Cybervictim vs. Cyberaggressor. Profile determination and comparison through artificial neural networks

Abstract

This research aims to determine the magnitude to which aspects of the sociodemographic profile of students (gender, age, religion, ethnicity and race) influence both the acts of harassment received as a cybervictim and those carried out as a cyberaggressor. Additionally, aiming to discover which of these acts suffered as cybervictim or carried out as cyberaggressor increase or decrease to a greater extent, comparing a profile of potential cyberaggressor with another of potential cybervictim. For this purpose, an artificial neural network of the multilayer perceptron type is employed, generating an estimation model of these cybervictim and cyberaggressor facts based on the students' profile using data obtained through a five-points' Likert questionnaire. That is especially useful for detecting specific behaviours based on a certain profile, being able to determine which of these attitudes are most at risk of occurring to put the relevant measures in place to prevent them.

Keywords

Cyberbullying, victim, aggressor, artificial neural networks, multilayer perceptron

Introduction

This research aims to determine the magnitude to which aspects of the sociodemographic profile of students (gender, age, religion, ethnicity and race) influence both the acts of harassment received as a cybervictim (CV) and those carried out as a cyberaggressor (CA). Additionally, aiming to discover which of these acts received (CV) or carried out (CA) increase or decrease to a greater extent, comparing a profile of potential CA with another of potential CV. For this purpose, an artificial neural network (ANN) of the multilayer perceptron (MLP) type is employed, generating an estimation model of these CV and CA facts based on the students' profile using data obtained through a survey.

The use of MLP models in education has some references in the literature. Thus, Latham et al. (2013) use it in the estimation of the most convenient learning style for the student. Similarly, Kardan et al. (2013) use it to predict student choice in online course enrolment. Recently, Stanković et al. (2021) used MLP in predicting student success in a learning programme. Finally, this methodology has been used in profiling schoolchildren about their attitudes and behaviours on sustainable development (Solano-Sánchez et al., 2022). However, no examples have been found in the literature on the use of MLP in detecting and preventing cyberbullying, and this paper aims to fill the gap found in this regard.

Literature review

Cyberbullying overview

Cyberbullying is aggressive behaviour that employs different electronic devices to harm others or make them feel uncomfortable by repeatedly sending offensive messages or visual materials (Perera & Fernando, 2021). The victim is usually in an inferior position and has difficulty defending themself (Marciano et al., 2020). Depending on the media tools used in this type of bullying, the behaviour can be more or less direct and/or close to the target (Kwan et al., 2020). Thus, Kashy-Rosenbaum and Aizenkot (2020) divide cyberbullying into direct cyberbullying, in which the aggressor interacts directly and immediately with the victim, and indirect, where the aggressor communicates through public or semi-public channels, such as posting negative comments about the victim on social networks (Murnion et al., 2018).

Situations are becoming increasingly aggravated as the school population is becoming more culturally diverse due to globalisation and increased migration flows in recent times (Kastoryano, 2018). These movements are rose diversity in school environments, as these minority groups are characterised by different cultural, ethnic or religious backgrounds to the majority social group (Keuma et al., 2022). The last means that peer relationships are between culturally diverse groups (Beltrán-Catalán et al., 2018). Accordingly, Peker and Yalçın (2022) state that this scenario has been recognised as a prominent tendence that cause conflicts in social interactions produced in digital spaces. All these conflicts lead to cyberbullying produced by lack of empathy and intolerance, especially toward adolescents of different religions and ethnicities (Ortiz-Marcos et al., 2021). Following Tintori et al. (2021), this cyberbullying is characterised by a collection of stereotypes, prejudices and beliefs exercised against those who identify as different from the majority of the population.

This cultural cyberbullying, according to Faris et al. (2020), starts with a series of threats, insults, mockery regarding attire, racist comments to the customs of a group or person; shaping in impersonation and/or the sending of contents, using different electronic devices that are within reach of the youngest (Francisco & Felmlee, 2021). The latter leads to harmful consequences at the psychosocial (Ong et al., 2021), behavioural (Lazuras et al., 2019) and educational levels (Delgado et al., 2019). Students who suffer from it present difficulties in integration in the short term into the host society caused by the rejection of the majority (Barlett et al., 2021).

This type of bullying does not need that the victim be present to cause social alarm or to feel humiliated degrading their ethnicity or religion (Kumari et al., 2021). Thus, Schultze-Krumbholz et al. (2018) establish how victims who suffer these acts may turn to electronic devices to engage in harsh behaviour and retaliate, becoming the aggressor in digital communications. That is due to the psychological pressure experimented for stress from online insults or humiliation, leading to problems of depression and social anxiety (Guo et al., 2021). The cyberbullying complexity due to ethnic or religious intolerance, and the steady increment of intercultural classrooms (Ergin et al., 2021), justify the relevance of the present study. It seeks to fill the gaps identified in the scarce studies on this type of cultural cyberbullying (Espinoza & Wright, 2018). Occasionally, ethnic cyberbullying or religious intolerance can trigger violent attitudes in victims (Akgul & Artar, 2020). Thus, studies on adolescents suggest that aggressiveness increases the risk of victimisation, stating that victims are more likely to display violent behaviour (Nariman et al., 2022).

