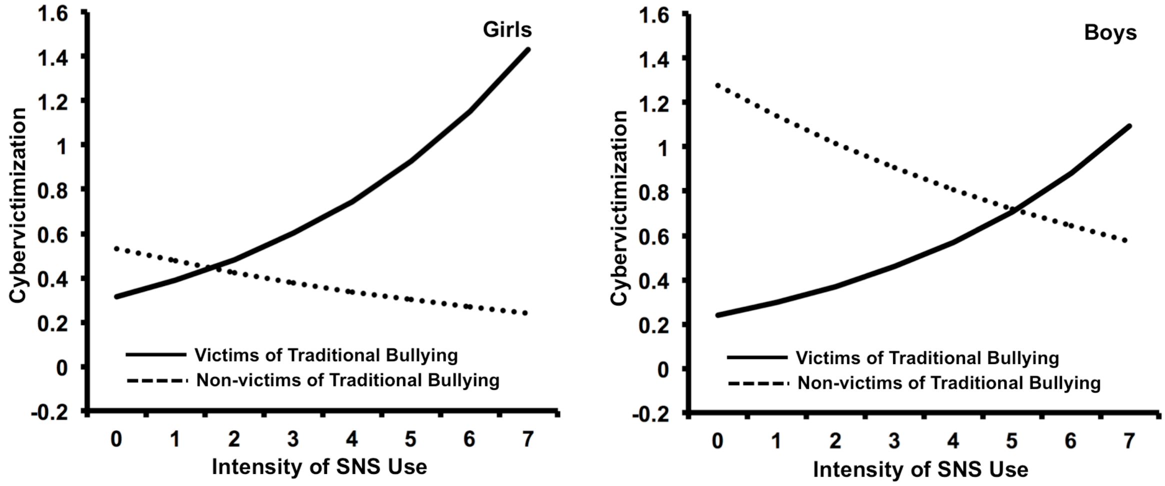

Figure 3. *Plots illustrating the simple slopes between traditional victimization and cybervictimization as a function of intensity of SNS use, depicted separately for girls (left panel) and for boys (right panel).*

4 EXTENDING THE CONVENTIONAL ANALYTIC APPROACH TO PROBE MODERATION EFFECTS

As an extension of the conventional analytic approach to studying moderation effects, the author of this paper developed an R-based package, called *probemod*, which can be freely downloaded from CRAN (http://cran.R-project.org). It is worth mentioning briefly that while R is being used with increasingly being used by social science researchers for their analyses, there is at the moment no R-based package that offers the capability to conduct the type of analysis. With its emphasis on probing moderation effects, the *probemod* package implements two techniques that will be elaborated on in the rest of this paper.

4.1 Pick-a-Point Technique to Probing Moderation Effects

One of the methods that can be used to probe moderation effects is the pick-a-point technique, which is sometimes called a spotlight analysis in the literature (Bauer & Curran 2005; Rogosa 1980; Spiller et al. 2013). This approach requires the researcher to pick one or more representative points or values on the moderator variable (M), estimate the conditional effect of the predictor variable (X) on the outcome variable (Y) on those points, and then compute the t-statistic or construct a confidence interval (CI) to ascertain whether the effect is greater than chance. The formulae and the steps involved in the manual computations for the pick-a-point technique can be found in several textbooks that discuss multiple regression and interactions (see Aiken & West 1991; Cohen et al. 2003; Jaccard & Turrisi 2003). As a computational aide to help researchers probe significant moderation effects, the *probemod* package implements this technique and it provides the researcher with three possible methods to select representative points.

