Qeios

Emotional Intelligence and Cybervictimization: Stratified Multilevel Analysis With Synthetic Data

The study used multilevel analysis with synthetic data in SPSS to investigate the association between emotional intelligence (EI) and cybervictimization among adolescents aged 11-18 years.

The analysis relied on dividing the data according to emotional intelligence profiles or strata, including attention, clarity, and emotional regulation. A method was developed to assess the quality of the synthetic sample through comparing the distributions of the reference and synthetic data.

The analysis employing Linear Mixed-Effects (SPSS) utilized the strata of emotional intelligence as a grouping variable along with eighteen predictive variables, including eleven level 1 and seven level 2. The neural network analysis determined the analytical levels of variables associated with risk factors and peer bullying.

The choice of the reference variable for analyzing the variability of the slopes was determined based on scatter diagrams. On the one hand, population patterns that predict cybervictimization include excessive levels of interpersonal attention and low levels of emotional regulation. Additionally, an increase in social anxiety, offline victimization, older age, or parental control leads to increased cybervictimization, while higher self-esteem correlates with decreased cybervictimization. Finally, being men and heterosexual constitutes a lower risk profile for cybervictimization compared to being women and non-heterosexual.

On the other hand, the study revealed that cybervictimization was dependent on the emotional intelligence profile, and the explanatory variables held varying degrees of significance based on the strata-EI. Each profile or stratum exhibited unique characteristics regarding their predisposition to cybervictimization.

Keywords: Multilevel analysis; Stratified analysis; Synthetic data; Emotional Intelligence; Cybervictimization; School psychology.

1. Introduction

The relationship between emotional intelligence and cybervictimization is extensively documented in the scientific literature (Rueda et al., 2022).

According to Martinez-Monteagudo et al. (2019), cybervictimization affects between 3-6% of adolescents, which Calmaestra et al. (2020) specify as 9.8% as cybervictims, 3% as cyberaggressors, and 6.1% as both cybervictims and cyberaggressors.

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Cybervictimization is the act of harassing, intimidating, impersonating, or bullying another person through digital media such as the Internet or social networking communication applications and can be occasional or reiterative (Álvarez-García et al., 2015a). The intention of the harasser is to do harm, and he or she does so from a position of power (Nixon, 2022; Pérez-Gómez et al., 2020) that feeds back, with an increase in popularity (Wiertsema et al., 2023). It can have different levels of severity and include insults, defamation, publication of compromising photos or videos without consent, or impersonation of others (Perren et al., 2012). Cybervictimization is a stressor with serious health implications (Cañas et al., 2020), especially in adolescents (Nixon, 2022).

Cybervictimization has been explained by individual variables such as gender or sexual orientation (Angoff & Barnhart, 2021; Garairgordobil & Larrain, 2020), age (Patchin & Hinduja, 2021), self-esteem and social anxiety (Lei et al., 2020; Núñez et al., 2021), Internet risk behaviors (Zhu et al., 2021) or parental control (Martín-Criado et al., 2021), and partly explains lower academic performance (Martínez-Martínez et al., 2022; Wright & Wachs, 2021).

Traditional bullying and cyberbullying are two related but different phenomena, which when they concur in a mixed format have particularly negative consequences at the emotional level (Carmona-Rojas et al., 2023). Those who suffer cyberbullying and other forms of bullying between peers present greater problems of social and normative adjustment than their equals (Ortega et al., 2012). Their combination can generate a perception of continued harassment in which the victim does not find a safe environment, leading to great emotional distress (Quintana-Orts et al., 2020), and even feelings of shame and guilt (Carmona-Rojas et al., 2023).

Cyberbullying is related to risk perception and the performance of online behaviors (Grahan & Wood, 2019). Mickewright et al. (2015) found a positive association between better risk perception and higher emotional intelligence.

Emotional intelligence is one of the factors explaining the severity of perceived cyberbullying and its psychological implications for victims (Quintana-Orts et al., 2019). Emotional intelligence is a risk or protective factor against cybervictimization (Garcia et al., 2020).

Martinez-Martinez et al. (2020) found that low emotional intelligence scores predicted a higher likelihood of cybervictimization and lower academic achievement. A high level of emotional intelligence would act as a protector against school violence and positively influence academic success (Martínez-Martínez et al., 2022).

One of the most widely used tools to measure emotional intelligence in Spain and Latin America is the Trait-Meta-Moods Scale-24 (TMMS-24) (Extremera & Fernández-Berrocal, 2005; Fernández-Berrocal et al., 2004; González et al., 2020). It is a test based on the model of Salovey & Mayer (1990) to assess emotional intelligence.

It defines emotional intelligence as a composite ability that allows recognizing and manifesting emotions, understanding them, and adjusting actions to promote internal and external bonds with others (Mestre et al., 2006). It is not designed to provide an overall score, but for each of its component factors (attention, clarity, and emotional regulation), with three levels of measurement (low, adequate, and excessive) (Taramuel-Villacreces & Zapata-Achi, 2017).

Among the studies in which cybervictimization is related to the emotional intelligence factors proposed in the TMMS-24, we find that of Guerra-Bustamante et al. (2021) with adults between 21 and 62 years of age. They analyzed the relationship between cyberbullying profiles and factors of attention, clarity, and regulation. It was performed independently for each emotional intelligence factor in relation to the victim, aggressor, and victim-aggressor profiles. They identified, in the case of cyberbullying victims, a profile of excessive attention, low emotional clarity, and regulation, and for the victim-aggressor profile, excessive emotional attention and low understanding of their emotions. They concluded that inadequate clarity was the factor with the highest predictive capacity for the three profiles analyzed.

Martínez-Monteagudo et al. (2019) found that higher levels of understanding and regulation decrease the likelihood of being victims, aggressors, or victim-aggressors of cybervictimization.

Considering the factorial structure of the TMMS-24, each of the twenty-seven clusters resulting from the cross-stratification of the three factors (attention, clarity, and emotional regulation), with the three categories of each factor (low, adequate, and excessive), was considered as an emotional intelligence profile. We will call these clusters emotional intelligence strata (EI-strata) or latent EI profiles (Grommisch et al., 2020).

Assuming that part of the variability in cybervictimization is due to differences in emotional intelligence profiles, we propose to find out the differences in the relationships between the individual variables and cybervictimization within each of the strata-EI.

The main objective of this research was to analyze the impact of stratified emotional intelligence on the probability of suffering cybervictimization, considering the effect of different individual variables in the analysis **(Figure 1)**.

The following hypotheses were formulated:

1. The variability of average cybervictimization among the different strata-EI is significant and non-zero.
2. These differences can be explained by the individual characteristics of the subjects. According to previous evidence, it was expected that (a) inadequate levels of emotional intelligence increase the probability of cybervictimization, and (b) gender has a weak but significant relationship with the degree of cybervictimization, (c) non-heterosexual sexual orientation, (d) older age, (e) low self-esteem, (f) social anxiety, (g) risky Internet behaviors, or (h) low parental control increase the probability of cybervictimization.

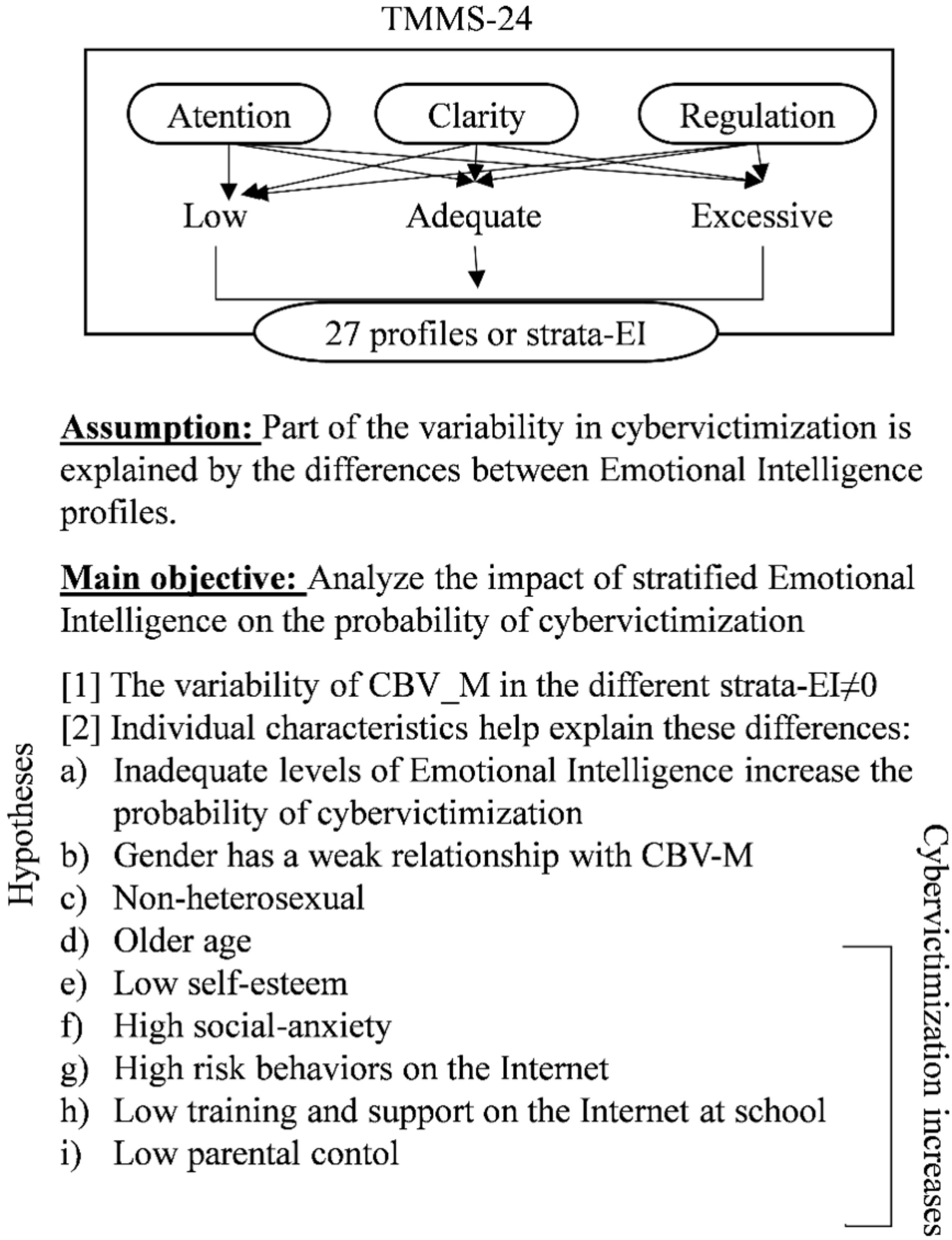


Figure 1. *Research objective*

2. Methods

2.1. Participants and procedures

The usual practice is to use data from anonymized informants with strict protection conditions (Quintana, 2020). We proposed using synthetic rather than anonymized data, generated with the tonic.ai app (https://app.tonic.ai/), that does not require protection and allowed a sufficiently large size to perform a stratified multilevel analysis (Evans et al., 2018).