Cyberbullying under age perspective

Cyberbullying has been shown to be a problem, especially in adolescence and young adulthood, where the prevalence of victimisation and perpetration is intensified across all age groups (Barlett and Chamberlin, 2017; Wang et al., 2019; Pichel et al., 2021). Similarly, Gómez et al. (2020) indicate that the most common risks of religiously or ethnically motivated cyberbullying occur among adolescents from diverse backgrounds between the ages of 12 and 18. Özbey & Başdaş (2020) and Perret et al. (2020) show that young people are more active on social networks from early adolescence onwards, which means more implications for this cyberbullying.

This significant and negative impact has led researchers and education professionals to highlight the need to study and prevent cyberbullying as early as possible (Kowalski et al., 2019). Earlier and earlier access to technology is contributing to an increase in the prevalence of cyberbullying among young people (Jiménez, 2019). Furthermore, how cyberbullying is perpetrated or experienced can change across the lifespan (Luik & Naruskov, 2018). There is a consensus in the literature about the curvilinear relationship between age and cyberbullying (Wang et al., 2019), with a peak prevalence between the ages of 12 and 15 (Garmendia et al., 2019).

The contexts in which cyberbullying occurs can also vary, with pre-teens mainly using chat rooms and 13–14-year-olds primarily using instant messaging, social networking or sharing platforms (Macaulay et al., 2022). Some studies claim this behaviour decreases as age increases (Sittichai & Smith, 2018). Similarly, Tong & Talwar (2020) argue that perpetration tends to fall in late adolescence. According to Cross (2019), this is because younger adolescents with assertive deficits show high impulsivity in handling social networks, which diminish at later ages when they display greater self-control in their attitude towards social networks and the social context in which they operate. However, more research on age-specific bullying behaviours is needed to better target prevention and intervention efforts (Jiang et al., 2020).

Cyberbullying regarding gender, culture and race

Other variables that can influence this type of cultural cyberbullying are gender and race (Zhu et al., 2021). Thus, although Internet use among adolescents continues to increase, it is shown that online bullying offences are more likely to involve males (Sheanoda et al., 2021). Adolescent girls score higher than boys on indicators of social and emotional understanding and, in turn, exhibit more prosocial responses than boys in hypothetical conflict scenarios in digital media (Hui et al., 2022; Piqueras et al., 2019). Additionally, regardless of their cultural background, adolescent girls identify themselves as more socially and emotionally competent than boys and even show themselves through self-reports with greater perspective and empathic concern towards others, in contrast to the male gender (Bętkowska-Korpała et al., 2021; Sparre, 2021). Different studies (Mendoza & DiMaria, 2019; Salwender et al., 2022) confirm this theory, reporting that girls have higher levels of social competence than boys in diverse contexts. This situation occurs because, in both genders, differences are found in the moral disconnection associated with aggressive behaviour when using social networks (Hamal et al., 2019).

Additionally, Rizzo et al. (2022) and Mulholland et al. (2021) reveal increased cases of female adolescents, mainly from African and Muslims cultural backgrounds, as cyber-victims on social networks (Kowalski et al., 2020), making them the main subjects of cyberbullying. Watson et al. (2020) show that out of 65.44 % of the female population, 25.7% include adolescents who report being victims of racially, ethnically or religiously motivated cyberbullying. For this reason, female racial discrimination as a potentially dangerous means of motivation for cyberbullying (Arnon et al., 2022; Rodríguez-Hidalgo et al., 2019).

Finally, according to race, Hong et al. (2021) showed that Latino and Black students are the most likely to experience cybervictimisation (12.6% and 11.6%, respectively), as opposed to other major groups who were less likely to experience cybervictimisation (10.8%). When asked about their experiences in online social networks, black adolescents reported that people their age did not interact in a friendly way with each other online, especially with adolescents from majority groups or collectives (Fandrem et al., 2021). Kowalski et al. (2020) and Wright and Wachs (2019) found no differences in cybervictimisation between most majority and minority groups among Spanish adolescents. However, when all ethnic minority groups were pooled into a single group, differences were shown when examining specific ethnic minorities: Romanies experienced significantly more cybervictimisation than students from the majority ethnic group (Castilians) (Jimenez, 2019). Therefore, it should be noted that, although a variety of studies on cyberbullying have been developed in recent decades, there are still knowledge gaps that need to be addressed regarding this type of culturally motivated cyberbullying (Choi et al., 2020).