First, a challenge that researchers sometimes face when using the pick-a-point technique to probe a significant moderation effect is in finding the appropriate values on the moderator variable (M). A widely used strategy that is implemented in *probemod* is to estimate the conditional effect of X on Y when M is equal to the mean, one standard deviation (SD) below the mean, and one SD above the mean (Helm & Mark 2012). This strategy allows the researcher to ascertain whether X is related to Y among those who are "low" (i.e. 1 SD below the mean), "moderate" (i.e. sample mean), and "high" (i.e. 1 SD above the mean) on M. The syntax required to the pick-a-point technique can be found in the Appendix. In the absence of explicit instruction by the user, the pick-a-point syntax produces a table containing the conditional effect of X on Y, the value of the moderator, along with statistical information such as the standard error (SE), t-statistic, p-value and 95% confidence interval that are computed on the basis of the mean plus/minus one SD method. The output of the application of this method to the cyberbullying dataset is given in Table 3. Showing the results separately for teenage girls and boys, Table 3 provides the exponentiated effect of traditional victimization on cybervictimization conditional on specific values of intensity of SNS use (where the second value represents the mean, while the first and third values being 1 SD below and above the mean, respectively). Comparing the results for girls and for boys, it could be seen that none of the conditional effects across the given values for intensity of SNS use were significant for boys. But for girls, conditional effects were significant for values 4.208 and 6.827 on the intensity of SNS use. The conditional effects associated with the two significant values implies that the expected self-reports of cybervictimization would increase by a factor of 2.372 and 5.658 if the teenage girl had experienced traditional victimization if her intensity of SNS use falls in the ballpark of the two values. However, the caveat when interpreting the results from the mean plus/minus one SD method is that the values of M generated on the basis of mean plus/minus one SD are sample dependent. Meaning to say, depending on the distribution of M, for instance, if it were skewed, one or more of the generated values could be out of range of the data (Spiller et al. 2013). This issue can be ameliorated somewhat by the second method, which computes the results on the basis of percentiles in the sample distribution of M.

Gender	Intensity of SNS Use	Effect	SE	t	p	95% CI
Girls	1.589	.995	.863	.007	.994	.226, 4.367
	4.208	2.372	1.552	2.017	.044	1.024, 5.498
	6.827	5.658	3.241	5.280	.000	2.971, 10.776
Boys	1.589	.317	.276	1.517	.130	.072, 1.402
	4.208	.756	.499	.644	.520	.321, 1.777
	6.827	1.802	1.047	1.743	.082	.929, 3.497

Table 3. *Conditional effects of traditional victimization on cybervictimization at different values (mean and ±1 SD) of intensity of SNS use and gender. Notes: 95% CI = 95% confidence interval; effects have been exponentiated to transform the estimates to the original metric of the outcome variable.*

As an alternative to the mean plus/minus one SD method, a second method that could be used to aid researchers find appropriate values to probe a significant moderation effect is to estimate the conditional effect of X on Y at values of M corresponding to the 10th, 25th, 50th, 75th, and 90th percentiles in M's sample distribution (Hayes & Matthes 2009). To activate this method, all that is needed is to indicate "method=percentiles" when running the *probemod* package. Running the *probemod* package with this second method on the cyberbullying dataset yields the output in Table 4. In this alternative presentation, the t-statistic and the 95% CI intervals of the exponentiated conditional effects for the 10th, 25th, 50th, 75th, and 90th percentiles on the intensity of SNS use indicate once again that none of the conditional effects across the given values for Intensity of SNS use were significant for boys. For girls, the conditional effects were significant for values 5, 6 and 7 on the intensity of SNS use, which correspond to an increase in self-reports of cybervictimization by a factor of 3.086, 4.300 and 5.993, respectively. While one could infer, on the basis of the results in Table 4 that if a teenage girl who had experienced traditional victimization were to score a 5 or more on the intensity of SNS use scale is expected, this interpretation would be considered tenuous since we do not know if values 3 and 4 on the intensity of SNS use significantly impacts the conditional effects for traditional victimization on cybervictimization. Similarly, the question can be raised as to what range of values on the intensity of SNS use, other than the values provided by the mean plus/minus SD or percentiles method, would a highly significant conditional effect of traditional victimization on cybervictimization be revealed among teenage boys. One way to address this issue is to directly specify particular values on M (e.g. 3 or 4) for which the conditional effect should be tested by the pick-a-point technique.

Thus, instead of leaving it to the prior two methods to generate sample-dependent values that has no real meaning, the *probemod* provide the option to specify one or more values of M that are particularly relevant or interesting to the researcher (e.g. cut-off score for clinical diagnosis of Internet addiction; see Appendix for the syntax). In some sense then, spotlight analysis would be a more appropriate label for this method since the goal is to illuminate a particular value of M for which the conditional effect of X on Y is of interest. That said, there are not many instances where there is just one single value of M for which the conditional effect of X on Y is of particular interest to a researcher. Instead, a more likely situation would be to ask if across the entire continuum of M, what is the range of values that predicts a significant conditional effect of X on Y and what is the range of values that does not. In such situations, it may be more appropriate to use the Johnson–Neyman (JN) technique, also dubbed as floodlight analysis by Spiller et al. (2013), to probe the moderation effect.