A dummy sample with 48,000 synthetic data was constructed from the statistical parameters of previous studies (Martinez-Martinez, 2020). A predictive model based on Multiple Imputation by Chained Equations (MYCE) was estimated (Royston & White, 2011), which allowed the creation of a new dataset with the statistical properties and relationships between variables of the primary data (Reiter & Raghunathan, 2012).

To assess data quality, the distributions of observed and imputed data were compared (Budu et al., 2023; Giuffrè & Shung, 2023). For the scale variables, the means, standard deviations, maximum, and minimum values were compared, and for the categorical variables, the percentages of each category **(Table 1)**.

	Primary sample. N: 3451				Synthetic sample. N: 48000			
	Descriptive statistics							
Variables	**Mean**	**SD**	**Min.**	**Max**	**Mean**	**SD**	**Min**	**Max**
Age	13.6572	1.36025	11	18	13.6405	1.36266	11	18
Peer bullying	43.6883	9.23655	39	117	43.7606	9.40724	39	117
FCR Parental Controls	13.91	5.103	7	28	13.9386	5.0756	7	28
FCR Self-esteem	17.1759	2.558	5	20	17.1584	2.6035	5	20
FCR School Vict.	9.357	3.21248	6	24	9.3569	3.20538	6	24
FCR Training-Support	22.7517	3.77	7	28	22.7533	3.78472	7	28
FCR Shyness-Soc.anxiety	8.4028	2.87438	4	16	8.3870	2.86147	4	16
FCR Risk-behaviors	9.4367	3.34495	5	20	9.43852	3.2818	5	20
Academic-Performance	6.068	1.75317	0	10	6.0548	1.76014	0	10
CBV Average	1.1687	.2666	1	3.69	1.1692	.26907	1	3.54
	Percentages							
Variables	**Categories**		**N**	**%**	**Categorías**		**N**	**%**
Gender	Men (1)		1695	49.1%	Men (1)		23905	49.8%
	Women (2)		1756	50.9%	Women (2)		24095	50.2%
Sexual orientation	Heterosexual (1)		3304	95.7%	Heterosexual (1)		23905	95.6%
	Non-heterosex. (2)		147	4.3%	Non-heterosex. (2)		2088	4.4%
TMMS Attention	Low-attention (1)		1749	50.7%	Low-attention (1)		24127	50.3%
	Adequate-attent. (2)		1418	41.1%	Adequate-attent. (2)		19816	41.3%
	Excessive-attent. (3)		284	8.2%	Excessive-attent (3)		4057	8.5%
TMMS Clarity	Low-clarity (1)		1362	39.5%	Low-clarity (1)		19017	39.6%
	Adequate-clarity (2)		1659	48.1%	Adequate-clarity (2)		23048	48.0%

	Primary sample. N: 3451				Synthetic sample. N: 48000			
	Descriptive statistics							
Variables	Mean	SD	Min.	Max	Mean	SD	Min	Max
	Excessive-clarity (3)		430	12.5%	Excessive-clarity (3)		5935	12.4%
TMMS Regulation	Low-regulation (1)		1378	39.9%	Low-regulation (1)		19323	40.3%
	Adequate-reg. (2)		1556	45.1%	Adequate-reg (2)		21511	44.8%
	Excessive-reg. (3)		517	15.0%	Excessive-reg. (3)		7166	14.9%
CBV Severity	CBV occasional (1)		3218	93.2%	CBV ocsasional (1)		44641	93.0%
	CBV severe (2)		233	6.8%	CBV severe (2)		3359	7.0%

Table 1. Comparison of descriptive statistics of the primary sample and the synthetic sample

The difference of typed means was calculated for the scale variables, and the difference of percentages was calculated for the categorical variables **(Table 2).**

Data	Primary sample: $\bar{x}_1, \delta_1, n_1; p_1$ Synthetic sample: $\bar{x}_2, \delta_2, n_2; p_2$
Standardized mean difference	$d = c(gl) \cdot \frac{\bar{x}_1 - \bar{x}_2}{\hat{S}}$ $c(gl) = 1 - \frac{3}{4 \cdot gl - 1}$ $\hat{S} = \sqrt{\frac{[(n_1 - 1) \cdot \delta_1^2] + [(n_2 - 1) \cdot \delta_2^2]}{n_1 + n_2 - 2}}$ $\vartheta_d = \frac{n_1 + n_2}{n_1 \cdot n_2} + \frac{d^2}{2 \cdot (n_1 + n_2)}$ $CI95\% = d \pm 1.96 \cdot \sqrt{\vartheta_d}$
Difference of proportions	$d_{p_2 - p_1} = p_2 - p_1$ $\vartheta_{d_{p2-p1}} = \frac{p_2 \cdot (1 - p_2)}{n_2} + \frac{p_1 \cdot (1 - p_1)}{n_1}$ $CI95\% = d_{p2-p1} \pm 1.96 \cdot \sqrt{\vartheta_{d_{p2-p1}}}$

Table 2. Formulas to calculate differences in standardized mean differences and differences in proportions (Botella-Ausina & Sánchez-Meca, 2015)

In both mean differences (scale variables) and percentage differences (categorical variables), the values were close to zero, and in all cases, the confidence intervals contained the null value (no significant differences) **(Table 3).**

Standardized mean differences	S estim.	d	Var_d	Lower CI 95%	Upper CI 95%
Age	1.3625	-0.0123	0.0003	-0.0468	0.0223
Peer-bullying	9.3959	0.0077	0.0003	-0.0268	0.0422
FCR Parental-controls	5.0774	0.0056	0.0003	-0.0289	0.0402

Standardized mean differences	S estim.	d	Var_d	Lower CI 95%	Upper CI 95%
FCR Self-estem	2.6005	-0.0067	0.0003	-0.0413	0.0278
FCR School-Vict.	3.2059	0.0000	0.0003	-0.0346	0.0345
FCR Training-Support	3.7837	0.0004	0.0003	-0.0341	0.0350
FCR Shyness-Soc.anxiety	2.8623	-0.0055	0.0003	-0.0401	0.0290
FCR Risk-behviors	3.2861	0.0006	0.0003	-0.0340	0.0351
Academic-performance	1.7597	-0.0075	0.0003	-0.0420	0.0270
CBV-Average	0.2689	0.0019	0.0003	-0.0327	0.0364
Differences of proportions	**Categories**	**d p2-p1**	**Var d_{p2-p2}**	**Lower CI 95%**	**Upper CI 95%**
Gender	Men (1)	0.0070	0.0003	0.0407	-0.0267
Gender	Women (2)	-0.007	0.0003	0.0261	-0.0401
Sexual-Or.	Heterosexual (1)	-0.001	0.0000	0.0088	-0.0108
Sexual-Or.	Non- heteros. (2)	0.0010	0.0006	0.0476	-0.0456
TMMS-Attention	Low-attention (1)	-0.004	0.0003	0.0291	-0.0371
TMMS-Attention	Adequate-attent. (2)	0.0020	0.0003	0.0382	-0.0342
TMMS-Attention	Excessive-attent. (3)	0.0030	0.0005	0.0485	-0.0425
TMMS-Clarity	Low-clarity (1)	0.0010	0.0004	0.0377	-0.0357
TMMS-Clarity	Adequate-clar. (2)	-0.001	0.0003	0.0330	-0.0350
TMMS-Clarity	Excessive-clar. (3)	-0.001	0.0005	0.0431	-0.0451
TMMS-Regulation	Low-regulation (1)	0.0040	0.0003	0.0406	-0.0326
TMMS-Regulation	Adquate-reg. (2)	-0.003	0.0003	0.0320	-0.0380
TMMS-Regulation	Excessive-reg. (3)	-0.001	0.0005	0.0425	-0.0445
CBV-Severity	CBV-ocassional (1)	-0.002	0.0000	0.0104	-0.0144
CBV-Severity	CBV-severe (2)	0.0020	0.0006	0.0480	-0.0440

Tabla 3. Calculation of standardized mean differences and differences of proportions

To ensure sampling equivalence, the two-dimensional distribution of the relationship between the dependent variable (mean cybervictimization) and the different independent variables was compared through their regression coefficients (slope and constant) **(Table 4)**. Bivariate correlation analysis was performed on the slopes and intercepts of the primary and synthetic samples, with a Pearson correlation coefficient of .917 (Sig..000) for slopes and .999 (Sig..000) for intercepts. Both samples are statistically equivalent.