Methodology

Survey design, fieldwork, sampling and sampling error

The sample was selected considering the different provinces of Southern Spain, and the Autonomous Cities of Ceuta and Melilla since these are the Spanish geographical areas where the greatest cultural interactions between adolescents are manifested (Zych & Llorent, 2021). Cyberbullying Scale for Students with Cultural and Religious Diversity (CSCRD) (Tomé-Fernández et al., 2019) is employed. This questionnaire method is divided into two sections. Firstly, sociodemographic variables such as city, gender, age, ethnicity, nationality, institution, religion and culture are analysed. Secondly, the CV and CA profile of the surveyed participants is assessed with 38 items that use a five-point Likert scale with response options ranging from 1 = never to 5 = always. Confirmatory factor analysis indicating an excellent fit of the presented questionnaire model (X^2 = 2414.536, p = 0.00, NNFI = 0.80 CFI = 0.83, IFI = 0.80 and RMSEA = 0.05) (Boštjančič et al., 2018; Iniguez-Berrozpe et al., 2022).

Out of a total of 1,478 surveys, 1,451 were valid. Assuming an infinite population, the last would be a sampling error of ±3% and a sample confidence level of 95%. The age of the participants is between 12 and 16 years (mean=13.95; standard deviation=1.336), with 720 males (49.6%) and 731 females (50.4%). In addition, participants are distributed as follows: in terms of race, 982 (67.7%) students are White, 298 (20.5%) are Latino, 64 (4.4%) are Black, 21 (1.4%) are Asian, 13 (0.9%) are Nordic, and 73 (5.0%) did not answer. As for their ethnicity, 45 (3.1%) students are Romany, 7 (0.5%) are of Celtic origin, 17 (1.2%) Armenian, 194 (13.4%) Mongolian, 958 (66.0%) Castilian and 230 (15.9%) did not answer. Finally, in terms of religion, 1004 (69.2%) are Christian, 58 (4%) are Jewish, 78 (5.4%) are Muslim, 16 (1.1%) are Taoist, and 5 (0.3%) are Buddhist. The rest of the students, 290 (20%), do not practice religion.

Data analysis

Rumelhart and McClelland (1986) define an artificial neural network (ANN) as a network composed of several process elements (PE) or nodes with a small amount of storage capacity. These units are crafted of a vector of inputs ($x_1, x_2, ..., x_n$), with synaptic weights ($w_1, w_2, ..., w_n$) that are applied to these input vectors using a propagation rule (based on the corresponding linear combination). Applying an activation function to that propagation rule provides the output value of these nodes. The nodes are grouped into several layers: input, output, and intermediate or hidden layers (one or more).

Using SPSS version 23, an MLP ANN is constructed, in which the input values correspond to the items of the sociodemographic profile of the students (gender, age, religion, ethnicity and race) and the output values to the estimates of the answers to the Likert-type questions on the acts of bullying suffered as CV and the attitudes as CA. Different types of networks are tested, choosing the one that finally offers the best degree of fit in terms of mean relative error (MAPE).

Results

Students' profile and question collection

The profile of the students surveyed is presented in Table 1. There is almost parity in terms of gender. The different age groups studied (from 12 to 16 years old) are closely even in terms of the total percentage of the sample. Regarding religion, ethnicity and race, the differences between the majority option and the others are similar, with approximately one third of the sample having other options than the majority in terms of religion, ethnicity and race.

Table 1
Students' profile

Gender (GEN)		Age (AGE)	
Male	49.76%	12 years old	15.64%

Female	50.24%	13 years old	23.64%
Religion (REL)		14 years old	23.43%
Christianity	69.19%	15 years old	18.13%
Others	30.81%	16 years old	19.16%
Ethnicity (ETH)		**Race (RAC)**	
Castilian	65.75%	White/caucasian	67.61%
Others	34.25%	Others	32.39%

The responses obtained on the different acts of bullying suffered as CV, and the attitudes as CA are shown in Table 2 as mean and standard deviation. Cronbach's Alpha (1951) is used to confirm the scale's reliability, obtaining a value of 0.91 for the CV group and 0.94 for the CA group, values above those provided in the literature for confirmation (Nunnally & Bernstein, 1994).

Regarding actions suffered as CV, the dissemination of lies (CVQ04) and insults (CVQ01) referring to ethnicity, race or religion through social networks and/or the Internet, as well as a mockery about clothing (CVQ18) stand out. Conversely, the majority of attitudes as CA correspond to declared as CV in terms of insults (CAQ01) and lies (CAQ02) on social networks and/or the Internet, and in terms of attire (CAQ18). The use of social networks to make racist comments also highlights (CAQ03).

