



Research article

Applying artificial intelligence to explore sexual cyberbullying behaviour

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ABSTRACT

Sexual cyberbullying is becoming a serious problem in today's society. In the workplace, this issue is more complex because of the power imbalance between potential perpetrators and victims. Preventing sexual cyberbullying in organizations is very important for a safety and respectful workplace. Occupational Safety and Health (OSH) standards establish certain policies to be considered to create an organizational culture based on zero tolerance to sexual cyberbullying. The research aims to broaden knowledge about personality and sexual cyberbullying. Therefore, this paper proposes a crucial tool to explore potential sexual cyberbullying behaviour. This study analysed how personality traits, particularly those related to the Dark Triad (psychopathy, Machiavellianism and narcissism), might influence this behaviour. Participants (N = 374) were Spanish young adults, using the convenience sampling to recruit them. The methodology focused on the use of structural equation modelling and ensemble classification tree. First, we tested the proposed hypotheses with structural equation method based on covariance using the Lavaan R-package. Second, for the ensemble of classification trees, we applied the package randomForest and Adabag (bagging and boosting) in R. Results proposed high levels of psychopathy and Machiavellianism are more likely to be related to sexual cyberbullying behaviours. Organizations could use the tool proposed in this research to develop internal policies and procedures for detection and deterrence of potential cyberbullying behaviours. By raising awareness about cyberbullying behaviour including its conceptualisation and measurement in training courses, organizations might build an organizational culture based on a respectful workplace without sexual cyberbullying behaviours.

1. Introduction

The way people communicate has changed significantly over the last decades and is still doing so. Rapid technological progress has led to the emergence of bullying behaviours that are not limited to the physical context or face-to-face settings. Traditional bullying is defined as a repeated and intentional aggressive behaviour against a powerless victim [1]. This power imbalance can be physical and/or psychological, and the aggression can be verbal (e.g., insults), physical (e.g., hitting) or psychological/relational (e.g., gossiping) [2,3]. Bullying can range from simple teasing to violent physical conduct, such as sexual assault, stalking episodes, death threats, and homicide [4]. From another perspective, it is possible to refer to direct and indirect bullying [1,3]. Direct bullying means relatively open aggressions against the victim, so the aggressor may be identified. However, indirect bullying is addressed to the victim through a third party (e.g., rumours), to achieve the social isolation of the victim, so the aggressor might not be identified.

The development of information and communication technologies (ICT) has enabled people to exchange information in an easier, more entertaining and faster way, although it also has undesirable effects [5]. In the current digital context, misuse or abuse of ICT could lead to the development of antisocial behaviour in cyberspace, such as cyberbullying [4]. It is common today to hear in the media about cyberbullying, such as hurtful emails or instant messages, videos and images with explicit sexual content or threats. Therefore, an important risk comes from using ICT to humiliate and offend others [6].

1.1. Cyberbullying phenomenon

According to Nocentini et al. [7], initially studies on cyberbullying have defined the phenomenon on the basis of the concept of traditional bullying proposed by Olweus [1]. From this approach, cyberbullying also includes characteristics such as repetition, intention, harm, and power imbalance, but perpetrated in a digital context [8–12]. It is an intentional

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act to incur injury or damage over time, by using computers, cell phones, and other electronic devices, against others who cannot prevent or stop this behaviour [11]. However, some researches [13,14] indicate the need to address cyberbullying as an independent term with its own specificities. Indeed, there is no consensus regarding attributes such as repetition and power imbalance to label a certain behaviour as cyberbullying.

On the one hand, repetition is a key component of cyberbullying, although not considering the repetition of the act only by the first perpetrator [13]. In online context, a single post could be visible and shareable by others, so bystanders would be contributing to cyberbullying [11]. Therefore, the repetition refers to the large audience who may access to the hurtful online contents [13]. On the other hand, power imbalance in cyberbullying definition may involve the abusive behaviour of a group of people in digital context (e.g., chat, social media) towards a member is considered [13] and the higher reputation or social status of the bully within the virtual community [7].

Moreover, additional specific aspects for understanding cyberbullying, such as anonymity and public exposure, have been addressed by several studies [7,12,15]. The invisibility of the aggressor, the increased potential of the number of spectators, and the lack of “safe spaces” for the victim could be major problems of cyberbullying [16]. Thus, the perpetrator remains anonymous and unaccountable, and could post messages to a large audience without any socially visible consequences [15]. Therefore, ICT offers an ideal forum to harass others taking advantage of the feeling of impunity [6].