DV: CBV Average	Primary sample. N=3451			Synthetic sample. N=48000		
IV		B (Not- St)	CI95%		B (Not- St)	CI 95%
Age	Const	.813	.724; .902	Const	.843	.819; .867
	Age	.026	.020; .033	Age	.024	.022; .026
Peer-bullying	Const	.447	.412; .482	Const	.465	.455; .474
	Peer-bull.	.017	.016; .017	Peer-bull.	.016	.016; .016
FCR-Parental-Control	Const	1.224	1.198; 1.250	Const	1.227	1.220; 1.234
	Parent-Cnt	-.004	-.006; -.002	Parent-Cnt	-.004	-.005; -.004
FCR-Self-esteem	Const	1.589	1.530; 1.648	Const	1.585	1.570; 1.601
	Self-esteem	-.024	-.028; -.021	Self-esteem	-.024	-.025; -.023
FCR-School-Vict.	Const	.819	.795; .844	Const	.837	.831; .844
	School-Vict	.037	.035; .040	School-Vict	.035	.035; .036
FCR-Training-Support	Const	1.426	1.373; 1.480	Const	1.458	1.443; 1.472
	Training	-.011	-.014; -.009	Training	-.013	-.013; -.012
FCR-Shyness-Soc.Anxiety	Const	1.098	1.070; 1.125	Const	1.105	1.098; 1.112
	Soc. Anxiety	.008	.005; .012	Soc. Anxiety	.008	.007; .008
FCR-Risk-behaviors	Const	.943	.918; .969	Const	.952	.945; .959
	Risk-behav.	.024	.021; .026	Risk-behav.	.023	.022; .024
Academic-Performance	Const	1.355	1.324; 1.387	Const	1.348	1.340; 1.357
	Ac.Perform.	-.031	-.036	Ac.Perform.	-.030	-.031; -.028

Table 4. Comparison of regression coefficients of the reference sample and the synthetic sample. CBV-Average as dependent variable

The synthetic sample consisted of 48,000 cases, representing a population between 11 and 18 years of age (Mean: 13.64; SD: 1.36), which were distributed as 23,905 boys and 24,095 girls.

2.2. Instruments and variables

The sociodemographic variables considered were sex (1: male, 2: female), sexual orientation (1: heterosexual, 2: non-heterosexual), and age (age-centered), and as school variables, final performance or grade-centered and whether any grade had been repeated. For variables related to emotional intelligence (EI), the reference was the Trait Meta-Mood Scale-24 (TMMS-24) (Fernández-Berrocal et al., 2004). Categorization was performed according to the authors' indications, taking into account score and gender. The TMMS-24 test does not offer a global sum score of its component factors, so a latent variable was generated, formed by the intersections of the categories of each one of the factors. Thus, we would have, for the case of too much emotional attention (3), adequate emotional clarity (2), and poor regulation (1), category 321. Each of the 27 categories of this variable made up the level 2 subjects in the multilevel model. That is, individuals (level 1) were nested according to the corresponding strata-EI (level 2) **(Figure 2)**.

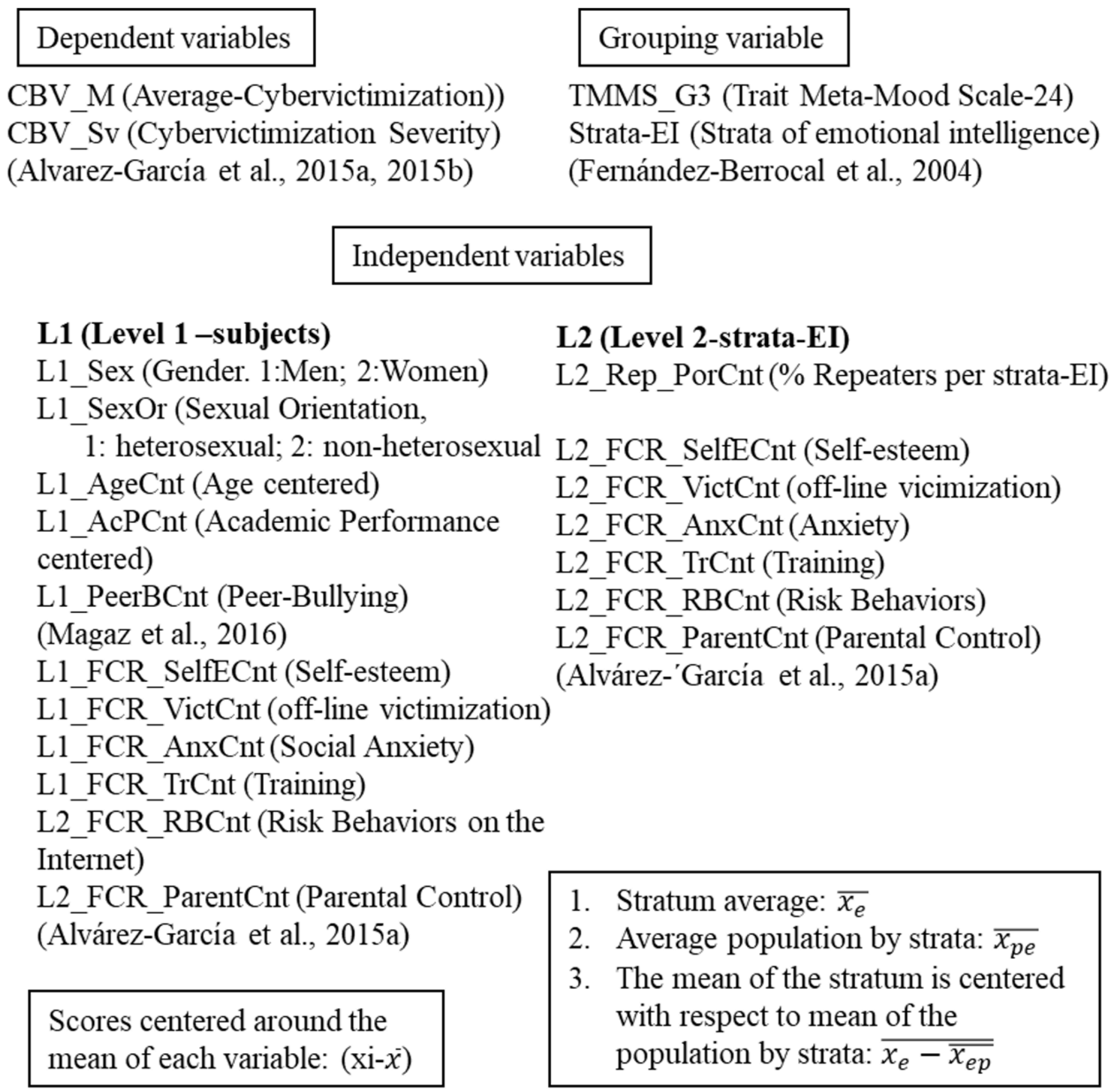


Figure 2. *Variables*

The variables of parental control, self-esteem, off-line victimization, training-support regarding Internet risks, shyness-social anxiety, and Internet risk-behaviors were estimated with the Alvarez-García et al. (2015a) risk factor questionnaire, following the indications that the authors detailed for each subscale (Alvarez-García et al., 2015b).

At level 1, scores were centered with respect to the mean of each factor. For level 2, variables were constructed with the group scores centered (Enders & Tofighi, 2007; Peugh & Enders, 2005). The mean value of the factor in each stratum was subtracted from the mean value of all strata.

For the measurement of peer-bullying, the reference was the bullying questionnaire in primary and secondary education by Magaz et al. (2016).

Regarding cybervictimization (dependent variable), the reference test was the cybervictimization questionnaire of Alvarez-García et al. (2015a). The total score corresponds to the sum of the scores of each factor, calculating its mean value for each case (CBV_M). From the mean cybervictimization scores (CBV_M), the variable Severity-Cybervictimization was created with two categories: occasional for mean scores less than 1.57 (direct score less than 41), and severe for mean scores greater than 1.57 (direct score greater than 41) (Alvarez-García et al., 2015b, p. 231).

2.3. Statistical analysis

2.3.1. Statistical description of the variables and justification for cross-stratification

The descriptive statistics of the subject-level variables were indicated in Table 1, as well as the estimators and regression intercepts of each independent variable with respect to mean cybervictimization (CBV_M) in Table 4.

The use of cross-stratification of emotional intelligence factors was justified with the calculation of linear regression estimators for mean cybervictimization (Table 5) and the calculation of mean values for each strata-EI (linear mixed model).

2.3.2. Analysis procedure

Unconditional means model or null model

First, the unconditional means model (model 0) was calculated in which only the dependent variable (mean cybervictimization) and the variation of its mean values in the strata-EI were considered. The Wald-Z statistic, the Intraclass Correlation Coefficient (ICC), and the Design Effect (Deff) were calculated to estimate how much variance in the cybervictimization-mean variable is explained by belonging to a strata-EI (Austin & Merlo, 2017; Martínez-Garrido & Murillo, 2014).

The Wald-Z statistic is the ratio of the estimator to its standard error ($\mathbf{Z} = \hat{\boldsymbol{\beta}} / \widehat{\mathbf{SE}}$) (Arango-Botero et al., 2023, Huang & Valdivia, 2023), assuming that if the p-value<.05, it is possible to reject the null effect hypothesis of the Strata-EI variable.

The Intraclass Correlation Coefficient (ICC) is the ratio of the level 2 variance to the sum of the level 1 and level 2 variances, "measuring the degree of similarity within the same group" (Muthen & Satorra, 1995, p. 289). In SPSS, it can be calculated from the covariance parameter estimates (variance strata-EI~$s^2_{\text{level 2}}$; residuals~$s^2_{\text{level 1}}$).

$$\mathbf{ICC} = \frac{\mathbf{s}^2_{\mathbf{level\ 2}}}{\mathbf{s}^2_{\mathbf{level\ 1}} + \mathbf{s}^2_{\mathbf{level\ 2}}}$$

The ICC was used to estimate the Design Effect (Deff) (Muthen & Satorra, 1995; Peugh 2010), defining the design effect as " the ratio of the variance of the actual sample [$\boldsymbol{var_c(\hat{k})}$], to the variance of a random sample with the same number of elements $\boldsymbol{var_{SRS}(\hat{k})}$ " (Kish, 1965, p.258). ICC≠0 and Deff>2 (Lai & Kwok, 2015) were taken as criteria for determining the multilevel analysis advantage.

$$\boldsymbol{Deff} = \frac{\boldsymbol{var_c(\hat{k})}}{\boldsymbol{var_{SRS}(\hat{k})}} = \mathbf{1} + (\boldsymbol{n_c} - \mathbf{1}) \cdot \boldsymbol{ICC}; \boldsymbol{n_c} = {}^{\boldsymbol{N}}\!/_{\boldsymbol{n^{\underline{o}}\ cluster}}$$

b) Importance of predictive variables in cybervictimization

Conceptually, the variables gender, sexual orientation, age, and academic performance were appropriate for level 1, and the mean percentage of repeaters per stratum was appropriate for level 2.