Table 2
Question collection

Code	Question	Mean	SD*
	Cyber-victim (CV)		
CVQ01	Someone has called me bad words or insulted me for having a different skin colour using email, WhatsApp or another social network.	1.25	0.77
CVQ02	Someone has called me bad words or insulted me for being of a different ethnicity or religion using email, WhatsApp or another social network.	1.19	0.64
CVQ03	I have had racist comments made to me on social media content about my race, ethnicity or religion.	1.18	0.61
CVQ04	Someone has told other colleagues lies about my race, ethnicity or religion using the Internet, WhatsApp or social media.	1.27	0.77
CVQ05	I have been threatened through messages on Messenger, WhatsApp or other social media because of my religious or ethnic background.	1.17	0.63
CVQ06	Someone hacked my social network account and extracted information to create hatred towards my racial, ethnic or religious group.	1.17	0.68
CVQ07	They have hacked my account and impersonated me on Facebook and Twitter to ridicule my religious or ethnic traditions.	1.18	0.70
CVQ08	They have created a fake account pretending to be me to spread fear about the customs of my country or my ethnicity or religion.	1.18	0.71
CVQ09	Someone has posted personal information about my family on the Internet to mock our traditions and customs.	1.17	0.70
CVQ10	Someone has posted videos or photos on the Internet about my group's religious or ethnic traditions to humiliate me.	1.17	0.66
CVQ11	Someone has posted videos or photos on the Internet about my race to humiliate me.	1.16	0.62
CVQ12	They have posted trick photos on the Internet to ridicule my group's religious or ethnic activity.	1.14	0.59
CVQ13	They have posted trick photos on the Internet to ridicule my race.	1.13	0.57

CVQ14	I have been excluded or ignored from a social network or chat room because I am of a different race, religion or ethnicity than my peers.	1.18	0.68
CVQ15	They have beaten me and recorded and spread the video on the Internet because I am different from them (skin colour, hair, clothing, tradition, religion).	1.13	0.61
CVQ16	They called me by cell phone and imitated my speech to mock my language.	1.17	0.59
CVQ17	I have been sent threatening WhatsApp audios telling me that my race, religion or ethnicity should be exterminated.	1.15	0.60
CVQ18	I have been made fun of for dressing or wearing different clothes from the rest of my classmates.	1.27	0.72
CVQ19	They have impersonated me on a forum or social network, insulting and threatening others to create fear towards people of my race, ethnicity or religion.	1.11	0.54
	Cyber-agressor (CA)		
CAQ01	I have said swear words to someone or insulted other colleagues for having a different skin colour using email, WhatsApp or another social network.	1.15	0.55
CAQ02	I have used profanity or insulted other colleagues for being of a different ethnicity or religion using email, WhatsApp or other social media.	1.10	0.46
CAQ03	I have made racist comments on social media content about other races, ethnicities or religions.	1.14	0.56
CAQ04	I have told other colleagues lies about other races, ethnicities or religions using the Internet, WhatsApp or social media.	1.12	0.51
CAQ05	I have threatened other religious or ethnic traditions through Messenger, WhatsApp or other social media messages.	1.12	0.55
CAQ06	I hacked a social network account and extracted information to create hatred towards other racial, ethnic or religious groups.	1.10	0.50
CAQ07	I have hacked an account and posed as someone else on Facebook and Twitter to ridicule religious or ethnic traditions other than my own.	1.08	0.47
CAQ08	I have created a fake account impersonating others to promote fear about the customs of other countries, ethnicities or different religions.	1.09	0.46
CAQ09	I have posted personal information about other classmates' families on the Internet to make fun of their traditions and customs.	1.10	0.49
CAQ10	I have posted videos or photos on the Internet about other groups' religious or ethnic traditions to humiliate them.	1.10	0.51
CAQ11	I have posted videos or photos on the Internet about the race of others to humiliate them.	1.10	0.51
CAQ12	I have posted trick photos on the Internet to ridicule another group's religious or ethnic activity.	1.10	0.52
CAQ13	I have trick photos on the Internet to ridicule the race of another group.	1.08	0.46
CAQ14	I have excluded or ignored others from a social network or chat because they are of a different race, religion or ethnicity than my peers.	1.11	0.54
CAQ15	I have pasted and recorded and spread videos on the Internet of classmates for being different from me (skin colour, hair, dress, tradition, religion).	1.08	0.47
CAQ16	I called by cell phone and imitated my partner's speech to mock their language.	1.11	0.50
CAQ17	I have sent threatening WhatsApp messages saying that other classmates' race, religion or ethnicity should be exterminated.	1.09	0.46
CAQ18	I have made fun of other classmates for dressing or wearing different clothes from the rest of my classmates.	1.13	0.52
CAQ19	I have impersonated others on a forum or social network, insulting and threatening others to create fear towards people of other races, ethnicities or religions.	1.10	0.53

*Note: SD, standard deviation

Artificial neural network performance

The network architecture achieved is presented in detail in Table 3, and graphically in Fig. 1. Thus, the input layer (Table 1) is composed of the different neurons that correspond to the various items of the sociodemographic profile of the students. These have to be previously numbered for the arithmetic process used by the ANN, and subsequently normalised and multiplied by their respective synaptic weights (Fig. 1), giving rise to the different values of the neurons of the hidden layer. After passing through the hyperbolic tangent activation function (Table 1), these are multiplied by their synaptic weights (Fig. 1), producing the different output values corresponding to the act estimates as CV and CA. These values, although they do not require an activation function (since the identity function leaves the value as it is before passing through it), are normalised, so it is proceeding to invert this normalisation to obtain results in its original form, that is, on a Likert scale from 1 to 5 points.