Gender	Intensity of SNS Use	Effect	SE	t	p	95% CI
Girls	0.000	.587	.580	.546	.585	.086, 3.985
	2.000	1.140	.952	.188	.851	.290, 4.487
	5.000	3.086	1.845	3.151	.002	1.529, 6.226
	6.000	4.300	2.407	4.654	.000	2.324, 7.955
	7.000	5.993	3.479	5.312	.000	3.092, 11.614
Boys	0.000	.187	.185	1.713	.087	.027, 1.277
	2.000	.363	.304	1.422	.150	.091, 1.442
	5.000	.983	.595	.047	.962	.479, 2.017
	6.000	1.370	.779	.972	.331	.726, 2.584
	7.000	1.909	1.123	1.866	.062	.967, 3.767

Table 4. *Conditional effects of traditional victimization on cybervictimization at different values (10th, 25th, 50th, 75th, and 90th percentiles) of intensity of SNS use and gender. Notes: 95% CI = 95% confidence interval; effects have been exponentiated to transform the estimates to the original metric of the outcome variable.*

4.2 Johnson-Neyman Technique to Probing Moderation Effects

In contrast to the pick-a-point technique, the JN technique offers a more systematic way to examine the magnitude and precision of the conditional effect of predictor variable (X) on the outcome variable (Y) across the entire range of the moderator variable (M). Thus, whereas the pick-a-point technique is concerned with whether the p-value for the t-statistic for the conditional effect given a selected value of M exceeds the level of significance chosen for inference, the JN technique asks, at what values of M does the t-statistic equal or exceed the critical value for t so as to produce a p-value that is statistically significant? To find values of M where the t-statistic for the conditional effect is equal or greater than the critical t-value, some computational steps are necessary and these are covered in the paper by Bauer and Curran (2005). Obviating the need for manual computation, the *probemod* package implements the JN technique and the syntax for applying this technique to the cyberbullying dataset can be found in the Appendix.

Figure 4 shows the JN plot that is generated by the plot.jn function in the *probemod* package. Here, the y-axis is the conditional effect of traditional victimization on cybervictimization while the x-axis is the moderator variable, intensity of SNS use. The solid and dotted lines on the JN plot represent the conditional effect estimates and the confidence bands. Depending on the alpha value (with the default alpha of .05, 95% confidence bands are shown; but this can be changed by setting the alpha parameter to .10 or .01), the confidence bands graphically convey the certainty in the conditional effect estimates and how that certainty changes along the range of intensity of SNS use scale while the region of significance (as indicated by the shaded region on the plot, and these are points where the confidence bands do not cross zero on the y-axis) define the range of values on the intensity of SNS use scale for which the conditional effect is significant. To facilitate interpretation of the results in the original metric, exponentiation has been applied to the conditional effect estimates and confidence bands, which produces slight curvature in the lines as shown in the plots. As can be seen from the plots, 4.07 for girls and 8.11 for boys on the intensity of SNS use scale was identified as a point of transition between a statistically significant and a statistically non-significant effect, with the exponentiated conditional effect of traditional victimization on cybervictimization being 2.55 for girls and 2.75 for boys. Below the transition point down to the minimum value of 0 on the intensity of SNS use scale, the conditional effect is non-significant. But above that point and as indicated by the shaded region of significance, the conditional effect of traditional victimization on cybervictimization is both significant and positive.