We had doubts about the variables related to risk factors and peer harassment. It was not possible to consider them simultaneously as level 1 and 2 because of the multicollinearity problems involved (by definition, one is a linear combination of the others) (Shieh & Fouladi, 2003).

Their importance in predicting mean cybervictimization as subject-level (L1) and strata-EI level (L2) variables was determined through neural network analysis. A random number was generated for replication purposes (SET SEED=9191947). The dependent variable used was mean cybervictimization, and the independent variables were, on the one hand, L2_FCR_SelfECnt, L2_FCR_VictCnt, L2_FCR_AnxCnt, L2_FCR_RBCnt, L2_FCR_ParentCnt, L2_FCR_TrCnt, and L2_PeerBCnt; on the other hand, L1_FCR_SelfECnt, L1_FCR_VictCnt, L1_FCR_AnxCnt, L1_FCR_RBCnt, L1_FCR_ParentCnt, and L1_PeerBCnt. The sample was divided into 62.5% training, 25% test, and 12.5% reserve. The training was performed on minibatches, and the automatic architecture selection function was used as the output layer (Aggarwal, 2018).

c) Random intersection models or main effects averages as outcomes

Four models were generated. One model of random intersections with all level-2 variables (model 1), another with the significant level-2 variables found in model 1 (model 1-simplified), a third with significant level-2 variables, together with the level-1 variables (model 2), and a fourth model (model 2-simplified) with the significant level-2 and level-1 variables from model 2.

The variables social anxiety and parental control were not significant at level 2. We explored including the corresponding level-1 variables in the 2-simplified model, which did not improve the fit indicators of the model and decreased the ICC. A separate multilevel model (model 6) was chosen, which analyzed only the variables related to risk factors in cybervictimization (Alvarez-García et al., 2015a).

d) Model of random coefficients (slopes) as outcomes

In the previous models, the significant predictor variables (level 1 and level 2) were considered as fixed effects. The only coefficient that varied randomly from stratum to stratum was the constant or intercept (β_{0j}). The variables age, peer-bullying, and academic performance were tested subject-centered (L1), with unstructured covariance type, to explain the variability of slopes (Pardo et al., 2007). Only the variable peer-bullying (model 3) was significant.

e) Model of random intersections (averages) and coefficients (slopes) as outcomes

Based on the variables that were significant in the random intersection model as main effects (model 2-simplified) and the variable harassment among equals, which was significant in the random coefficients model (model 3), a new model was developed that considered the randomness of means and slopes (model 4). With the variables that were found to be significant in model 4, model 5 (model of random means and slopes as outcomes) was developed.

f) Measurement of changes in reporting criteria

We calculated the likelihood ratio ($G^2_{0\text{-}j}$ = Deviance null-model - Deviance model-5) between each of the models generated and the null model (Pardo-Merino & Ruiz-Diaz, 2012), and the estimate of the significance value of this value in a Chi-square distribution from the difference between degrees of freedom of each model (number of parameters-1) (Constante-Amores et al., 2021).

g) Characterization of the strata-EI

It was based on models 5 and 6. Characterization of strata-EI was performed by segmenting the data by the variable TMMS-G3 (strata-EI) and performing regression analysis with the variables involved at level 1. Since the variable L2_FCR_SelfECnt (self-esteem) is the mean of L1_FCR_SelfECnt for each strata-EI, the level 2 variable was substituted for the level 1 variable for this calculation.

Stratum 222 (adequate attention, clarity, and emotional regulation) was analyzed, as well as those with higher and lower levels of average cybervictimization. It was observed that the lower the number of cases, the lower the accuracy, and it was not possible to make predictions for those with the lowest number of cases (e.g., 313 with 19 cases).

The values of the standardized estimators were used as a reference to assess the importance of each variable in the relationship of each strata-EI to cybervictimization.

The assumption of multicollinearity was tested with the Variance Inflation Value (VIF) test or proportion of the variability of the i-th variable in relation to the rest of the independent variables (Álvarez-Cáceres, 1995). It was taken as a criterion that values lower than 10 (tolerance greater than .1) do not entail multicollinearity problems (Field, 2000), and the Durbin-Watson test to detect autocorrelation of the residuals (they must be independent), assuming that values between 1.5 and 2.5 indicate independence of the errors (Pardo & San-Martín, 2010).

3. Results

3.1. Justification for cross-stratification (TMMS-G3)

The relationship between each of the factors that make up the emotional intelligence profiles (attention, clarity, and regulation) (Fernández-Berrocal et al., 2004) with mean cybervictimization (Álvarez-García et al., 2015a) was verified using linear regression analysis **(Table 5)**.

Factor EI	B	Dev. Error	t	Sig	IC95%
Attention	Cnst: 1.34	.012	105.99	.000	1.32; 1.36
	-.008	.001	-15.01	<.001	-.009; -.007
Clarity	Cnst: 1.43	.012	116.38	.000	1.40; 1.45
	-.011	.000	-22.56	<.001	-.012;-.010
Regulation	Cnst: 1.44	.012	119.09	.000	1.41; 1.46
	-.011	.000	-23.69	<.001	-.012;-.010

Table 5. Regression analysis of emotional intelligence and average cybervictimization factors

The statistical description of the predictor variables for each of the strata-EI showed that the cases with low attention, clarity, and regulation were not those with the least parental control; with a mean of 13.74 (mean between strata: 13.94), their average academic performance was among the lowest (mean between strata: 6.05), they presented low levels of self-esteem and support formation, and high levels of off-line victimization. Meanwhile, the cases of the stratum with adequate values of attention, clarity, and regulation (222) were characterized by having values very close to the total means in all variables. On the other hand, the analysis of the ICCs showed that the variables self-esteem (.161), risk behavior (.124), anxiety (.111), and peer bullying (.118) contributed the most variability to the strata-EI **(Table 6)**.

EI	N	Age	A.Per.	P.Cnt	Self- E	Vict	Train.	Anx.	R.B.	P.B.	Rep%
111	12328	13.74	5.51	13.64	15.98	11.69	21.63	9.19	9.89	5.51	26.9
112	1552	13.64	6.15	13.65	16.94	8.85	22.41	8.76	9.11	6.15	21.8
113	180	13.00	6.47	14.11	18.22	8.33	23.22	9.56	8.67	6.47	22.2
121	1333	13.76	6.47	13.35	17.13	8.71	22.43	7.98	9.60	6.47	13.4
122	6250	13.43	6.32	13.65	17.67	8.35	22.54	7.98	8.62	6.32	18.8
123	813	13.51	6.97	16.10	18.46	7.54	24.41	7.94	7.82	6.97	12.3
131	217	13.54	6.13	12.01	17.72	9.26	23.30	7.35	9.55	6.13	0
132	239	12.83	7.34	16.51	18.49	7.65	24.75	8.60	6.75	7.34	8.4
133	1215	13.37	5.67	14.05	18.60	8.13	23.67	7.61	8.89	5.67	23
211	2600	14.02	6.01	12.39	15.94	9.59	21.62	8.76	10.40	6.01	30.6
212	1684	13.75	6.46	14.44	17.01	9.06	23.08	8.88	9.71	6.46	26
213	217	13.64	6.74	16.51	17.44	7.82	24.45	7.75	8.90	6.74	18.4
221	1847	13.73	6.01	14.10	16.98	9.01	22.49	8.43	9.31	6.01	23.7
222	9482	13.64	6.24	14.02	17.79	8.42	23.33	7.89	9.51	6.24	20.6

EI	N	Age	A.Per.	P.Cnt	Self- E	Vict	Train.	Anx.	R.B.	P.B.	Rep%
223	1152	13.33	6.58	15.54	18.14	8.03	24.02	8.16	8.52	6.58	19.1
231	140	13.57	6.47	13.00	18.43	9.00	23.86	6.43	8.71	6.47	0
232	532	13.51	6.98	15.60	18.23	8.37	23.82	7.59	8.92	6.98	14.7
233	2162	13.44	6.38	15.48	18.71	7.97	25.15	7.41	8.25	6.38	21.1
311	318	14.63	5.22	10.70	14.86	9.32	22.27	10.21	11.37	5.22	56
312	119	14.50	4.96	11.67	17.48	8.13	23.38	8.13	8.65	4.96	49.6
313	19	13.00	7.50	11.00	19.00	7.00	23.00	8.00	6.00	7.50	0
321	500	13.64	6.04	11.52	15.48	10.16	22.80	9.16	10.80	6.04	24
322	1393	13.82	5.87	14.75	17.46	8.83	23.37	8.49	10.05	5.87	24.2
323	278	12.92	6.48	15.69	18.64	9.57	23.85	9.36	6.87	6.48	0
331	40	13.00	7.21	15.50	16.00	8.00	27.00	11.00	6.00	7.21	0
332	260	13.77	5.68	15.85	18.23	7.77	23.69	6.31	9.15	5.68	23.1
333	1130	13.35	6.07	14.50	18.18	8.15	23.77	7.49	9.17	6.07	22.8
Total	48000	13.64	6.05	13.94	17.16	9.36	22.75	8.39	9.38	6.05	22.7
ICC		0.079	0.098	0.092	0.161	0.093	0.074	0.111	0.124	0.118	

Table 6. Mean values and Intraclass Correlation Interval of the independent variables by strata-EI

EI (strata-EI); A.Per (Academic-performance), P.Cnt (Parental-controls); Self-E (Self-esteem); Vict (off-line victimization); Train. (Training-Support), Anx. (Social-anxiety); R.B. (Risk-Behaviors); P.B. (Peer-Bullying); Rep% (Percentage of repeat students by strata-EI); ICC (Intraclass Correlation Cofficients)

3.2. Unconditional means model

The average cybervictimization in relation to the emotional intelligence profile of the participants was different from zero [Hypothesis 1], finding statistically significant differences in the levels of cybervictimization, both at level 2 (emotional intelligence profile) and level 1 (subjects). Cybervictimization varied significantly across strata-EI. The intraclass correlation coefficient (.059) indicated that of the total variability in cybervictimization, 5.9% corresponded to the difference between the means of the strata-EI of membership **(Table 7)**.

