Class-level effects on cybervictimization in secondary students: A multilevel analysis

Efecto del grupo-clase sobre la cibervictimización en estudiantes de Secundaria: un análisis multinivel

https://doi.org/10.4438/1988-592X-RE-2022-397-543

David Álvarez-García
https://orcid.org/0000-0002-5100-0233
Universidad de Oviedo

Andrea Núñez
https://orcid.org/0000-0001-9459-8872
María del Carmen Pérez-Fuentes
https://orcid.org/0000-0001-5950-5175
Universidad de Almería

Guillermo Vallejo
https://orcid.org/0000-0002-8010-6854
Universidad de Oviedo

Abstract

Introduction: Cyberbullying is a complex phenomenon that has significant consequences for the victims. Understanding it requires a systemic-ecological approach, aiming to identify both individual and contextual predictors. During adolescence, peer group influence becomes particularly important, especially the influence of classmates, who spend much of their time together. The main objective of this study was to analyze the possible effect of group-class characteristics on the probability of being the victim of cyberbullying, controlling for the effects of personal variables, in a sample of adolescents in

Received: 11-06-2021 Accepted: 28-01-2022

Asturias (Spain). For this purpose, we first determined possible variability in cybervictimization between group classes, along with the effects of personal variables in the sample examined. Method: Self-report scales were administered to 1923 secondary school students (aged 12-18). Multilevel regression analysis was performed. Results: There were differences in cybervictimization between classes, with 5% of the variance explained by group-class variables. A positive relationship was found between cybervictimization and the following student variables: age, social anxiety, engaging in high-risk behaviors on the internet, being the victim of traditional violence at school, and being a cyberaggressor. The group-class variables that had a positive relationship with cybervictimization were the average level of cyberaggression and the average level of traditional victimization in the group, even when controlling for the effects of personal variables. Discussion: It is important to develop students' social skills, including working on peer group dynamics, promoting support and friendship networks, offering guidance on safe, responsible use of the internet, and promoting empathy and pro-victim responses to bullying that is witnessed or known about. The importance of these variables as indicators for early detection of the problem is highlighted.

Keywords: cybervictimization, adolescence, Secondary Education, predictors, multilevel.

Resumen

Introducción. La cibervictimización es un fenómeno complejo, con importantes consecuencias para quien la padece. Para su comprensión, es necesario un enfoque sistémico-ecológico, tratando de identificar no sólo predictores individuales, sino también contextuales. Durante la adolescencia cobra particular importancia la influencia del grupo de iguales y, dentro de ellos, los compañeros de clase, con los que comparten gran parte de su tiempo. El objetivo principal de este estudio ha sido analizar el posible efecto de características del grupo-clase sobre la probabilidad de cibervictimización, controlando el efecto de variables individuales, en una muestra de adolescentes de Asturias (España). Para ello, previamente se analizó si existía variabilidad en cibervictimización entre los grupos-clase; y el efecto de las variables individuales, en la muestra analizada. Metodología. Se aplicaron escalas de autoinforme a 1923 estudiantes de Educación Secundaria Obligatoria (12 a 18 años). Se realizaron análisis de regresión multinivel. Resultados. Se hallaron diferencias en cibervictimización entre las clases, explicadas en un 5% por las variables de grupo-clase. Entre las variables referidas al estudiante, se obtuvo una relación positiva de la edad, la ansiedad social, las conductas de riesgo en Internet, ser víctima de violencia escolar tradicional y ser ciberagresor, con la cibervictimización. Entre las variables de grupo-clase, el nivel promedio en el grupo tanto de ciberagresión

Received: 11-06-2021 Accepted: 28-01-2022

ejercida como de victimización en violencia escolar tradicional, mostraron una relación positiva con la cibervictimización, incluso controlando estadísticamente el efecto de las variables individuales. Discusión. Importante desarrollar en el alumnado habilidades sociales; trabajar las dinámicas de grupo, promoviendo redes de apoyo y amistad; ofrecer pautas para el uso seguro y responsable de Internet; y trabajar la respuesta empática y a favor de la víctima ante agresiones conocidas o presenciadas. Se destaca asimismo la importancia de estas variables como indicadores para la detección temprana del problema.

Palabras clave: cibervictimización, adolescencia, Educación Secundaria, predictores, multinivel.

Introduction

Cybervictimization is a complex phenomenon with important consequences for those who suffer from it (Marciano et al., 2020). In order to understand it, we must adopt a systemic-ecological approach, trying to identify not only individual factors that influence its appearance, but also contextual ones. In this sense, during adolescence, the influence of the peer group and, within it, the group of classmates with whom adolescents share much of their time, not only inside but, in many cases, also outside the classroom, becomes particularly important.

Research on the risk factors for peer cyber-victimization in adolescence has focused primarily on the analysis of *individual variables*. The most analyzed variable has been *sex* but with inconsistent results (Kowalski et al., 2014). In general terms, the relationship between sex and cybervictimization is weak and complex, depending on the age and context of the sample, and the type of cyberaggression analyzed. Thus, in Spanish adolescents, Álvarez-García, Barreiro-Collazo et al. (2017) found no differences between boys and girls in most types of cybervictimization analyzed and, in those that did present differences, they were small: boys tended to suffer more aggressions in online gaming environments, while girls suffered more rumors on social networks or sexual cyberaggression.

Other individual variables show a clearer relationship with the likelihood of being a victim of cyberaggression in adolescence. Meta-analyses indicate that *age*, low *self-esteem, social anxiety*, *risky Internet* *behaviors*, being *a victim of traditional violence in the school setting,* and being *a cyberaggressor* increase the likelihood of being a victim of cyberaggression (Kowalski et al., 2014; van Geel et al., 2018). *Antisocial behavior* also increases that probability (Garaigordobil, 2017).