Table 3
Network architecture

Input Layer	Bias	Value=1
	Factors	GEN=0 (male), GEN=1 (female) REL=0 (Christianity), REL=1 (others) ETH=0 (Castilian), ETH=1 (others) RAC=0 (White/Caucasian), RAC=1 (others)
	Covariates	AGE (from 12 to 16)
	Number of Units (excluding the bias unit)	9
Hidden Layer	Rescaling Method for Covariates	Standardised
	Number of Hidden Layers	1
	Number of Units in Hidden Layer	19
	Activation Function	Hyperbolic tangent
Output Layer	Dependent Variables	CVQ01 CVQ02 CVQ03 CVQ04 CVQ05 CVQ06 CVQ07 CVQ08 CVQ09 CVQ10 CVQ11 CVQ12 CVQ13 CVQ14 CVQ15 CVQ16 CVQ17 CVQ18

	CVQ19
	CAQ01
	CAQ02
	CAQ03
	CAQ04
	CAQ05
	CAQ06
	CAQ07
	CAQ08
	CAQ09
	CAQ10
	CAQ11
	CAQ12
	CAQ13
	CAQ14
	CAQ15
	CAQ16
	CAQ17
	CAQ18
	CAQ19
Number of Units	38
Rescaling Method for Scale Dependents	Standardised
Activation Function	Identity
Error Function	Sum of Squares

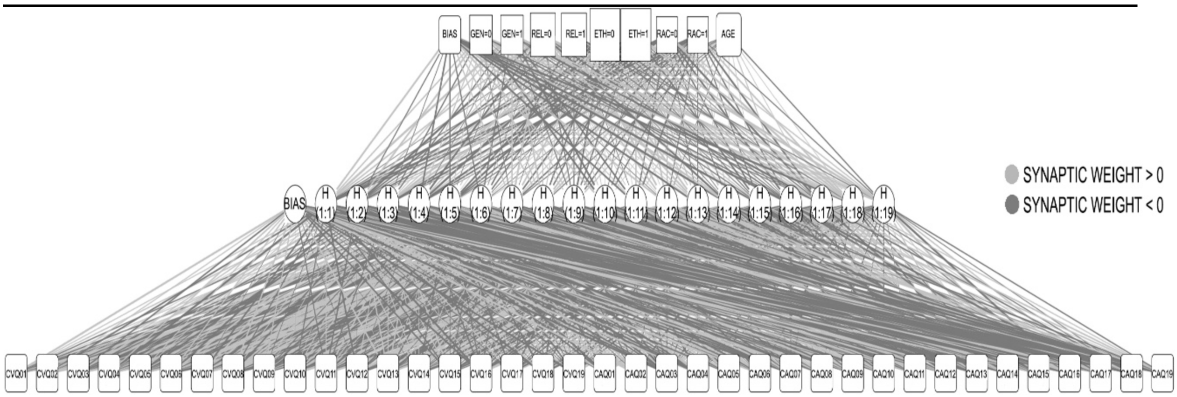

Fig. 1. ANN’s graphic representation.

The elaboration process of the ANN is reflected in Table 4. First, the sample is randomly divided between the training and testing groups, following a partition of approximately 70%-30%. Next, the training group is in charge of the arithmetic process of configuring the synaptic weights of the network, while the test group is used to calculate the error committed. Finally, when this error cannot be lowered any further, the stopping rule is produced, and the elaboration of the network is finished. Thus, Table 4 presents the errors made by both groups, the stop rule used and the ANN training time.

Table 4

Model summary

	Sum of Squares Error		18,965.184
	Average Overall Relative Error		0.981
		CVQ01	0.974
		CVQ02	0.973
		CVQ03	0.944
		CVQ04	0.957
		CVQ05	0.985
		CVQ06	0.974
		CVQ07	0.985
		CVQ08	0.977
		CVQ09	0.976
		CVQ10	0.962
		CVQ11	0.972
		CVQ12	0.969
		CVQ13	0.934
		CVQ14	0.987
		CVQ15	0.988
		CVQ16	0.977
		CVQ17	0.982
		CVQ18	0.975
Training (N=1019; 70.22%)	Relative Error for Scale Dependents	CVQ19	0.983
		CAQ01	0.997
		CAQ02	0.987
		CAQ03	0.986
		CAQ04	0.996
		CAQ05	0.996
		CAQ06	0.999
		CAQ07	0.992
		CAQ08	0.987
		CAQ09	0.993
		CAQ10	0.978
		CAQ11	0.997
		CAQ12	0.994
		CAQ13	0.990
		CAQ14	0.978
		CAQ15	0.992
		CAQ16	0.973
		CAQ17	0.977
		CAQ18	0.985
		CAQ19	0.988
	Stopping Rule Used		1 consecutive step(s) with no decrease in error (based on the testing sample)
	Training Time		0:00:02.58
	Sum of Squares Error		8,277.951
	Average Overall Relative Error		0.983