Many studies analyse the risk and protective factors for cyberbullying perpetration, but point out that it is necessary to assess which one has the greatest effect on cyberbullying [17]. The growing concern about cyberbullying has been reflected in increased research and publications, focusing on managing and preventing cyberbullying [12,18]. Concretely, Slonje et al. [12] emphasize the importance to work most directly to address cyberbullying prevention and intervention programs. Cyberbullying can appear across the lifespan, showing a significant increase in the transition from youth to emerging adulthood [19]. Then, it is necessary to make society aware of the effects, types and tools of cyberbullying, along with the main strategies against cyberbullying [18]. It is important to clarify all these issues to make useful advances in cyberbullying phenomenon.

1.2. The Dark Triad and sexual cyberbullying behaviour

The impact of cyberbullying has been analysed (e.g. [20]), but, as Pabian et al. [21] state, there are not so many studies focused on antecedents of the online potential aggressions. However, some specific examples that analyse antecedents can be mentioned. In [22], Romera et al. assess social motivation of roles involved in cyberbullying. In [23], Cross et al. describe the factors that influence on cyberbullying perpetration at the individual, family, peers, and community levels, and specially online. Similarly, Baldry et al. [24] examine risk factors that could be related to cyberbullying, including individual, interpersonal, community and society levels.

Indeed, literature evidences the role of personality variables as antecedent of cyberbullying phenomenon. As Spain et al. [25] state, there has been a growing interest in the “dark personality”, but deeper study is needed in an organisational context. The existence of socially aversive personality traits such as psychopathy, Machiavellianism and narcissism has been widely studied in clinical and social psychology. Following Lee and Ashton [26], psychopathy refers to a pattern of insensitivity, manipulation and exploitation of others without remorse; Machiavellianism is related to manipulation, lack of sincerity and insensitivity, and, finally, narcissism is characterized by domination, exhibitionism, exploitation, and feelings of superiority. The Dark Triad is the term used to describe the joint occurrence of the three aforementioned personality traits [27]. Each of the three traits of the Dark Triad has unique characteristics, but they share some common elements, such as exploitation, manipulation and a grandiose sense of self-importance [26]. The

existence of three independent constructs with some overlap is also described by other authors [27,28]. According to Jonason et al. [29], recent evidence suggests that there are good theoretical and empirical reasons to treat them as different measures of the same latent construct.

Dark Triad traits have traditionally been linked to negative personal and social results considered undesirable [30]. Thus, the three constructs imply a socially malevolent character with tendencies toward self-promotion, emotional frailty, deceptive behaviour and aggressiveness [27]. In addition, the Dark Triad traits might present characteristics such as impulsivity, high-risk taking and low rates of awareness [30], and lack of honesty and humility [28]. Furthermore, researches analyse the link between the lack of honesty and humility, and the insensitivity [28, 31]. In addition, research suggests that individuals with high Dark Triad levels might show considerable insensitivity toward the negative emotions of others [31]. Due to all the above, people with the triad might usually disagreeable [32], manipulating [28] and lacking in empathy [30,33]. Empathy is understood as having a social conscience through which a person shares an emotional experience with others, whether at an affective or cognitive level, or both [33]. Without empathy, people tend to develop less prosocial behaviour [34]. In sum, the Dark Triad represents personality traits that are mainly seen as socially aversive [31].

According to this research context, literature evidences the role of personality factors on undesirable behaviours such as cyberbullying. Thus, Baldry et al. [24] state that low empathy is the most reported individual risk factor of cyberbullying. Similarly, reduced empathic responsiveness and moral disengagement may increase potential cyberbullying behaviours [23]. Moreover, some studies analyse the relationship between the Dark Triad personality traits and cyberbullying [21,35, 36]. Their findings suggest that the dark personality plays some role as predictor of cyberbullying behaviours.

Furthermore, literature has supported links between Dark Triad traits and sexual harassment behaviours (e.g. [37–39]). For example, some studies evidence that psychopathy and narcissism are related to the perpetration of aggressive sexual behaviour (see [39] for a review). Within sexual harassment framework, sexual cyberbullying is a relatively new issue to which literature is devoting greater focus. According to Ehman and Gross's [40] review, cyberbullying should be analysed deeper specifically in such romantic interactions and relationships. These authors define sexual cyberbullying as “any sexually aggressive or coercive behaviour facilitated through the use of electronic media (i.e., text messages, social networking sites, cell phone applications, etc.)” [40, p.80].

In order to broaden the research in this field, the objective of this study is to better understand the relationship between the Dark Triad (i.e. psychopathy, Machiavellianism and narcissism) and sexual cyberbullying behaviour. Derived from previous arguments, we propose the following hypotheses:

H1: High level of psychopathy is more likely to be related to sexual cyberbullying behaviours.

H2: High level of Machiavellianism is more likely to be related to sexual cyberbullying behaviours.