However, as indicated, *contextual factors* must also be taken into account. Among the contexts with the greatest impact on the development of the adolescent's personality is their peer group and, within it, their classmates. However, the *group class* has hardly been studied as an explanatory context of cybervictimization among adolescents. So far, there is very little research on the variability of cyber-victimization between group classes and its comparison with individual variability within groups or about the effect of variables related to the group class in the likelihood that the students in it will become victims of cyberaggression.

Concerning the variability of cybervictimization between group classes, to our knowledge, only Festl et al. (2015) offered data, indicating that 5% of the cybervictimization in their sample could be attributed to the class context. In Spain, only the study of Gámez-Guadix and Gini (2016) offered data in this line, although referring to performed cyberaggression: the classes explained 8% of the variance in cyberbullying performed by the students.

Regarding the possible effect of variables related to the group class, a variable that some studies indicate affects the probability of being a victim of aggression, is the *size of the group*. Although contrasting results have been found (Menesini & Salmivalli, 2017), some studies have indicated that, in large groups, it is more likely to be a victim both of traditional school violence (Khoury-Kassabri et al., 2004) and cyberaggression (Heirman et al., 2015). In fact, being *a victim of traditional violence* in the school environment and being a victim of cyberaggression are closely related (Beltrán-Catalán et al., 2018). Although cyberaggression occurs predominantly outside the school, it can originate from situations experienced in the physical environment, sometimes in the school environment. Some studies conclude that cybervictimization among adolescents is more likely among students in the same class (Wegge et al., 2014) and that the larger the size of the group, the more likely it is that there will be one or more students in it who perform cyberaggression (Festl et al., 2015).

Other factors related to the group class with possible impact on cybervictimization have to do with the dynamics of the peer group.

Received: 11-06-2021 Accepted: 28-01-2022

Peer influence shows a significant and robust effect on a wide variety of behaviors (externalizing, internalizing, and academic behaviors) in adolescence (see Giletta et al., 2021, for a recent meta-analysis of longitudinal studies). In this sense, a negative school climate and a negative influence of peers increase the probability that a student in the group will be a victim of cyberaggression (Guo, 2016). In groups in which students justify or even reinforce aggressions between peers, the probability of aggressions occurring increases and, therefore, the levels of victimization also increase (Saarento et al., 2015). More specifically, Gámez-Guadix and Gini (2016) found in a Spanish sample that the degree to which classmates justify cyberbullying is a risk factor for cyberbullying behaviors in the students in the group over time. Therefore, in groups where peers show a higher level of *antisocial behavior* or, in particular, a higher level of *traditional aggression* in the classroom or *cyberaggression*, a student will be more likely to be a victim of cyberaggression.

Continuing with the factors at the group class level, adolescents who carry out cyberbullying tend to perform more risky Internet behaviors (Gámez-Guadix et al., 2016) and present poorer academic performance (Kowalski, & Limber, 2013). Therefore, it can be expected that in group classes in which there are more *risky Internet behaviors* and worse *academic performance,* there will be more cyberaggressions and, therefore, also more cybervictimization. Among the few studies in this line, Heirman et al. (2015) found that the proportion of students above the normative age for the group class (i.e., repeating students) is positively associated with the degree of cyberbullying among students belonging to that same class.

Given the social, educational, and clinical relevance of the problem and the scarcity of studies that analyze the effect of group class variables, the present work had three objectives. The main objective was to analyze the possible effect of group class characteristics in the probability of cybervictimization, controlling for the effect of individual variables, in a sample of adolescents from Asturias (Spain). For this purpose, the variability in cybervictimization between the group classes and the effect of the individual variables in the target sample were previously analyzed.

The following hypotheses were proposed. First, we expected to find variability in the average frequency of cybervictimization between group classes, with the characteristics of the group explaining a small but significant part of the variance (around 5%, in accordance with

Received: 11-06-2021 Accepted: 28-01-2022

previous evidence). Secondly, we expected that the students' individual characteristics would explain these differences. In line with previous evidence, sex was expected to have a weak but significant relationship with the degree of cybervictimization, and age, low self-esteem, social anxiety, risky Internet behaviors, being a victim of traditional violence in the school environment, antisocial behavior, and being a cyberaggressor would increase the likelihood of being a victim of cyberaggression. Finally, concerning the main objective of this study, which constitutes its main novelty and contribution, in accordance with prior evidence, we expected that the size of the group class, as well as the percentage of repeaters, risky Internet behaviors, traditional victimization, traditional aggression, cyberaggression, and antisocial behavior in the group would increase the probability of cybervictimization.

Method

Participants

Participants in the study were 1923 students (48.8% girls) of Compulsory Secondary Education (CSE) in Asturias (Spain), aged between 12 and 18 years (M = 14.01, SD = 1.38). They belonged to 97 group classes, from 11 schools (six public and five concerted), randomly selected from among the publicly funded schools of Asturias in which CSE is taught. In each selected school, all CSE students who presented informed consent from their parents or guardians were evaluated.

Instruments

Sociodemographic variables. Participants were asked about their age (open question) and sex (dichotomous question: male/female).

School variables: We asked the tutor of each group how many students were in the group (group size), as well as how many repeater students were in the course.

Received: 11-06-2021 Accepted: 28-01-2022

Self-esteem. The respondents completed a self-report scale composed of five items (e.g., "I like the way I am") (Álvarez-García et al., 2015). Responses are rated on a 4-point Likert scale ranging from 1 (*Totally false*) to 4 (*Totally true*). The total score of the scale was obtained by adding the scores of its items, with higher scores reflecting high self-esteem. The internal consistency of the scale scores in the sample of this study was adequate (α = .742).

Social anxiety. To determine the extent to which respondents felt inhibited and uncomfortable in their relationships with others, especially with people with whom they are not familiar, a five-item self-report scale was used (e.g., "I get nervous when I have to be with a group of kids I don't know well") (Álvarez-García et al., 2015). Responses are rated on a 4-point Likert scale ranging from 1 (*Totally false*) to 4 (*Totally true*). The total score of the scale was obtained by adding the score of its items, with higher scores reflecting high levels of social anxiety. The internal consistency of the scores in the sample of this study was adequate (α = .751).