Testing (N=432; 29.78%)	Relative Error for Scale Dependents	CVQ01	0.973
		CVQ02	0.971
		CVQ03	0.945
		CVQ04	0.950
		CVQ05	0.987
		CVQ06	0.962
		CVQ07	0.985
		CVQ08	0.985
		CVQ09	0.987
		CVQ10	0.970
		CVQ11	1.013
		CVQ12	1.012
		CVQ13	0.975
		CVQ14	0.981
		CVQ15	0.964
		CVQ16	0.993
		CVQ17	0.994
		CVQ18	0.987
		CVQ19	0.964
		CAQ01	0.968
		CAQ02	1.003
		CAQ03	0.980
		CAQ04	1.006
		CAQ05	0.982
		CAQ06	0.991
		CAQ07	0.962
		CAQ08	0.999
		CAQ09	0.991
		CAQ10	0.952
		CAQ11	0.995
		CAQ12	0.979
		CAQ13	0.982
		CAQ14	0.999
		CAQ15	0.974
		CAQ16	0.985
		CAQ17	0.968
		CAQ18	1.011
		CAQ19	0.994

The goodness of fit achieved in the model is shown in Table 5 in terms of MAPE. The MAPE is the difference in percentage terms between the real values and those obtained by the network. In general, these percentages present shallow values, almost all of them below 10%, being the average of the total less than 5%, so it can be considered that the ANN estimates the results with a high degree of adjustment.

Table 5
ANN goodness of fit

Code	MAPE	Code	MAPE
CVQ01	8.91%	CAQ01	5.16%
CVQ02	6.52%	CAQ02	3.74%
CVQ03	9.38%	CAQ03	4.69%
CVQ04	14.35%	CAQ04	3.88%
CVQ05	5.29%	CAQ05	3.69%
CVQ06	4.89%	CAQ06	2.92%
CVQ07	4.88%	CAQ07	2.46%
CVQ08	8.20%	CAQ08	2.82%
CVQ09	4.51%	CAQ09	2.97%
CVQ10	4.79%	CAQ10	3.08%
CVQ11	4.68%	CAQ11	3.02%
CVQ12	4.44%	CAQ12	2.91%
CVQ13	5.52%	CAQ13	2.45%
CVQ14	5.28%	CAQ14	3,11%
CVQ15	3.63%	CAQ15	2,39%
CVQ16	5.75%	CAQ16	3,75%
CVQ17	4.56%	CAQ17	2,48%
CVQ18	12.64%	CAQ18	4,63%
CVQ19	3.14%	CAQ19	2,87%
	Overall		4.85%

Additionally, it is possible to quantify the relative importance that each of the independent variables contribute to the ANN (Fig. 2). Thus, the most influential item is ethnicity (ETH), followed by religion (REL) and age (AGE), which have a similar influence. Gender (GEN) and race (RAC) are shown to be the least influential in estimating these CV/CA acts.

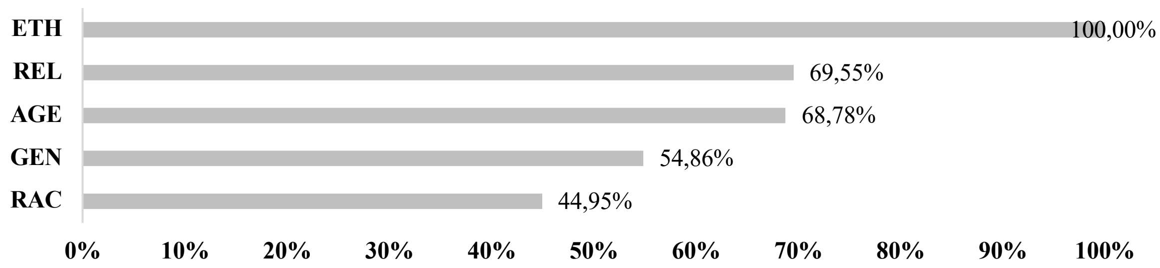

Fig. 2. ANN exogenous variables' relevance

Finally, the ANN allows customisation of the results obtained by configuring specific input values. In this way, a given profile will result in a collection of 38 estimated responses on those CV/CA acts based on that profile. Thus, a potential CA profile is compared: male -as reflected in the scientific literature (Sheanoda et al., 2021)-, Christian, Castilian and White; with another potential CV profile: female of another religion, ethnicity and race different from the majority. Table 6 presents, in each age group, the five questions that experienced the most significant increase (and decrease) to shift from a potential profile of CA to CV.