Fixed-effects						
Parameter	Estimator	Standard error	df	t	Sig	CI95%
Intercept	1.117	.013	26.025	84.74	<.001	1.089;1.144
Random-effects						
Covariance parameter	Estimator	Standard error	Wald Z		Sig	CI95%
Residue	.064	.000	154.877		.000	.063; .064
Level I+II Effect	.004	.001	3.443		.004	.003; .008
ICC	.004/ (.064+.004)= .059					

Null model fit information for cybervictimization.

Descriptión	Value
Deviance	4122.11
AIC	4126.11
BIC	4143.67
df (parameters -1): 2	

Table 7. Results of the unconditional mean model

Note. t= estimator/ Standard error= standard estimator; df= Degree of freedom. Deviance= -2Log-likelihood; AIC= Akaike Information Criterion; BIC: Bayesian Information Criterion; ICC: Coefficient of Intraclass Correlation

Design-Effects for the null model (Deff=105.83>2) and ICC (.059≠0), indicating the appropriateness of multilevel modeling (Lai & Know, 2015; Peugh, 2010).

1. 3.3. Importance of independent variables in cybervictimization.

The normalized significance of the variables cybervictimization risk factors (Álvarez-García et al., 2015a) and peer-bullying (Magaz et al., 2016) was determined using neural network analysis. The peer bullying variable had a normalized significance of 100% for level 1, and self-esteem (100%), off-line victimization (92.9%), and anxiety-timidity (78.1%) had better levels for level 2 **(Table 8)**. Variables related to risk factors for cybervictimization were assigned as level 2 variables, and peer-bullying was assigned as a level 1 variable.

Subject level (L1)	**Importance**	**Standardized Importance**	**Strata Level (L2)**	**Importance**	**Standardized Importance**
L1 Peer-Bullying	.412	100%	L2 Peer-Bullying by stratum	.116	45.6%
L1 FCR Parental Control	.027	6.5%	L2 FCR P. Control by stratum	.083	32.6%
L1 FCR Self-esteem	.099	24%	L2 FCR Self-E. by stratum	.254	100%
L1 FCR Vict	.141	34.1%	L2 FCR Vict by stratum	.236	92.9%
L1 FCR Training	.102	24.8%	L2 FCR Training by stratum	.055	21.6%
L1 FCR Anxiety	.068	16.4%	L2 FCR Anxiety by stratum	.198	78.1%
L1 FCR Risk-behaviors	.152	36.8%	L2 FCR Rislk-behav. by stratum	.060	23.5%

Table 8. Importance of independent variables in average-cybervictimization.

3.4. Random intersection models or main effects averages as outcomes

With the null or unconditional mean model, we inferred the level of cybervictimization based on emotional intelligence profiles. But cybervictimization could be explained by (a) the characteristics of the strata, (b) the characteristics of the subjects that make up each stratum, as well as by (c) the joint effect of both.

a) Random intersection model with L2 variables (characterization of the strata on the degree of cybervictimization) (models 1 and 1-simplified).

In the strata characteristics analysis model with all level-2 predictor variables (model 1), the variables L2_FCR_TrCnt (training) and L2_FCR_RBCnt (risk-behaviors) did not have significant t-values, eliminating them from the explanatory model of the effects of level-2 variables (model 1-simplified). In the 1-simplified model, a positive association with cybervictimization was found in the variables percentage of repeaters, victimization, social anxiety, and parental control, and a negative or protective association of self-esteem with cybervictimization.

b) Random intersection model with significant L2 and L1 variables (characterization of subjects and strata on the degree of cybervictimization) (models 2 and 2-simplified).

In the 1-simplified model (significant L2 variables), level 1 variables (L1_Sex, L1_SexOr, L1_AgeCnt, L1_AcPCnt, and L1_PeerBCnt) were added, forming model 2. The only level 2 variable that remained significant was self-esteem-L2, with a t-value (estimator:-.033/standard error:.013) of -2.60 (Sig..015).

The decrease in residuals in the covariance parameter estimates between model 0 and model 2-simplified was 26.5% [(.064-.047)/.064=.265], with a proportion of variance explained for level 1 and level 2 of 75% [.004-.001)/.004=.75) **(Table 9)**.

Fixed-effects						
Parameter	Estimator	Standard error	df	t	Sig	CI95%
Intercept	1.220	.009	47.74	136.62	<.001	1.202;1.238
L2_FCR_SelfECnt	-.022	.007	24.34	-3.12	.005	-.036;-.007
L1_Sex (1)	.009	.002	42897.26	4.02	<.001	.005;.013
L1_SexOr (1)	-.055	.005	47952.62	-11.13	<.001	-.005;-.046
L1_AgeCnt	.019	.001	47951.49	25.35	<.001	.018;.020
L1_AcPCnt	-.008	.001	47936.30	-14.00	<.001	-.010;-.007
L1_PeerBCnt	.016	.000	47704.57	119.99	.000	.016;.016
Random-effects						
Covariance parameter	Estimator	Standard error	Wald Z		Sig	CI95%
Residue	.047	.000	154.80		.000	.046; .047
Level I+II Effect	.001	.000	3.117		.002	.001; .002
ICC	.001/ (.047+.001) = .021					

2-simplified model fit information for cybervictimization

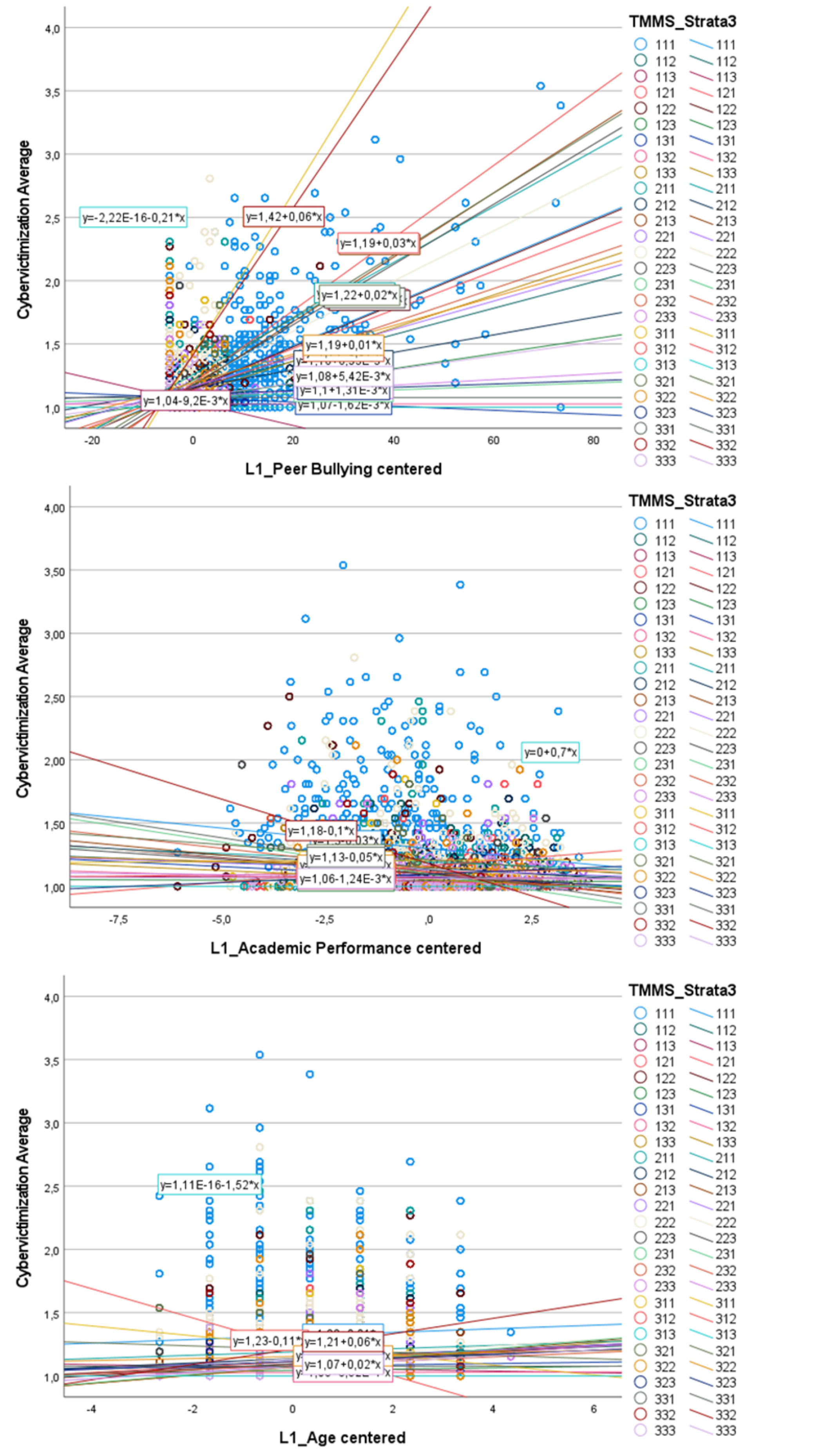
Description	Value	Likelihood-ratio
Deviance	-10582.59	4122.11-(-10582.59)=14704.7
AIC	-10578.59	
BIC	-10561.04	
df (parameters -1): 8		

Table 9. 2-simplified random intersection (mean) model characterizing average-cybervictimization at the strata-EI (L2) and subject (L1) levels.

Note. t= estimator/ Standard error= standard estimator; df= Degree of freedom. Deviance= -2Log-likelihood; AIC= Akaike Information Criterion; BIC: Bayesian Information Criterion; ICC: Coefficient of Intraclass Correlation

3.5. Model of random coefficients (slopes) as outcomes (model 3)

Of the three possible variables to use as random effects (peer-bullying, academic-performance, and centered-age), it was the first one that best explained the variations in slopes between strata **(Figure 3)**.