Traditional victimization at school. To know the frequency with which the respondent reported suffering from aggressions at school during the last three months, the Offline School Victimization scale (Álvarez-García et al., 2015) was used. It is a six-item self-report (e.g., "My classmates make fun of me, and laugh at me"), rated on a 4-point Likert scale, ranging from 1 (*Never*) to 4 (*Always*). The total score on the scale is obtained by adding the score of its items, with higher scores reflecting high levels of offline victimization at school. The internal consistency of the scale scores in the sample of this study was adequate (α = .744).

Traditional aggression at school. To know the frequency with which the respondent admits performing traditional aggressions at school, we employed a scale previously used by the research team (Álvarez-García et al., 2016), with the same number of items (six), the same indicators and type of response as the Offline School Victimization scale (e.g., "I've laughed at and made fun of a classmate"). The total score on the scale was obtained by adding the score of its items, with higher scores reflecting high levels of offline aggression at school. The internal consistency of the scores in the sample of this study was adequate (α = .757).

Antisocial Behavior. To determine the extent to which the respondent admits performing antisocial behaviors, we applied a 6-item scale, adapted from some items of the *Scale of Antisocial and Criminal Behavior in Adolescents* of Andreu and Peña (2013) (e.g., "I have entered private property without permission"). The response format is dichotomous (*Yes/No*), indicating whether or not the action was carried out over the past year. The internal consistency of the scores in the sample of this study was adequate (KR20 = .741).

Risky Internet Behaviors. To determine the extent to which the respondent performs risky behaviors on the Internet, we used the *High-Risk Internet Behaviors Questionnaire* (Álvarez-García et al., 2018). It is an eight-item self-report, each of which describes a risky Internet behavior (e.g., "I habitually publish personal information on my social networks: what I'm going to do, where, and with whom; personal or family photos or videos; etc."). The respondent rates each of the statements on a 4-point Likert scale ranging from 1 (*Completely false*) to 4 (*Completely true*). The total score on the scale was obtained by adding the scores of its items. High scores indicate high engagement in risky Internet behaviors. The internal consistency of the scores in the sample of this study was adequate (α = .758).

Cybervictimization. The *Cybervictimization Questionnaire for Adolescents* (CYVIC, Álvarez-García, Núñez et al., 2017) was used to determine the frequency with which the respondent reported having been a victim of aggression through the mobile phone or the Internet during the three months prior to the survey. It consists of 19 items, which measure verbal cybervictimization, visual cybervictimization, impersonation, and online exclusion. The response format is a 4-point Likert scale ranging from 1 (*Never*) to 4 (*Always*). The total score was calculated by adding the scores of its items. High scores indicate high levels of cybervictimization. The internal consistency of the scale was adequate (α = .781).

Cyberaggression. The *Cyberaggression Questionnaire for Adolescents* (CYBA) (Álvarez-García et al., 2016) was used to determine the frequency with which the respondent admitted having performed aggressions

Revista de Educación, 397. July-September 2022, pp. 145-168
Received: 11-06-2021 Accepted: 28-01-2022

through the mobile phone and the Internet during the three months prior to the survey. It consists of 19 items, with the same indicators and response format as the CYVIC. The total score of the scale is calculated by adding the scores of its items. High scores indicate high levels of cyberaggression. The internal consistency was (α = .830).

Procedure

After the sample and the measuring instruments had been selected, permission was requested from the school directors to apply the questionnaires. Each board of directors was informed of the goals and procedures of the study, its voluntary and anonymous nature, and the confidential treatment of the results. Once the school had agreed to participate, informed consent was sought from the students' parents or guardians if they were minors. Before completing the questionnaire, students were also informed of the anonymous, confidential, and voluntary nature of their participation. The questionnaires were applied by the research team during school hours. In general, the students had 20 minutes to complete the questionnaires, although this was flexible depending on the age and characteristics of the students.

Data analysis

Given the explanatory objective of the study and the hierarchical nature of the data (group class and students nested in the group classes), we used a two-level hierarchical regression procedure to analyze the refined effect of each variable by statistically controlling for the effect of the rest. The following process was used:

1st step: Unconditional means model

First, the null or unconditional means model (which does not include any explanatory variables) was adjusted, where Yij is the observed cybervictimization for the ith student nested in the jth class, γ00 is the global average cybervictimization of the students, u0j is the variability between classes in terms of the students' average cybervictimization, and eij is the variability in the cybervictimization of the students nested in the jth class. It is assumed that the random terms of the model are normally and independently distributed with a mean of zero and constant variance.

2nd step: Models with class level predictors

The unconditional means model does not contemplate the characteristics of the students or the classes but only provides a basis on which to compare more complex models. However, cybervictimization could be explained by the characteristics of the students who make up the classes, the characteristics of the classes, as well as the conjoint effect of both of them. Therefore, after confirming that the average cybervictimization was higher in some classes than in others, we sought the reason for this difference. For this purpose, a new analysis was carried out, incorporating seven explanatory variables recorded at the class level (Level 2) and centered on the general mean: class size (CS), percentage of repeaters in the class (REP_GR), average traditional aggression of the students in the class (AGR_GR), average traditional victimization of students in the class (VIC_GR), average cyberaggression of students in the class (CBA_GR), average antisocial behavior of the students in the class (AB_GR), and average risky Internet behaviors by students in the class (RB_GR). The last four variables were obtained from the individual scores of the students in each group and were incorporated into this Level 2, as they offer a measure of the contextual climate of behavior and internet use among the students of the group.