Firstly, it stands out that the change from potential CA to CV does not increase the acts received and consequently decreases the attitudes as aggressor, but both types of questions appear in direct and inverse influence (Table 6). Racist comments on social networks in victim and aggressor mode (CVQ03, CAQ03) highlight the increases when moving from a potential CA to a CV profile. Similarly, having suffered identity theft on social networks for religious or ethnic reasons (CVQ07) also increases significantly as the age of the respondent's profile does, in contrast to the rest of the questions, which either raise slightly or remain stable.

Regarding decreases (Table 6), there is a significant reduction in the attitude toward pasting, recording and broadcasting for reasons of ethnicity, race or religion on social networks (CAQ15), as well as the creation of fake accounts to impersonate others to promote fear based on different ethnicities or religions (CAQ08), both of which decrease to a greater extent as age increases. Finally, it is noteworthy that some of the questions with the highest scores in Table 2 also appear in Table 6 (CVQ01, CAQ03, CAQ18).

Table 6
Questions with the most direct and inverse influence in profile comparison by age

Code	**Age**				
	12	13	14	15	16
			Direct		
CVQ03	15.93%	16.43%	16.81%	17.05%	17.13%
CVQ07	15.84%	16.86%	17.61%	18.07%	18.22%
CAQ03	14.49%	14.97%	15.31%	15.49%	15.51%
CAQ11	12.50%	12.97%	13.33%	13.58%	13.69%
CAQ18	12.24%	12.27%	12.24%	12.14%	11.99%
			Inverse		
CAQ15	-13.30%	-13.89%	-14.46%	-14.99%	-15.42%
CAQ08	-10.67%	-11.06%	-11.30%	-11.39%	-11.33%
CVQ06	-9.71%	-10.06%	-10.11%	-9.84%	-9.29%
CVQ01	-7.82%	-7.34%	-6.95%	-6.68%	-6.54%
CVQ09	-6.09%	-6.43%	-6.72%	-6.95%	-7.09%

Discussion

The results obtained show that the adolescents evaluated who come from minority groups due to their race, ethnicity or religion stand out through their responses concerning the actions supported as CV, the dissemination of lies (CVQ04) and insults (CVQ01) referring to ethnicity, race or religion through social networks and/or Internet, as well as a mockery about clothing (CVQ18). Conversely, the majority of attitudes as CA correspond to what is declared as CV in terms of insults (CAQ01) and lies (CAQ02) on social networks and/or the Internet, and what is referred to attire (CAQ18). The use of social networks to make racist comments (CAQ03) also stands out. All of this is related to Tintori et al. (2021) indicating that this cyberbullying is characterised by a series of stereotypes, beliefs and prejudices of the majority group towards those who identify themselves as different from the majority of the peer group.

The latter leads to a collection of threats, insults, taunts directed at the way they dress, racist comments and the traditions of a person or group, and takes the form of impersonation and/or the sending of material through different electronic devices that are within reach of adolescents (Faris et al., 2020; Francisco & Felmlee, 2021). Following the results, adolescents who suffer this type of bullying, in the short term, present difficulties in integration into the host society caused by the rejection of the majority (Barlett et al., 2021). Thus, it is established how victims who suffer these acts can employ electronic devices to adopt violent and revengeful behaviours, becoming the aggressor in digital interactions as reflected in the results obtained (Kumari et al., 2021; Schultze-Krumbholz et al., 2018). The last is due to the psychological pressure experimented for the stress from online insults or humiliation, leading to problems of depression and social anxiety (Guo et al., 2021).

Additionally, the relative relevance that each of the independent variables analysed contribute to ANN is quantified (Fig. 2). These results indicate that the item that most influences this type of cyberbullying is ethnicity (ETH), followed by religion (REL) and age (AGE), which have a similar impact. These results are related to Peker and Yalçın (2022), stating that this scenario has been detected as one of the prominent trends that lead to conflicts in social connections produced in digital contexts. All these conflicts lead to cyberbullying caused by lack of empathy and intolerance, especially toward adolescents of diverse religions and ethnicities (Ortiz-Marcos et al., 2021). Other studies reinforce these theories. Thus, Kumari et al. (2021) show that ethnicity and/or religion are considered the main variables of cyberbullying to humiliate or cause social alarm to degrade their origins.

Regarding age, other research (Barlett & Chamberlin, 2017; Wang et al., 2019; Pichel et al., 2021) have been shown that this cyberbullying is reflected as a problem especially common in adolescence, where the prevalence of victimisation and perpetration intensifies in all age groups. Gómez et al. (2020) indicate that the most common risks of cyberbullying on religious or ethnic grounds occur among adolescents in diverse educational contexts between the ages of 12 and 18. Similarly, other studies (Özbey & Başdaş 2020; Perret et al., 2020) confirm that young people are more active on social networks from early adolescence onwards, which means more implications for this type of digital bullying.