Cybervictimization Average
L1_Peer Bullying centered
TMMS_Strata3
111
112
113
121
122
123
131
132
133
211
212
213
221
222
223
231
232
233
311
312
313
321
322
323
331
332
333
y=-2,22E-16-0,21*x
y=1,42+0,06*x
y=1,19+0,03*x
y=1,22+0,02*x
y=1,19+0,01*x
y=1,08+5,42E-3*x
y=1,04-9,2E-3*x
L1_Academic Performance centered
y=0+0,7*x
y=1,18-0,1*x
y=1,13-0,05*x
y=1,06-1,24E-3*x
L1_Age centered
y=1,11E-16-1,52*x
y=1,21+0,06*x
y=1,07+0,02*x

Figure

3. *Random coefficient (slope) models*

For the null model, the peer-bullying variable was included as a random effect and fixed effect (model 3).

Estimation of the two fixed-effects parameters indicated (a) that the constant or intercept or population mean cybervictimization estimate based on centered peer-bullying scores was $\hat{\gamma}_{00}$=1.157, and (b) that the coefficient associated with the variable L1_PeerBCnt or mean of all slopes was $\hat{\gamma}_{10}$=.015).

That is, for every point that peer bullying increased, the mean cybervictimization increased.015. The *p-value* (<.001) associated with the t-statistic indicated that the population slope is non-zero and that there is a positive association between peer-bullying and cybervictimization.

In this regard, it was relevant to note that the influence of the peer-bullying variable had different implications depending on the strata-EI.

For example, for cases in stratum 113 (low attention, low clarity, and high regulation), the initial cybervictimization is higher (1.44), but when there is peer bullying, cybervictimization tends to decrease (Y_{CBV_M}= 1.44 -.01* X_{PeerB}), while for others, such as 222 (adequate attention, adequate clarity, and adequate regulation; Y_{CBV_M}=.34+.02* X_{PeerB}), or 332 (high attention, high clarity, and adequate regulation; Y_{CBV_M}= -1.12+.06* X_{PeerB}), the initial position (Peer-BullyingCnt=0) is lower, but when there is peer bullying, cybervictimization tends to increase **(Figure 4)**.

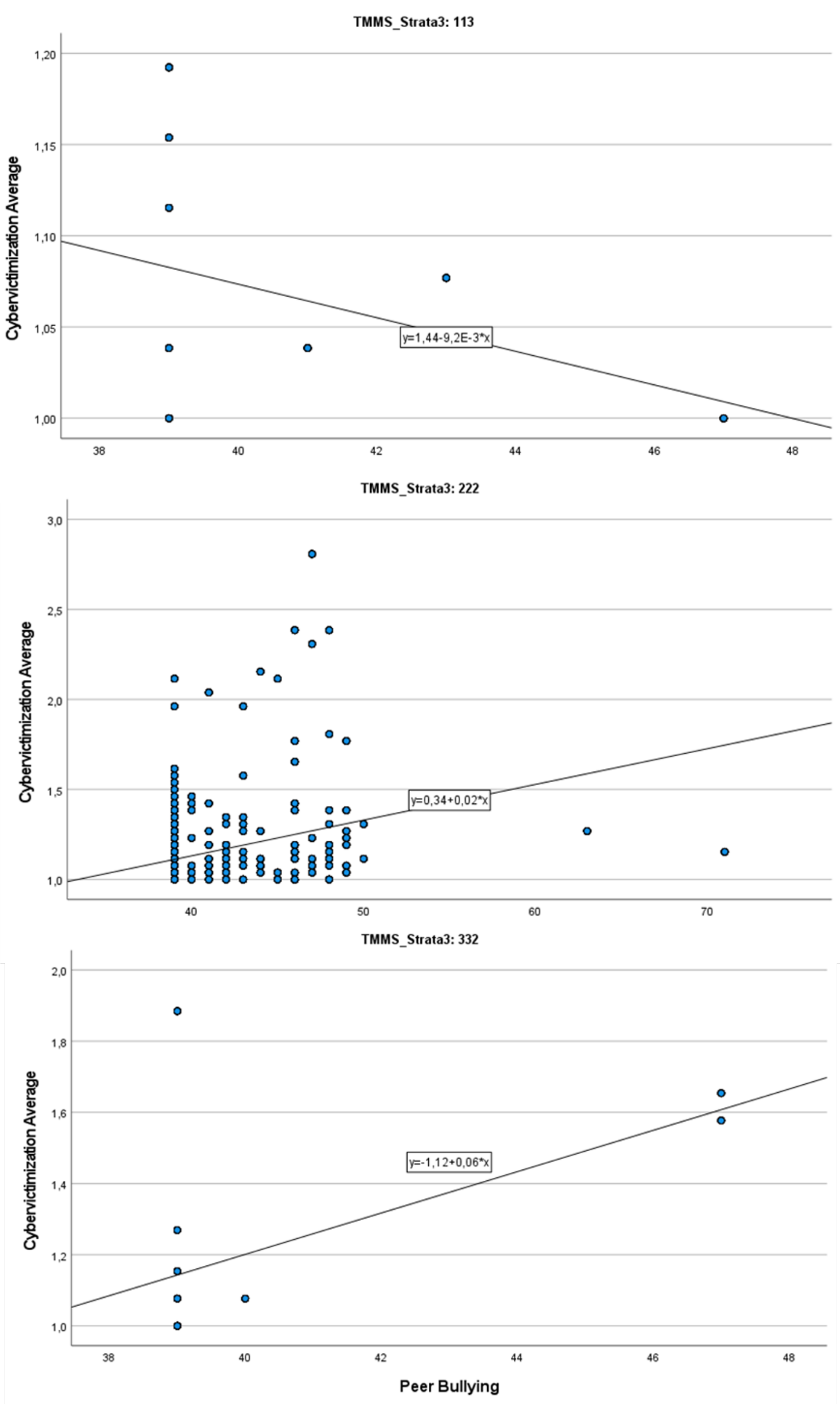

TMMS_Strata3: 113
Cybervictimization Average
y=1,44-9,2E-3*x
TMMS_Strata3: 222
Cybervictimization Average
y=0,34+0,02*x
TMMS_Strata3: 332
Cybervictimization Average
y=-1,12+0,06*x
Peer Bullying

Figure 4. *Cybervictimization and peer-bullying for strata-EI*

3.6. Model of random intersections (averages) and coefficients (slopes) as outcomes

Both intercepts (model 2-simplified) and coefficients (model 3) varied between strata-EI. A model has been created to explain this variation based on the previous two models (model 4). In model 2-simplified, there was a decrease in the residual estimator (.064 for the null model to .047 for model 2-simplified), indicating an improvement in precision, which reached .046 in model 4. That is, a 28.13% improvement in accuracy [(.064-.046)/.064=.2813].

On the other hand, if the ICC of the null model was .059, the ICC of model 4 was .08. Model 4 explained 8% of the variability between strata. It explained the interstrata variability 26.25% better than the null model.

It was observed that the average cybervictimization was higher for non-heterosexual cases than for heterosexual cases, with 6.1% of heterosexuals suffering severe cybervictimization, compared to 74.2% of non-heterosexuals **(Figure 5)**.

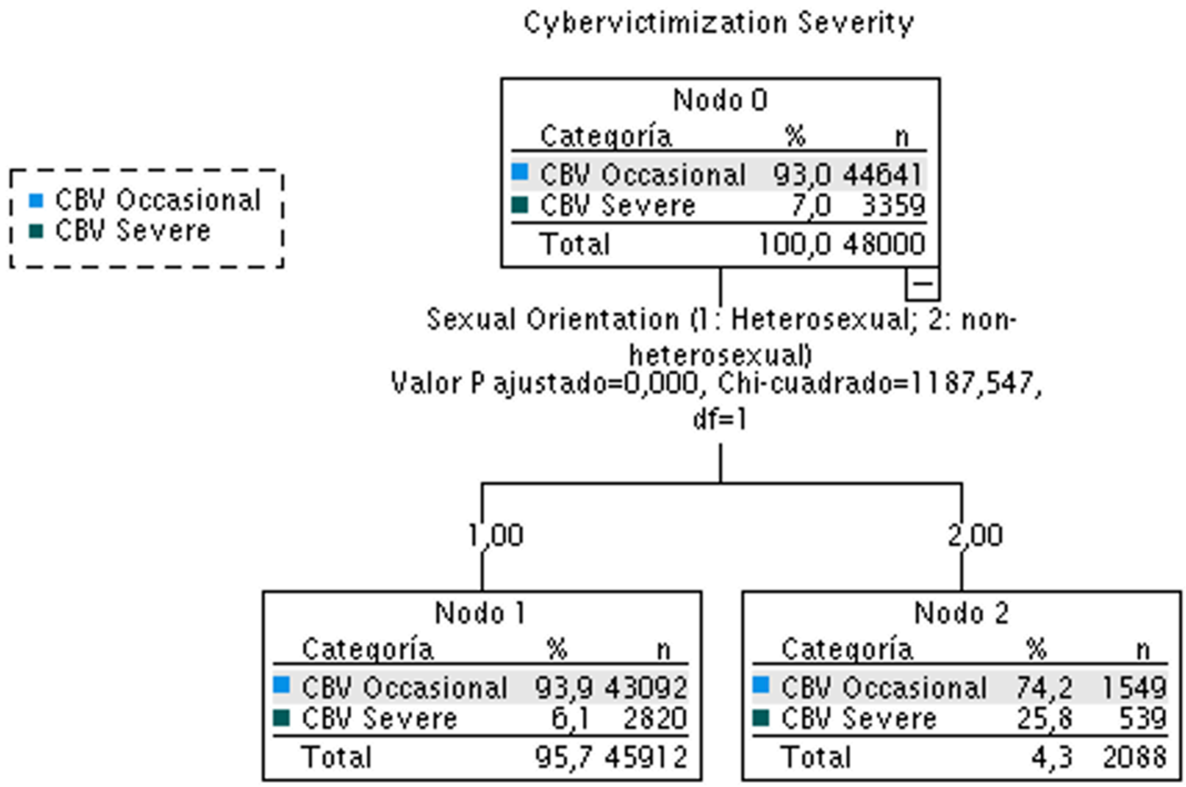


Figure 5. *Sexual orientation by cybervictimization severity classification tree*

Model 4 could be improved with the sexual orientation variable (L1_SexOr).