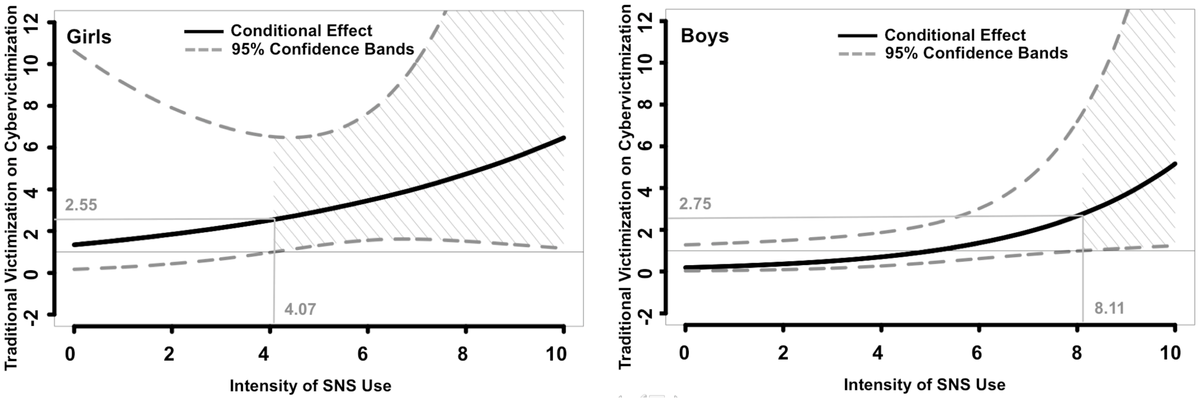

Figure 4. *Johnson-Neyman (JN) plot of the exponentiated conditional effect of traditional victimization on cybervictimization as a function of intensity of SNS use for girls (left panel) and for boys (right panel).*

5 SUMMARY AND CONCLUSION

Studies on cyberbullying are replete with questions about whether certain risk or protective factors are likely to predict cyberbullying outcomes such as cybervictimization. Such questions can often be reframed in terms of moderation effects, or hypothesis about how the effect of a predictor variable on an outcome variable depends on the value of a moderator variable. For example, a question that one might ask is whether the established relationship between traditional victimization and cybervictimization depends on specific factors such as teenager's intensity of SNS use. Another question that could be asked concerns whether teenage girls may be more susceptible to cybervictimization if they had experienced bullying in the traditional setting in the past 12 months. These are both legitimate questions about moderation effects which could be tested using the conventional analytic approach of adding an interaction term of the predictor variable and moderator variable to a regression model, and plotting the moderated regression model to understand the slopes of the moderation effect.

Demonstrating how these questions would typically be evaluated using the dataset from the Teens and Parents survey conducted by the Pew Research Centre's Internet and American Life Project, the current study found two sets of significant moderation effects that could be interpreted to mean that the predictive relationship between traditional victimization and cybervictimization indeed depend on the teenager's intensity of SNS use relationship and gender. With evidence of moderation effects, one may wish to then probe further to understand better the specific conditions under which the relationship between traditional victimization and cybervictimization is significant versus non-significant, or strong versus weak. Specifically, the expectation might be that traditional victimization may have a greater effect on the number of self-reported cybervictimization for teenagers with higher SNS use than for teenagers who score lower on SNS use. To address this question, however, researchers need to go beyond mere description of the observed moderation effect in the conventional analytic approach.

Fortunately, the two techniques offered by the R package *probemod*, namely, the pick-a-point and Johnson-Neyman techniques, can simplify the computations and facilitate the probing of moderation effects. First, the basic idea of the pick-a-point technique is that the researcher needs to specify a value or values within the range of the moderator variable, in order for the conditional effect of the predictor variable on the outcome variable to be estimated on the basis of that point. In the absence of clear practical or theoretical guidance on what values of the moderator to choose, the *probemod* package provide researchers with option to estimate the conditional effects either on the basis of mean plus/minus SD or on the basis of percentiles. The JN technique, on the other hand, eliminates the arbitrariness of choosing points in the pick-a-point approach by mathematically computing the values along the continuum of the moderator variable that indicate where the conditional effects are significant or non-significant. With the JN technique, in particular, the current study demonstrated how one can obtain more detailed information on the nature of the moderated relationship, such as the precision of the conditional effect estimate as well as the point on the intensity of SNS use scale that distinguishes between teenagers who are likely to experienced more cybervictimization and those who do not.

Although the extensions presented in this paper have some merits over the conventional analytic approach for studying moderation effects, there are several limitations that signify areas for further development. Firstly, because techniques for probing moderation effects presented here rely on regression modeling, the statistical assumptions underlying this modeling approach warrant some attention. Importantly, a fundamental assumption made in the present analysis is that there are no non-linear relationships (e.g. curvilinear) among the variables of interest in the moderation model. This is an assumption that is often made in studies of such models, yet it has been shown in several studies that if the presence of non-linear relationships are not properly accounted for, it is likely to adversely affect the estimation of moderation effects, which could in turn compromise the estimates computed by pick-a-point or the JN technique (Cortina 1993; Lubinski & Humphreys 1990; MacCallum & Mar 1995). The recommendation here is for researchers to first check the residual plots for potential non-linear relationships before embarking on the analyses presented here. Future research on the consequences of such deviations from the statistical assumptions for regression models would be useful for ascertaining the robustness of the two techniques introduced in this paper.