By contrast, gender (GEN) and race (RAC) are the minor influential variables in estimating CV/CA acts. Schultze-Krumbholz et al. (2022) reinforce these results, highlighting that gender and race are not significant factors in cyberbullying. However, Zhu et al. (2021) contrast the results obtained in the present research, reflecting that this type of cultural cyberbullying depends on gender and race, among others. Additionally, although Internet use among adolescents continues to increase among both genders, it is shown that online bullying crimes are more likely to be committed by males, White and Christians, as they are the majority group (Loh & Snyman, 2020; Sheanoda et al., 2021), where differences are found in the moral disconnection associated with aggressive behaviour in the use of social networks (Hamal et al., 2019).

Similarly, previous research on race (Hong et al., 2021) highlights that Latino and Black adolescents were the most likely to experience cybervictimisation (12.6% and 11.6%, respectively), while White and Christian students were less likely to be cybervictims online (10.8%). Generally, in the experiences of this group on social networks were founded differences across ethnic minority groups when examining specific ethnic minorities (Fandrem et al., 2021; Kowalski et al., 2020; Wright & Wachs, 2019). The previous studies showed that these minority groups experienced significantly more cybervictimisation than students from the majority ethnic group, such as, e. g. Castilian in Jimenez's (2019) case.

In addition, the ANN obtained in the study allows customisation of the results obtained by configuring specific input values. In this way, a given profile gave rise to a collection of 38 estimated responses on those CV/CA acts based on that profile. Thus, a potential CA profile (male, Christian, Castilian and white) is compared with a potential CV profile (female, of another religion, ethnicity and race different from the majority).

The results show the five questions that experienced the greatest increase (and decrease) in the different age groups when moving from a potential CA profile to a potential CV profile. The first thing that stands out is that the change from potential CA to CV does not increase the acts received and consequently decreases attitudes as an aggressor, but that both types of questions appear in the direct and inverse influence (Table 6). Racist comments on social networks in victim and aggressor mode (CVQ03, CAQ03) predominate in the increases when moving from a potential CA to a CV profile. Similarly, having suffered identity theft on social networks for religious or ethnic reasons (CVQ07) also increases significantly as the age of the respondent's profile rises, in contrast to the rest of the questions, which either increase slightly or remain stable.

Regarding decreases (Table 6), there is a significant reduction in the attitude toward pasting, recording and broadcasting on social networks based on race, ethnicity or religion (CAQ15), as well as the creation of fake accounts to impersonate others to promote fear based on different ethnicities or religions (CAQ08), both significatively decreasing as age growths. The latter is consistent with Sittichai and Smith (2018), stating that this behaviour tends to reduce as age increases. Ratifying this theory, Cross (2019) argues that younger adolescents with assertive deficiencies show greater impulsivity in the management of social networks that decrease at older ages when they achieve greater self-control in their attitude towards social networks and in the social context in which they develop.

Conclusions

Based on the aim proposed, a model is reached that fittingly estimates the increase or decrease of the acts received as VC or carried out as CA based on the items of the student's sociodemographic profile (gender, age, religion, ethnicity, race). Thus, going into the theoretical implications of the study, it can be seen that the most determining factors in these VC-CA behaviours come from ethnicity and religion, which are considered the primary triggers of the conflicts. The role played by age is also noteworthy as it has a direct relationship with these CV-CA acts, with the majority of them increasing as the age of the pupils rises from 12 to 16 years old. Gender and race, contrary to what may be considered, have a more secondary influence on these types of attitudes.

Regarding the comparison between a potential CA profile and a CV one, it does not always reveal increases in CA acts and decreases in acts received as a CV, as would be expected, but rather both appear mixed. The last leads to the conclusion that both profiles often match the same person, and thus the one who suffered harassment as a CV may take on CA attitudes in the future. The most reported CV-CA actions in the survey also appear as some of the most increased or decreased actions in comparing potential CV and CA profiles. These include using social networks and/or the Internet to make insults and/or negative comments about race, ethnicity and/or religion and mockery in terms of wearing clothes that are different from the majority group.

The main practical contribution of this work lies in using the ANN model developed so that specific input values, easily customisable by the researcher and consisting of a particular student profile, will result in a series of adjusted estimates of those acts suffered as CV or performed as CA. That is especially useful for detecting specific behaviours based on a given gender, age, race, ethnicity or religious context, being able to determine which of these attitudes are most at risk of occurring to put the relevant measures in place to prevent them.

The main limitation of this study is that the data is restricted to Andalusia, Ceuta and Melilla, highlighting the most representative cultural minorities in these Spanish geographical areas. Thus, as a future line of research, it is proposed to carry out more studies of these characteristics in different geographical regions in Spain and/or European level to find out the different profiles of racist or xenophobic cyberbullying, contextualised in the research on the several interactions that occur between adolescents on electronic devices for cultural reasons. Additionally, other more specific statistical analyses could be considered to reinforce the study (qualitative, quantitative or mixed) and examine different cyberbullying roles.

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