A new model was created from model 4, adding two interactions (gamma coefficients 11 and 12) (L1_SexOr * L1_PeerBCnt, y L1_PeerBCnt * L2_FCR_SelfECnt) to the five main effects at level 1 (L1_Sex, L1_SexOr, L1_AgeCnt, L1_AcP_Cnt, y L1_PeerBCnt) and one at level 2 (L2_FCR_SelfECnt) (model 5), and finding significance in all of its components **(Table 10)**.

Fixed-effects

Parameter	Estimator	Standard error	Df	t	Sig	CI95%
Intercept	1.208	.014	31.31	84.19	<.001	1.18;1.24
L2_FCR_SelfECnt	-.044	.012	24.67	-3.64	.001	-.07;-.02
L1_Sex (1)	.010	.002	47481.04	4.34	<.001	.005;.014
L1_SexOr (1)	-.039	.006	47829.29	-6.71	<.001	-.05;-.03
L1_AgeCnt	.019	.001	47948.86	24.93	<.001	.017;.020
L1_AcPCnt	-.008	.001	47940.66	-14.12	<.001	-01;-.007
L1_PeerBCnt	.019	.003	22.45	7.60	<.001	.014;.025
L2_FCR_SelfECnt * L1_PeerBCnt	-.007	.002	23.32	-3.08	.005	-.012; -.002
L1_SexOr(1)* L1_PeerBCnt	-.002	.000	47937.02	-5.28	<.001	-.003; -.001

Random-effects

Covariance parameter		Estimator	Standard error	Wald Z	Sig	CI95%
Residue		.046	.000	154.75	.000	.046; .047
	UN[1,1]	.005	.002	3.10	.002	.003; .009
Unstructured	UN[2,1]	.001	.000	2.91	.004	.000; .001
	UN[2,2]	$1.61\cdot10^{-5}$	$5.5\cdot10^{-5}$	2.96	.003	≈0
Covariance parameter Level I+II Effect		.004	.001	3.157	.002	.002; .007
Variance L1_PeerBCnt L1-L2		$1.31\cdot10^{-4}$	$4.4\cdot10^{-5}$	2.986	.003	≈0
ICC		.004/ (.046+.004) = .008				

Model 5 fit information for cybervictimization

Description	Value	Likelihood-ratio M0-M5 [SIG.CHISQ(14704.2, 9)]
Deviance	-10906.22	4122.11-(-10582.59)=14704.7 (Sig. .000)
AIC	-10900.22	Likelihood-ratio M2s-M5 [SIG.CHISQ(323.63, 3)] (Sig. .000)
BIC	-10873.89	
df (parameters -1): 11		

Table 10. Model 5 with intercepts (fixed effects & interactions) and random coefficients as outcomes characterizing average-cybervictimization at the level of strata (L2) and subjects (L1)

Note. t= estimator/ Standard error= standard estimator; df= Degree of freedom. Deviance= -2Log-likelihood; AIC= Akaike Information Criterion; BIC: Bayesian Information Criterion; ICC: Coefficient of Intraclass Correlation

3.7. Measurement of changes in reporting criteria

The likelihood ratio test ($G^2_{0\text{-}5}$) was performed by calculating the significance of the difference in deviance of model 5 from the null model (Chi2-distribution) (Gómez-Mejia, 2020).

An improvement was observed in the deviance of the unconditional model with respect to model 5 (Δ M-nulo-M-5=15028.33) **(Table 11)**; since -2LL has a Chi-square distribution, the significance value was calculated for 9 degrees of freedom in SPSS, obtaining *p-value*: .000.

Criteria of Information	Model null	Model 5	Δ M.null-M 5.
	2df	11df	9df
Deviance (-2LL)	4122.11	-10906.22	15028.33
Akaike Information Criterion (AIC)	5126.11	-10900.22	16026.33
Bayesian Information Criterion (BIC)	4143.67	-10873.89	15017.56

Table 11. Changes in Information Criteria (model 0 and model 5)

3.8. Random means model of cybervictimization risk factor (model 6)

Including the risk factor of cybervictimization (Alvarez-García et al., 2015a) as a level 1 and level 2 variable was not possible due to collinearity issues.

They were not significant in the 2-simplified model and were relevant as a research hypothesis. A mixed-effects regression model was created with the strata-EI (TMMS-G3) as the subject, the dependent variable being the average cybervictimization, and the independent variables being the risk factors for cybervictimization. Small estimates were obtained that were not significant for parental control **(Table 12)**.

Parameter	Estimator	St. E.	df	t	Sig	CI95%	
Intersection	1.144	0.008	25.51	144.01	0.000	1.128	1.161
L1_FCR_ParentCnt	0.000	0.000	47926.91	-0.88	0.377	-0.001	0.000
L1_FCR_SelfECnt	-0.006	0.000	47783.06	-11.83	0.000	-0.006	-0.005
L1_FCR_VictCnt	0.025	0.000	47953.68	62.39	0.000	0.024	0.025
L1_FCR_TrCnt	-0.002	0.000	47991.64	-6.73	0.000	-0.003	-0.001
L1_FCR_AnxCnt	-0.003	0.000	47916.48	-8.41	0.000	-0.004	-0.003
L1_FCR_RBCnt	0.015	0.000	47949.54	41.27	0.000	0.014	0.015

Table 12. Random means model of cybervictimization risk factor (Alvarez-Garcia et al., 2015b)

Note. t= estimator/ Standard error= standard estimator; St.E: Standard Error; df= Degree of freedom, CI95%: 95% confidence interval

3.9. Characterization of the strata-EI

The analysis focused on the stratum with adequate levels of EI (222), which was not the stratum with the most cybervictimization [Hypothesis 2.a], as well as the strata-EI with higher and lower levels of average-cybervictimization.

In stratum 222, out of 9087 cases, 4.17% showed severe cybervictimization. Suffering from peer-bullying ($\beta_{L1\_PeerBCnt}$=.275) and age (β_{L1_AgeCnt} =.141) had the greatest weight, with a mean VIF of 1.04 and Durbin-Watson of 1.89. All variables were significant. Those that had the least weight were sexual-orientation (-.003), self-esteem (-.06), and gender (-.06). The regression equation to estimate cybervictimization was Y_{ij}=1.25 -.03· (L1_Sex$_{men}$) -.004 · (L1_SexOr$_{heterosexual}$)-.006 · (L1_FCR_SelfECnt) +.023·(L1_AgeCnt)-.011·(L1_AcPCnt)+.019·(L1_PeerBCnt)+ε.

The strata with the highest average-cybervictimization were 111, 332, 321, and 211.

For stratum 111 (low attention, clarity, and regulation), a high level of average-cybervictimization was confirmed, also for those in whom attention was excessive, with peer-bullying being the variable with the greatest weight in predicting an increase in cybervictimization. In the case of stratum 311, gender (β_{L1_Sex}=-.323) and sexual orientation (β_{L1_SexOr}=-.411) were relevant, with women and non-heterosexuals experiencing greater cybervictimization. They were the strata with the highest percentage of severe cybervictimization (17.75% for 111, and 12.58% for 311).

In the case of stratum 332 (high attention, high clarity, and adequate regulation), cybervictimization was lower for non-heterosexuals.

With lower average-cybervictimization: 132, 123, 133, 333, 113, 213, 233.

It was found that they had in common a high level of emotional regulation and that gender and sexual orientation were of little relevance, being insignificant for strata 113, 123, 132, 133, and 213. In the case of stratum-IE 113, peer bullying had a negative standardized effect, resulting in the variable with the most weight ($\beta_{L1\_PeerBCnt}$=-.644). The behavior of peer-bullying was different from the rest of the strata-EI, where in general, as peer-bullying increased, cybervictimization also increased.

Similarly, for the age variable, in the case of stratum 113, the older the age, the lower the cybervictimization, while in the rest of the strata, cybervictimization increased as age increased.

In this stratum, the regression equation for risk factors in cybervictimization (independent variables) (Alvarez-García et al., 2015a) and average-cybervictimization (dependent variable) had an R^2 value of .944. Training in the educational center on Internet risks had a protective role, and contrary to expectations, greater parental control meant an increase in cybervictimization.

4. Discussion

Both the Design-Effects statistic (*Deff*=105.83) and the ICC of the unconditional model of means (ICC=.059), as well as the scatterplots (Figure 3), allowed us to accept that the average cybervictimization in relation to the emotional intelligence profile is different from zero [H1], which justified the multilevel analysis **(Figure 6).**