We started by formulating at Level-2 the conditional model, $Y_{ij} = \gamma_{00} + \gamma_{01}CS_j + \gamma_{02}REP\_GR_j + \gamma_{03}RB\_GR_j + \gamma_{04}VIC\_GR_j + \gamma_{05}AGR\_GR_j + \gamma_{06}CBA\_GR_j + \gamma_{07}AB\_GR_j + u_{0j} + e_{ij}$, where γ_{00} is the average cybervictimization when all predictors are zero; γ_{01} to γ_{07} is the effect of each explanatory variable while controlling for the effect of the rest; u_{0j} is the conditional or residual variation between classes; and e_{ij} is the variation within them. Subsequently, a simplified model was analyzed, in which only the variables that showed a significant effect were included.

3rd step: Models with student-level predictors

The model formulated in the previous section did not contemplate the students' characteristics. Thus, we could not know why there are

Received: 11-06-2021 Accepted: 28-01-2022

differences in students' cybervictimization, nor was there evidence that the variability observed between classes was not an artifact due to the different profiles of the students nested within the classes. To answer this question, a new analysis was carried out incorporating eight explanatory variables recorded at the student-level (Level 1): sex (SEX), antisocial behavior (AB), age (AGE), self-esteem (S-E), social anxiety (SA), Risky Internet behaviors (RB), traditional victimization in the school environment (VIC), and cyberaggression (CBA). Except for sex, the remaining variables were centered on the mean of their group. In the model specified in this section, we not only postulate that a student's score in cybervictimization is related to risky Internet behaviors and cyberaggression but, after evaluating whether each of the slopes of any of the explanatory variables at the student-level had a component of significant between-group variance, we also postulate that this relationship would not be identical in all classes.

The resulting conditional model of random intersections and slopes at Level-1 can be written as follows: $Yij = \gamma 00 + \gamma 10SEXij + \gamma 20ABij + \gamma 30AGEij + \gamma 40S\text{-}Eij + \gamma 50SAij + \gamma 60RBij + \gamma 70VICij + \gamma 80CBAij + u0j + u1jRB + u2jCBA + eij$, where Yij refers to the observed cybervictimization for the ith student nested in the jth class; $\gamma 00$ represents the average cybervictimization of classes across the class population; $\gamma 10$ to $\gamma 80$ denotes the relationship between each explanatory variable and the average cybervictimization, controlling for the effect of the other explanatory variables included; and u1j and u2j indicate whether the relationship between the average cybervictimization and the variables "risky behaviors" and "cyberaggression" varies across classes.

4th step: Models with predictors at the student-level and the class-level

After separately adjusting a model for the individual variables and one for the class-level variables, we considered a model containing variables from both levels. As no cross-interaction effects were found between the variables of different levels, they were not included in the model, which was as follows: $Yij = \gamma 00 + \gamma 01VIC\_GRj + \gamma 02CBA\_GRj + \gamma 10AGEij + \gamma 20SAij + \gamma 30RBij + \gamma 40VICij + \gamma 50CBAij + u0j + u1jRB + u2jCBA + eij$. That is, cybervictimization can be considered as a function of the general average fixed effects, the main effects of the explanatory variables included, plus the random effects that represent the variability between intersections (u0j), between slopes (u1j, u2j), and between students within the classes (eij).

Data analysis was performed using the MLM implemented in the PROC MIXED module of the SAS v.9.4 program (SAS Institute, Inc., 2020).

Results

Variability in cybervictimization between classes

Table 1 shows the results of the unconditional means model. The estimate of the average cybervictimization in this sample of classes differed from zero. There were statistically significant differences in the levels of cybervictimization both within classes and between classes. In 95% of the cases, the magnitude of the variation in average cybervictimization between classes could be expected to be within the range. This indicated a moderate to low range of variability in the levels of cybervictimization between the classes in this sample of data. In turn, about 95% of the variance observed in cybervictimization occurred within the classes, while the remaining 5% occurred between classes.

TABLE 1. Results of the unconditional model of means

Fixed effects					
Parameter	Estimator	Standard Error	df	*t* Ratio	Pr > |*t*|
Intercept	21.5908	0.1075	96	200.86	<.0001
Random effects					
Covariance parameter		Estimator		*Z*	Pr > |*Z*|
Class average		0.4968		3.00	.0014
Level-1 Effect		9.3573		26.76	<.0001
Model fit information for cybervictimization					
Description		Value			
Deviance		7836.5			
AIC		7842.5			
BIC		7050.2			

Note. df = degrees of freedom; Deviance = -2 Log Likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

Received: 11-06-2021 Accepted: 28-01-2022

Effect of class characteristics on the degree of cybervictimization

When adjusting the initial conditional model of random intersection with Level-2 predictors (Model A), no statistically significant effect was observed for group size, percentage of repeaters, risky Internet behaviors in the group, average traditional aggression at school performed in the group, and average antisocial behavior of the group (Table 2). Therefore, a second model (Model B) was tested, without these variables. The statistical deviance and the number of parameters estimated for models A and B were 7444.4 (10) and 7448.6 (5), respectively. The likelihood ratio test, which compares the deviance of Model B with that of Model A, indicated that there were no significant differences between the two models, $\chi2(5) = 11.07$, $p = .5209$. In the simplified model, there was a positive and highly significant association both of average traditional victimization at school in the group, and of average cyberaggression performed in the group, with average cybervictimization. The classes that differ by 1 point in both variables differ by around 0.5 points in cybervictimization.