Another limitation of the current study is that the testing of higher order interactions has been omitted from the present analysis due to space constraints. Since tests for higher order interactions follow the same general computational principles described in this paper, and because better treatment of this topic exist elsewhere (Aiken & West 1991; Cohen et al. 2003; Jaccard & Turrisi 2003), only a few brief points would be made. Specifically, in the case of the study's cyberbullying dataset, a possible angle would be to examine how the effect of traditional victimization as a function of intensity of SNS use varies as a function of gender. Since gender is dichotomous, the probing of moderation effects would involve estimating the two-way interaction between traditional victimization and intensity of SNS use for the two values of gender. Otherwise, if gender were to be substituted by another continuous moderator variable, a possible strategy would be to employ the pick-a-point approach or the JN technique to ascertain where on the continuum of the new variable the two-way interaction between traditional victimization and SNS use shows significance versus non-significance.

Finally, an important implication of these findings for IS researchers involved in cyberbullying research is that it may be necessary to consider intensity of SNS use when studying the relationship between traditional victimization and cybervictimization. Future research should investigate specific activities that constitute high intensity SNS use (e.g. playing games on Facebook) and how they might contribute to a teenager's vulnerability to cybervictimzation. Moreover, it is hoped that the current paper will help inform IS researchers of the analytical techniques, and be inspired to take advantage of these techniques to study moderation effects, leading to a deeper understanding of the moderation effects they might find, and not limit themselves to questions that merely establish if a predictor variable has an effect on an outcome variable.

6 APPENDIX: R SYNTAX FOR THE ANALYSES DESCRIBED IN THE ARTICLE

In this Appendix, variable names are shown in upper case (capitals) and R commands in lower case. Lines that are preceded by ‘#’ indicate comments that will not be executed in R.

```
#Variables:

#Dependent variable (dv) = Cybervictimization (CYBERVICTIM)

#Independent variable (iv) = Traditional Victimization (TRADVICTIM)

#Moderator variables (mod) = Gender (CGENDER), Intensity of SNS use (SNSUSE)

#Covariates  = Parent’s Income (PINCOME), Parent’s Education Level (PEDUC), Child’s Age (CAGE)

#syntax for zero-inflated Poisson regression in R

require(pscl)

MODEL <- zeroinfl(CYBERVICTIM ~ TRADVICTIM + SNSUSE + CGENDER + TRADVICTIM*SNSUSE + TRADVICTIM*CGENDER | PINCOME + PEDUC + CAGE + TRADVICTIM + SNSUSE + CGENDER, data=DATA)

require(probemod)

#syntax for pick-a-point using the mean +/- 1 SD method, which is the default method if the parameter method is not explicitly stated (link=‘log’ specifies that the estimates should be exponentiated in the output)

pickapoint(MODEL, dv=‘CYBERVICTIM’, iv=‘TRADVICTIM’, mod=c(‘CGENDER’,‘SNSUSE’), method=‘meansd’, yas=‘ratio’)

#syntax for pick-a-point using the percentiles method

pickapoint(MODEL, dv=‘CYBERVICTIM’, iv=‘TRADVICTIM’, mod= c(‘CGENDER’,‘SNSUSE’), method=‘percentiles’, yas=‘ratio’)

#syntax for pick-a-point and explicitly stating points that are relevant to the researcher

RELEVANTPOINTS=list(GENDER=c(0,1), SNSUSE=c(3,4))

pickapoint(MODEL, dv=‘CYBERVICTIM’, iv=‘TRADVICTIM’, mod=c(‘CGENDER’,‘SNSUSE’), points= RELEVANTPOINTS)

#prepare the model for Johnson-Neyman

JNRESULTS <- jn(MODEL, dv=‘CYBERVICTIM’, iv=‘TRADVICTIM’, mod=‘SNSUSE’, yas=‘ratio’)

plot(JNRESULTS, ylab=" Traditional Victimization on Cybervictimization", ylim = c(-2,12), xlim=c(0,10))
```

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