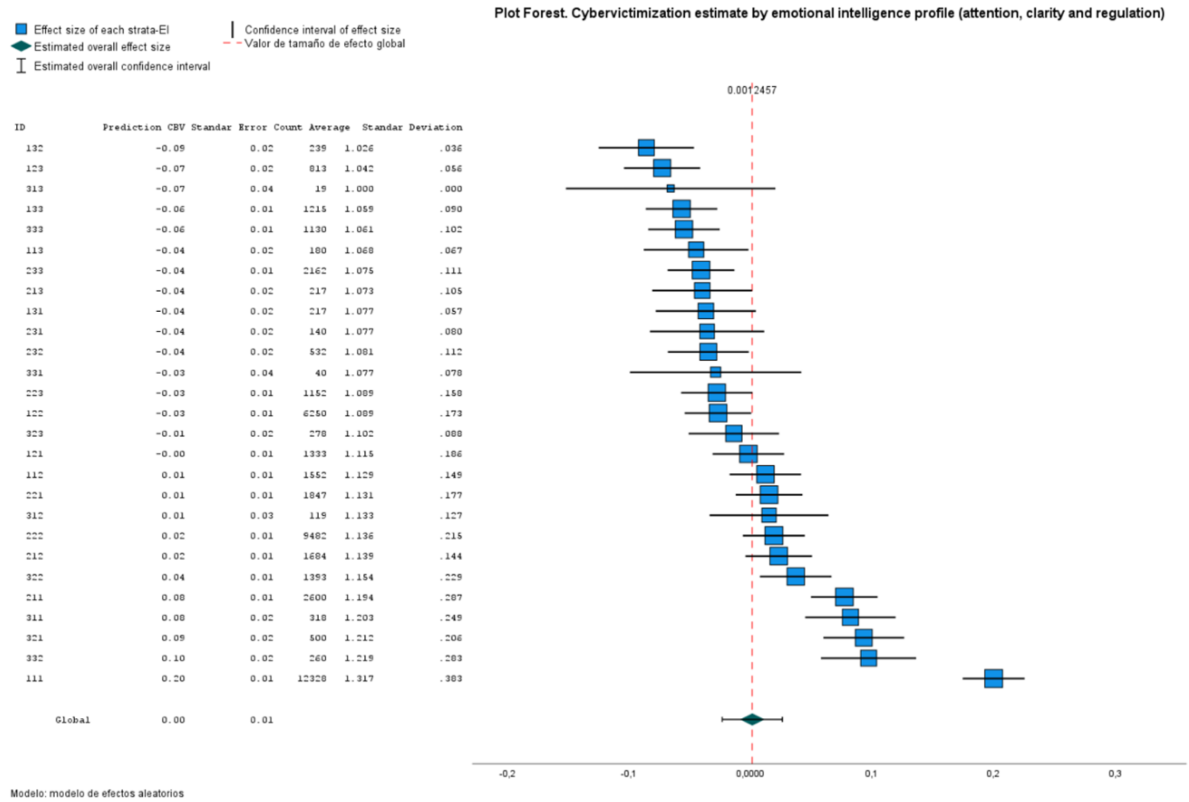


Figure 6. *Plot-Forest Average-Cybervictimization by Emotional-Intelligence Profile. Values further to the right of the mean indicate greater cybervictimization*

The level 2 random means model (1-simplified model) found a positive association between the variables percentage of repeaters in strata-EI, off-line victimization, social anxiety, and parental control (Álvarez-García et al., 2022) and negative or protective self-esteem in the face of cybervictimization [H2]. In the model that included both level 1 and level 2 random means (2-simplified model), only the self-esteem variable remained significant at level 2. A decrease of 26.5% was observed in the estimation of the residuals of the covariance parameters with respect to the null models, with a proportion of variance explained for levels 1 and 2 of 75%.

The positive association between peer-bullying and cybervictimization was tested in the random slopes model (model 3). Without taking into account other predictor variables, for every one point in peer-bullying, cybervictimization increased by .015. In model 4, the residual estimate decreased to .046, improving the precision by 28.13% relative to the null model. The ICC went from .059 in the null model to .08. Model 4 explained the variability in cybervictimization 26.25% better than the null model.

Model 5 included all predictor variables that were significant (Table 10). It was found that the cybervictimization prediction for the i-th case in the j-th strata-EI ($\widehat{Y_{ij}}$) resulted from **(1)** the mean cybervictimization of the strata-IE when all independent variables are set to 0. The significance level (sig. <.001) enabled us to conclude that there was a statistically significant difference between the average cybervictimization within the population and zero, **(2)** $\widehat{\gamma_{01}}$ ·

L2_FCR_SelfECnt =-.044 (Sig=.001), that is, for cases with a mean peer bullying centered score of zero (L1_PeerBCnt=0), self-esteem was negatively ($\widehat{\gamma_{01}} = -.044$) and significantly related to average cybervictimization (Sig.=.001). The value of the regression coefficient indicated that the average cybervictimization of subjects with average peer bullying scores decreased by 0.044 points for each point that self-esteem increased (the interaction between self-esteem and peer bullying was significant with p-value .005), **(3)** $\widehat{\gamma_{10}}$ · L1_Sex =.10 (Sig<.001), therefore, men's gender was positively related, at a small ($\widehat{\gamma_{10}} =.01$), but significant level (Sig.<.001), to predicted cybervictimization for women. The estimator is related to the category of men. That is, it is lower for the category of women (which was taken as a reference and assigned a value of 0 for cybervictimization), **(4)** $\widehat{\gamma_{20}}$ · L1_SexOr=-.039 (Sig <.001), heterosexual orientation was negatively ($\widehat{\gamma_{20}} = -.039$) and significantly (Sig.<.001) related to predicted cybervictimization for non-heterosexuals. That is, it is lower for the heterosexual category (which was used as a reference for the non-heterosexual category, assigning a value of 0 for cybervictimization), **(5)** $\widehat{\gamma_{30}}$ · L1_AgeCnt=.019 (Sig <.001), for cases with a centered mean score for peer bullying (L1_PeerBCnt=0), age was positively ($\widehat{\gamma_{30}} =.019$) and significantly (Sig.<.001) related to the mean score for cybervictimization. The value of the regression coefficient indicates that the average cybervictimization increased by .019 for each year, **(6)** $\widehat{\gamma_{40}}$ · L1_AcPCnt= -.008 (Sig <.001), academic performance (controlling for peer bullying) was related to average cybervictimization at a small, negative ($\widehat{\gamma_{40}}$=-.008), and significant level (sig. <.001). For every point increase in average academic performance, average cyber victimization decreased by -.008, **(7)** $\widehat{\gamma_{50}}$ · L1_PeerBCnt=.019 (Sig <.001), peer bullying is related to average cybervictimization ($\widehat{\gamma_{50}} =.019; sig. <.001$). This value refers to the average self-esteem centered on strata-EI (L2_FCR_SelfECnt=0). That is, for similar self-esteem levels, peer bullying increases cybervictimization by .019, **(8)** $\widehat{\gamma_{11}}$ · (L2_FCR_SelfECnt *L1_PeerBCnt)= -.007 (Sig.=.005), the interaction between self-esteem and peer bullying was significant (Sig.=.005), with self-esteem counteracting the influence of peer bullying on average cybervictimization. From .019 to -.007, each point increase in self-esteem means that for similar levels of peer bullying, the average cybervictimization decreases by 136.84%, **(9)** $\widehat{\gamma_{12}}$ · (L1_SexOr *L1_PeerBCnt)= -.002 (Sig.<.001), the interaction between heterosexual orientation and peer bullying was significant (Sig.<.001). For similar levels of peer bullying, heterosexual orientation reduced average cybervictimization by 110.52% compared to non-heterosexual orientation, controlling for self-esteem (L2_FCR_SelfECnt=0), **(10)** the conditional or residual variance between subjects (variability between slopes) was estimated to be σ^2_{u0} UN[1,1]=.005 (Sig.=.002), **(11)** the conditional or residual variance between strata-EI (variability between slopes) was found to be practically zero, indicating that the independent variables included in the model achieved an excellent prediction of the differences between strata-EI (σ^2_{ui} UN[2,2]= $5.52 \cdot 10^{-5}$, Sig.=.003), and **(12)** variability within each stratum-IE (level 1 random errors) was .046 (Sig..000).

The analysis of model 5, model 6, and the regression analyses of these for each of the strata-EI independently allowed us to conclude that gender had its greatest weight for stratum 311 (β=-.323), with a protective effect for men compared to women, and for stratum 321 (β=.274), that is, cybervictimization was lower in women than in men. In the case of 311, being heterosexual is also a protective factor compared to not being heterosexual (β=-.411). That is, in the case of 311, one of the strata with the most severe cybervictimization, being male and heterosexual reduces the risk of cybervictimization, while being female and non-heterosexual significantly predisposes to cybervictimization. Additionally, suffering peer bullying was the most weighted variable for this stratum (β=.801).

In the case of stratum 111, both gender and sexual orientation had a weak, although significant, relationship with average cybervictimization (β_{sex}=-.019; β_{or_sexual}=.0056).

For sexual orientation, being heterosexual is a protective factor for all strata ($\beta_{modelo5}$=-.039), especially for those with higher levels of cybervictimization, as in the case of 311.

In general, the higher the age, the higher the cybervictimization. This was particularly the case in the strata with higher levels of regulation (β_{213}=.555, β_{133}=.396, β_{323}=.386, β_{333}=.315, y β_{233}=.296), although in the case of 113 it was a protective factor (β_{113}=-.484).

Self-esteem functioned as a protective factor against cyber victimization. There was no clear pattern in its relationship to the three stratification factors of emotional intelligence (attention, clarity, and regulation). The greatest protective weight of self-esteem was found in strata 232, 132, and 311 (β_{232}=-.313, β_{132}=-.282, y β_{113}=-.253). This aspect is relevant to stratum 311, with the highest levels of severe cybervictimization, for which self-esteem is the relevant protective factor.

Shyness-Social anxiety ($\beta_{L1\_FCR\_AnxCnt}$=-.006; Sig. <.001) and risky behavior on the Internet ($\beta_{L1\_FCR\_RBCnt}$=.015; Sig..00) at the subject level had a small weight in cybervictimization as fixed effects and were not significant at the strata-EI level, which is consistent with what was found by Romera et al. (2022), that "social anxiety did not significantly affect victimization" (p. 114).

It was evident that each profile or EI stratum had its own peculiarities in terms of predisposition to cybervictimization and the weight that the variables gender, sexual orientation, academic performance, or risk factors had in cybervictimization, and that in general, they presented levels of excessive interpersonal attention and low emotional regulation as predictors of cybervictimization (Arrivillaga et al., 2021).

Limitations and suggestions for future research

Limitations of this work include the self-reported nature of the primary data, which implies biases that could be amplified by the synthetic sample, as well as its cross-sectional nature. Presumably, belonging to an EI stratum is transitory in nature, but we do not know the possibilities of transit and the facilitating elements that can catalyze change toward profiles characterized by greater emotional regulation.

The methodological approach used deserves special attention. The use of synthetic data and its evaluation, as well as the use of stratified categorical variables as subjects of multilevel analysis, provides useful tools for identifying differences in the patterns followed by the predictor variables of cybervictimization according to different emotional intelligence profiles.

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