TABLE 2. Results of the conditional model of random intersection with multiple Level-2 predictors

Model A					Model B				
Fixed effects									
Parameter	Estimator	*SE*	*df*	Pr>|*t*|	Estimator	*SE*	*df*	*t* Ratio	Pr>|*t*|
Intercept	21.1587	0.4526	89	<.0001	21.5799	0.0774	94	278.91	<.0001
CS	0.0181	0.0187	89	.3355					
REP_GR	0.0018	0.0057	89	.7507					
RB_GR	0.0852	0.0593	89	.1547					
VIC_GR	0.5340	0.1123	89	<.0001	0.4550	0.0949	94	4.80	<.0001
AGR_GR	-0.2080	0.1353	89	.1278					
CBA_GR	0.5143	0.1004	89	<.0001	0.4906	0.0685	94	7.16	<.0001
AB_GR	0.0758	0.2035	89	.7105					
Random effects									
Covariance parameter	Estimator	*SE*	*Z*	Pr>|*Z*|	Estimator	*SE*		*Z*	Pr>|*Z*|

Received: 11-06-2021 Accepted: 28-01-2022

Class average	0				0.1001	0.0835	0.11	.4547
Level-1 Effect	9.1515	0.3305	27.89	<.0001	9.1717	0.3315	27.69	<.0001
Model fit information for cybervictimization								
Description	Value				Value			
Deviance	7744.4 (10)				7748.6 (10)			
AIC	7762.4				7756.7			
BIC	7758.6				7767.0			

Note: CS = Class size; REP_GR = Percentage of repeaters in the class; RB_GR = Risky Internet Behaviors, class average; VIC_GR = Traditional victimization at school, class average; AGR_GR = Aggressor of traditional school violence, class average; CBA_GR = Cyberaggression_class average; AB_GR = Antisocial_behavior, class average; SE = Standard error; df = degrees of freedom; Deviance = -2 Log Likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

The variance corresponding to Level 2 was substantially reduced after incorporating the predictor variables “traditional victimization at school, group average” and “cyberaggression performed, group average”. Specifically, whereas the unconditional variance was 0.497, the conditional variance was 0.10. This indicates that around 80% of the variability observed in the average cybervictimization was explained by the main effects reported. Thus, the significant variation in the intersections disappeared after controlling for these two variables; in fact, the residual intraclass correlation was .01, indicating that about 1% of the variation in cybervictimization was between classes.

Effect of student characteristics on the degree of cybervictimization

Table 3 shows the main results obtained after adjusting three models of intersections and random slopes with multiple predictors of the student-level (Level 1). According to the likelihood ratio test, which compares the deviance of the simplified Model B with the deviance of the initial Model A, there were no significant differences between the two models, $\chi2(3) = 3$, $p = .3916$, so the simplest model (Model B) was chosen. Next, we compared the model in which the intersections but not the slopes varied across classes (Model C) with the model in which both the intersections and the slopes varied (Model B). The likelihood ratio test revealed statistically significant differences between Models B and C, $\chi2(5) = 91.8$, $p < .0001$. In addition, Model B presented the lowest AIC and BIC values. Therefore, we selected Model B.

Revista de Educación, 397. July-September 2022, pp. 145-168
Received: 11-06-2021 Accepted: 28-01-2022

TABLE 3. Results of random intersection and slope models with multiple Level-1 predictors

	Model A			Model B			Model C		
Fixed Effects									
Parameter	Estimator	*SE*	*t* Ratio	Estimator	*SE*	*t* Ratio	Estimator	*SE*	*t* Ratio
Intercept	21.5179	0.1294	166.24	21.6093	0.1127	191.68	21.6059	0.1110	194.69
SEX	0.1810	0.1252	1.45						
AB	0.1015	0.0566	1.79						
AGE	0.2400	0.0900	2.67	0.2646	0.0890	2.97	0.2891	0.0923	3.13
S-E	-0.0013	0.0236	-0.05						
SA	0.0445	0.0179	2.48	0.0439	0.0171	2.57	0.0483	0.0179	2.69
RB	0.0713	0.0219	3.26	0.0794	0.0217	3.66	0.0813	0.0172	4.72
VIC	0.3669	0.0266	13.81	0.3640	0.0259	14.06	0.3697	0.0269	13.75
CBA	0.4554	0.0434	10.50	0.4698	0.0424	11.09	0.4502	0.0253	17.83
Random Effects									
Covariance parameter	Estimator	*SE*	*Z*	Estimator	*SE*	*Z*	Estimator	*SE*	*Z*
Class mean	0.8812	0.1960	4.50	0.8776	0.1958	4.48	0.7914	0.1865	4.24
RB-CBV	0.0167	0.0058	2.70	0.0162	0.0059	2.74			
CBA-CBV	0.0831	0.0212	3.81	0.0835	0.0219	3.80			
Level-1 Effect	5.1025	0.2018	25.29	5.1128	0.2022	25.29	5.8446	0.2194	26.64
Model fit information for cybervictimization									
Description	Value			Value			Value		
Deviance	7069.0 (16)			7074.0 (13)			7165.8 (8)		
AIC	7101.0			7100.0			7181.8		
BIC	7142.2			7133.5			7202.4		

Note: SEX = Sex; AB = Antisocial behavior; AGE = Age; S-E = Self-esteem; SA = Social anxiety; RB = Risky Internet Behaviors; VIC = Traditional victimization in the school environment; CBA = Cyberaggression; CBV = Cybervictimization. SE = Standard Error; Deviance = -2 Log Likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion;

The first conclusion after adjusting Model B is that, on average, there was a positive and statistically significant relationship between the explanatory variables age, social anxiety, risky Internet behaviors, traditional victimization at school, and performed cyberaggression with the cybervictimization scores within the classes. Concerning the predictors whose slopes were not fixed, we note that, on average, there was a statistically significant relationship within the classes between cybervictimization and the variables risky behaviors and cyberaggression ($\gamma 06 = 0.079$, $p = .0003$; $\gamma 08 = 0.469$, $p<.0001$). Adolescents who make less secure use of the Internet tend to suffer more aggressions through this medium than those who make more responsible use. Something similar can be said of the relationship between the aggressions performed and the aggressions suffered. In addition, the results also show that, although the effects of the variables "risky behaviors" and "cyberaggression" were constant for all the adolescents within the classes, they varied significantly between classes.

The second notable aspect is that there were highly significant differences between the 97 school averages ($Z = 4.48$, $p<.0001$), a result quite similar to that found in the unconditional means model. In other words, the classes differed in average cybervictimization levels after controlling for the effects of the explanatory variables. The inclusion of these variables in the student level accounted for 45% [(9.36 - 5.11)/9.36] of the variation within the classes. Finally, we rejected the null hypothesis that stated that the slopes would not differ across the classes ($Z = 4.74$, $p = .0010$; $Z = 3.80$, $p = .0010$). Thus, we can infer that the relationship between the variables risky Internet behaviors and cybervictimization in the classes varied significantly between the classes. The same goes for the relationship between the variables cyberaggression and cybervictimization.

Joint effect of class and student characteristics on the degree of cybervictimization

Table 4 shows the main results obtained after adjusting the model that includes Level-1 and Level-2 predictors. The average traditional school victimization in the group was positively related to the average cybervictimization, controlling for the effect of the average perpetrated cyberaggression. The average perpetrated cyberaggression was positively related to the average cybervictimization of the group, controlling for the effect of the average traditional school victimization in the group. The previously found statistically significant relationship of age, social anxiety, risky Internet behaviors, traditional victimization at school, and cyberaggression performed by the student with cybervictimization was maintained.

Received: 11-06-2021 Accepted: 28-01-2022

TABLE 4. Results of the combined model of random intersections and slopes

Fixed effects					
Parameter	Estimator	*SE*	*df*	*t* Ratio	Pr>|*t*|
Intercept	21.5756	0.0703	94	307.02	<.0001
VIC_GR	0.4171	0.0758	94	5.50	<.0001
CBA_GR	0.5319	0.0550	94	9.67	<.0001
AGE	0.2765	0.0880	1431	3.14	.0017
SA	0.0432	0.0170	1431	2.54	.0113
RB	0.0784	0.0215	1431	3.65	.0003
VIC	0.3602	0.0257	1431	14.02	<.0001
CBA	0.4855	0.0416	1431	11.68	<.0001
Random effects					
Covariance parameter		Estimator			
Class average		0.1501			
CR-CBV		0.0160			
CBA-CBV		0.0801			
Level-1 Effect		5.3037			
Model fit information for cybervictimization					
Description		Value			
Deviance		6962.0			
AIC		6992.0			
BIC		7030.6			

Note. VIC_GR = Traditional victimization in the school environment, class average; CBA_GR = Average cyberaggression in the class; AGE = Age; SA = Social anxiety; RB = Risky Internet Behaviors; VIC = Traditional victimization in the school environment; CBA = Cyberaggression; CBV = Cybervictimization. ***SE*** = Standard Error; ***df*** = degrees of freedom; Deviance = -2 Log Likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

We conclude the Results section, highlighting two aspects related to the random effects. On the one hand, the variance component for intersections remained significantly different from zero (Z = 2.11, p = .0170), suggesting that there is additional variation between the average cybervictimization levels of the classes that is not explained by the factors included in the final model. Thus, there is reason to believe that there are additional factors at the class level that could explain the variation in class averages. However, a very substantial reduction in the variance of class averages was observed after controlling for the variables "risky Internet behaviors" and "cyberaggression" because, whereas the unconditional variance of the intersections was 0.87, the conditional variance of the final model was 0.15. On another hand, the interpretation of the variance components referring to the slopes is very similar to that given for the student-level adjusted model. That is, the relationship between the average cybervictimization and the variables risky behaviors and cyberaggression varied across classes (Z = 2.78, p = .0027; Z = 3.76, p < .0001). Therefore, both tests suggest that the significant variation in slopes remains unexplained after controlling for the Level-2 variables "average traditional victimization " and "average cyberaggression". The variability of the slope corresponding to "risky Internet behaviors" was only reduced by 1% [(.0162-.0160) /.0162] after controlling for the effects of the explanatory variables of Level 2, whereas the reduction of the variability of the slope corresponding to "cyberaggression" reached 4% [(.0835-.0801) /.0835].

Discussion

This work had three objectives. The first was to analyze the possible variability in the frequency of cybervictimization between the group classes analyzed. According to previous evidence (Festl et al., 2015), we expected to find that the characteristics of the group would explain a small but significant part of the variability (around 5%). The results obtained in this work confirm the working hypothesis: statistically significant differences were found in cybervictimization between the classes in the sample analyzed, with 5% explained by the group class variables.

A second objective was to analyze the possible effect of individual variables on the degree of cybervictimization. Sex was expected to have a weak but significant relationship with the degree of cybervictimization (Álvarez-García, Barreiro-Collazo et al., 2017). Age, low self-esteem, social anxiety, risky Internet behaviors, being a victim of traditional violence at school, antisocial behavior, and being a cyberaggressor were expected to show a positive relationship with being a victim of cyberaggression (Garaigordobil, 2017; Kowalski et al., 2014; van Geel et al., 2018). As expected, in the present work, we found a positive and statistically significant relationship of age, social anxiety, risky Internet behaviors,

Received: 11-06-2021 Accepted: 28-01-2022

being a victim of traditional violence at school, and cyberaggression with cybervictimization. On another hand, contrary to our expectations, the students' sex, level of self-esteem, and degree of antisocial behavior did not have a significant explanatory capacity, after statistically controlling for the effect of the rest of the analyzed variables.

Finally, the third objective, the main one of the study and its main novelty and contribution, was to analyze the possible effect of the characteristics of the group class on the probability of cybervictimization, controlling for the effect of the individual variables. Whereas previous evidence on this is very scarce so far, we expected that the group class size, as well as the percentage of repeaters, and average risky Internet behaviors, traditional victimization, traditional aggression, cyberaggression, and antisocial behavior in the group would show a positive relationship with the probability of cybervictimization. However, in the present work, only the average traditional victimization and the average cyberaggression in the group had a significant explanatory capacity, after statistically controlling for the effect of the rest of the analyzed variables.

These results not only have relevant theoretical implications, as they allow us to advance in the understanding of peer cybervictimization in adolescence, but also practical ones, referring both to the individual student and to their group class.

From an individual point of view, the fact that social anxiety and being a victim of traditional aggression in the educational environment are risk factors for peer cybervictimization reminds us of the great importance of developing social skills in students and promoting support and friendship networks among them, in this case, to prevent the specific problem of cybervictimization. It also shows the importance of taking into account these two variables as indicators for the early detection and treatment of the problem.

The fact that risky Internet behaviors and being a cyberaggressor are risk factors for being a victim of cyberaggression shows the importance of sensitizing and training students about the risks of the Internet, and offering guidelines for its safe, responsible, healthy, and respectful use.

The positive relationship found between age and the likelihood of cyberaggression suggests that the problem occurs to a greater extent in the last years of CSE than in the first years. Therefore, we should be especially vigilant in these courses and ages for its early detection and treatment. As these problems can occur in virtual contexts to which teachers have no access, the collaboration of student witnesses is particularly important to detect and report the problem. Different peer support systems can be useful in this regard (Avilés, 2017). However, prevention should begin in the first years of CSE (Ortega-Barón et al., 2021) or even in Primary Education (Flores et al., 2020) to try to prevent the problem from occurring.

From the point of view of the group class to which the student belongs, the results obtained show that when an adolescent belongs to a group class in which it is common for classmates to be victims of traditional violence in the school and to be aggressors outside the school through the mobile phone and the Internet, it is more likely for this student to be the victim of cyberaggression. Previous studies have highlighted the importance of taking into account the processes of social influence and the role of subjective norms in the classroom: in groups in which students consider peer aggression as normal, they justify or even reinforce it, the probability of aggressions occurring increases and, therefore, the levels of victimization also increase (Dang & Liu, 2020; Gámez-Guadix & Gini, 2016; Saarento et al., 2015). Therefore, it is important not only to take into account the role of students as potential victims or aggressors but also as witnesses (Álvarez-García et al., 2021), developing attitudes and behaviors favoring the victim, rather than passive attitudes or attitudes favoring aggressor.

Although this work is a contribution to the field of study, it is not without limitations. One of them is the use of self-reports, which, although they have many advantages, also have some drawbacks, such as the informants' possible falsification of the response or the bias of social desirability. Another limitation is the sample, which, although it is large and randomly selected, is restricted to specific ages and a geographical context, so any generalization of the conclusions to other contexts should be done with caution. Finally, the model tested did not include all the variables related to the characteristics of the group class that can explain or predict cybervictimization. In the present work, a part of the variability was not explained by the factors included in the final model. That is, there are additional factors at the class level that could explain the differences in cybervictimization between classes. Thus, for example, some variables related to the teachers who teach in the group explain or predict traditional school victimization (Menesini & Salmivalli, 2017) and could also have a significant effect on cybervictimization. Also,

Received: 11-06-2021 Accepted: 28-01-2022

other contextual variables, which could affect the characteristics of the groups, such as the ownership of the school, could have an impact on the probability of an adolescent becoming a victim of cyberaggression (Machimbarrena et al., 2018).

In short, although cyberaggression usually occurs outside the school, the characteristics of the group class to which the adolescent belongs significantly influence the probability of their becoming a victim of cyberaggression. In particular, adolescents who belong to groups where peers are routinely victims of traditional school violence and who attack others through mobile phones and the Internet are more likely to be victims of cyberaggression. These results constitute further proof of the connection between offline and online socialization contexts, as well as the importance of peers and, in particular, classmates, in the socio-emotional well-being of adolescents in a problem as complex and potentially harmful as cybervictimization among adolescents.

Acknowledgements

This work was supported by the Government of the Principality of Asturias (Spain) (Plan of Science, Technology and Innovation 2018–2022) and the European Union (European Regional Development Fund—ERDF) under Grant Ref. FCGRUPINIDI/2018/000199; and by the Spanish Ministry of Science, Innovation and Universities under Grant Ref. MCIU-19-PGC2018-097739-B-I00.

References

Álvarez-García, D., Barreiro-Collazo, A., & Núñez, J.C. (2017). Cyberaggression among adolescents: Prevalence and gender differences. *Comunicar*, *25*(50), 89-97. https://doi.org/10.3916/C50-2017-08

Álvarez-García, D., Barreiro-Collazo, A., Núñez, J.C., & Dobarro, A. (2016). Validity and reliability of the Cyberaggression Questionnaire for Adolescents (CYBA). *The European Journal of Psychology Applied to Legal Context*, *8*, 69-77. https://doi.org/10.1016/j.ejpal.2016.02.003

Álvarez-García, D., García, T., & Suárez-García, Z. (2018). The relationship between parental control and high-risk internet behaviours in adolescence. *Social Sciences*, *7*, 87. https://doi.org/10.3390/socsci7060087

Álvarez-García, D., Núñez, J.C., Barreiro-Collazo, A., & García, T. (2017). Validation of the Cybervictimization Questionnaire (CYVIC) for adolescents. *Computers in Human Behavior*, *70*, 270–281. https://doi.org/10.1016/j.chb.2017.01.007

Álvarez-García, D., Núñez, J.C., Dobarro, A., & Rodríguez, C. (2015). Risk factors associated with cybervictimization in adolescence. *International Journal of Clinical and Health Psychology*, *15*, 226-235. https://doi.org/10.1016/j.ijchp.2015.03.002

Álvarez-García, D., Thornberg, R., & Suárez-García, Z. (2021). Validation of a Scale for Assessing Bystander Responses in Bullying. *Psicothema*, *33*(4), 623-630. https://doi.org/10.7334/psicothema2021.140.

Andreu, J.M., & Peña, M.E. (2013). Propiedades psicométricas de la Escala de Conducta Antisocial y Delictiva en Adolescents [Psychometric properties of the Scale of Antisocial and Criminal Behavior in Adolescents]. *Anales de Psicología*, *29*, 516–522. https://doi.org/10.6018/analesps.29.2.135951

Avilés, J.M. (2017). Los sistemas de apoyo entre iguales (SAI) y su contribución a la convivencia escolar [Peer support systems and their contribution to school social co-existence]. *Innovación Educativa*, *27*, 5-18. https://doi.org/10.15304/ie.27.4278

Beltrán-Catalán, M., Zych, I., Ortega-Ruiz, R., & Llorent, V.J. (2018). Victimisation through bullying and cyberbullying: Emotional intelligence, severity of victimisation and technology use in different types of victims. *Psicothema*, *30*(2), 183-188. https://doi.org/10.7334/psicothema2017.313

Dang, J., & Liu, L. (2020). When peer norms work? Coherent groups facilitate normative influences on cyber aggression. *Aggressive Behavior*, *46*(6), 559-569. https://doi.org/10.1002/ab.21920

Festl, R., Scharkow, M., & Quandt, T. (2015). The individual or the group: A multilevel analysis of cyberbullying in school classes. *Human Communication Research*, *41*(4), 535–556. https://doi.org/10.1111/hcre.12056

Flores, R., Caballer, A., & Romero, M. (2020). Effect of a cyberbullying prevention program integrated in the primary education curriculum. *Revista de Psicodidáctica*, *25*(1), 23-29. https://doi.org/10.1016/j.psicod.2019.08.001

Gámez-Guadix, M., Borrajo, E., & Almendros, C. (2016). Risky online behaviors among adolescents: Longitudinal relations among problematic internet use, cyberbullying perpetration, and meeting strangers online. *Journal of Behavioral Addictions*, *5*(1), 100-107. https://doi.org/10.1556/2006.5.2016.013.

Gámez-Guadix, M., & Gini, G. (2016). Individual and class justification of cyberbullying and cyberbullying perpetration: A longitudinal analysis among adolescents. *Journal of Applied Developmental Psychology*, *44*, 81-89. https://doi.org/10.1016/j.appdev.2016.04.001

Garaigordobil, M. (2017). Psychometric properties of the Cyberbullying Test, a screening instrument to measure cybervictimization, cyberaggression, and cyberobservation. *Journal of Interpersonal Violence*, *32*(23), 3556-3576. https://doi.org/10.1177/0886260515600165

Giletta, M., Choukas-Bradley, S., Maes, M., Linthicum, K., Card, N., & Prinstein, M.J. (2021). A meta-analysis of longitudinal peer influence effects in childhood and adolescence. *Psychological Bulletin*, *147*(7), 719-747. https://doi.org/10.1037/bul0000329

Guo, S. (2016). A meta-analysis of the predictors of cyberbullying perpetration and victimization. *Psychology in the Schools*, *53*(4), 432-453.https://doi.org/10.1002/pits.21914

Heirman, W., Angelopoulos, S., Wegge, D., Vandebosch, H. Eggermont, S., & Walrave, M. (2015). Cyberbullying-entrenched or cyberbully-free classrooms? A class network and class composition approach. *Journal of Computer-Mediated Communication*, *20*(3), 260–277. https://doi.org/10.1111/jcc4.12111

Khoury-Kassabri, M., Benbenishty, R., Avi Astor, R., & Zeira, A. (2004). The contributions of community, family, and school variables to student victimization. *American Journal of Community Psychology*, *34*(3-4), 187-204.

Kowalski, R.M., 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. https://doi.org/10.1037/a0035618

Kowalski, R.M., & Limber, S.P. (2013). Psychological, physical, and academic correlates of cyberbullying and traditional bullying. *Journal of Adolescent Health*, *53*(1 Suppl), S13-20. https://doi.org/10.1016/j.jadohealth.2012.09.018

Machimbarrena, J.M., Calvete, E., Fernández-González, L., Álvarez-Bardón, A., Álvarez-Fernández, L., & González-Cabrera, J. (2018). Internet Risks: An overview of victimization in cyberbullying, cyber dating abuse, sexting, online grooming and problematic internet use. *International Journal of Environmental Research and Public Health*, *15*(11), 2471. https://doi.org/10.3390/ijerph15112471

Marciano, L., Schulz, P.J., & Camerini, A.L. (2020). Cyberbullying perpetration and victimization in youth: A meta-analysis of longitudinal studies. *Journal of Computer-Mediated Communication*, *25*(2), 163-181. https://doi.org/10.1093/jcmc/zmz031

Menesini, E., & Salmivalli, C. (2017). Bullying in schools: The state of knowledge and effective interventions. *Psychology, Health & Medicine*, *22*:sup1, 240-253. https://doi.org/10.1080/13548506.2017.1279740

Ortega-Barón, J., González-Cabrera, J., Machimbarrena, J.M., & Montiel, I. (2021). Safety.Net: A pilot study on a multi-risk internet prevention program. *International Journal of Environmental Research and Public Health*, *18*(8), 4249. https://doi.org/10.3390/ijerph18084249

Saarento, S., Boulton, A.J., & Salmivalli, C. (2015). Reducing bullying and victimization: Student- and classroom-level mechanisms of change. *Journal of Abnormal Child Psychology*, *43*(1), 61–76. https://doi.org/10.1007/s10802-013-9841-x

SAS Institute Inc. (2020). *SAS/STAT® 14.3 user's guide*. SAS Institute Inc.

van Geel, M., Goemans, A., Zwaanswijk, W., Gini, G., & Vedder, P. (2018). Does peer victimization predict low self-esteem, or does low self-esteem predict peer victimization? Meta-analyses on longitudinal studies. *Developmental Review*, *49*, 31-40.

Wegge, D., Vandebosch, H., & Eggermont, S. (2014). Who bullies whom online: A social network analysis of cyberbullying in a school context. *Communications*, *39*(4), 415-433.

Contact address: David Álvarez-García, Universidad de Oviedo, Facultad de Psicología, Departamento de Psicología. Plaza Feijóo, s/n, CP 33003, Oviedo. E-mail: alvarezgardavid@uniovi.es

Received: 11-06-2021 Accepted: 28-01-2022