H3: High level of narcissism is more likely to be related to sexual cyberbullying behaviours.

One of the main contributions of this research focuses on the use of artificial intelligence to explore the relationship between the Dark Triad traits and potential sexual cyberbullying behaviours. By using a hybrid method (structural equation modelling and ensemble classification tree), the current study aims to provide new findings in this relatively novel issue.

2. Methods

Using the convenience sampling, 374 higher education students from the Canary Islands (Spain) participated in the study. According to Liñán and Chen [41], the use of students is frequent in studies that try to

explore professionals' behaviour in the future. Furthermore, it is relevant that there is a relationship between the ethical standards that people have while studying, and the ones that they have in their professional work [42,43].

The anonymous survey used in this study comprises Dark Triad and cyberbullying behaviours. We used the measure of the Dark Triad adapted from Jonason and Webster [29], which is called "The Dirty Dozen". To measure sexual cyberbullying behaviour, we developed a scale adapted from items proposed in previous research [44,45]. All items were rated on a 7-point Likert scale. After consultation with the ethics committee of the University of Las Palmas de Gran Canaria, and according to the anonymous, voluntary and non-threatening nature of this research, we have considered that the waiver of the requirement for ethical approval is justifiable. Ethical approval for research studies based on behaviour is not required, if there is no risk for participants and anonymity is guaranteed.

The data analysis was conducted following a hybrid methodology of structural equation modelling and artificial intelligence. On the one hand, we tested the proposed hypotheses with a structural equation model, based on covariance using the Lavaan R-package [46]. On the other hand, we applied ensemble classification tree (a method of artificial intelligence) to analyse the Dark Triad traits that might most likely relate to sexual cyberbullying behaviours. We used the Adabag package in R [47], which allows the bagging and boosting techniques for the ensemble classification trees [48–51], and the randomForest package for the Random Forest [52]. In addition, we implemented two methods to assemble the results obtained with the techniques described above. In the first one, for the assembly the value of the distance between the probabilities of the possible values to classify was used, and in the second one through the mean value. Also, we used logistic regression as the baseline and compared the performance of the mentioned methods.

3. Results

As recommended in the literature [53,54], we followed a two-step procedure to analyse the causal relationship between personality traits and sexual cyberbullying behaviour. The first step was to refine and determine the dimensionality of the scale [55]. The second step was to examine the construct validity using confirmatory factor analysis [56].

Convergent validity is indicated by high factor loadings for each variable on each factor [57]. Table 1 shows factor loadings greater than 0.756 (p -value < 0.001), evidencing the convergent validity of the measures.

Additionally, we analysed Cronbach's alpha, composite reliability index [58] and the average extracted variance (AVE). According to literature [59,60], Cronbach's alpha and composite reliability should be greater than 0.70, and AVE greater than 0.5. Table 2 evidences Cronbach's alpha values greater than 0.895, composite reliability greater than 0.892 and AVE greater than 0.640.

Discriminant validity refers to the extent to which constructs are distinct and uncorrelated. For determining the discriminant validity, the square root of the AVE of each latent variable should be greater than its correlations with any other latent variable [59,61]. The Chi-square difference test showed that all constructs were significantly different. As shown in Table 2, there are no discriminant validity problems.

3.1. Test of hypotheses

Some goodness-of-fit measures were used to gauge the goodness-of-fit of the structural model. We used robust maximum likelihood estimators to adjust the measurement model [62]. As reported in Table 3, all of them satisfied the recommended thresholds (CFI = 0.942; TLI = 0.931; RMSEA = 0.079; SRMR = 0.045). Hence, the structural model was able to fit very well with the collected data.

We used structural equation modelling for testing the hypotheses (see Figure 1), fitting a structural model that could include simultaneously

Table 1. Confirmatory analyses of the constructs.

Construct/Items	Standardized loading	z-value	p-value
<i>Psychopathy:</i>			
I tend to lack remorse	0.758		
I tend to not be too concerned with morality or the morality of my actions	0.815	20.279	0.000
I tend to be callous or insensitive	0.823	14.332	0.000
I am not concerned if I have to lie or do something that is not correct to get my way	0.891	16.388	0.000
<i>Machiavellianism:</i>			
I tend to manipulate others to get my way	0.779		
I have used deceit or lied to get my way	0.871	17.690	0.000
I have used flattery to get my way	0.790	13.939	0.000
I tend to exploit others towards my own end	0.883	18.981	0.000
<i>Narcissism:</i>			
I tend to want others to admire me	0.881		
I tend to want others to pay attention to me	0.812	22.754	0.000
I tend to seek prestige or status	0.827	21.201	0.000
I tend to expect special favors from other	0.822	21.914	0.000
<i>Sexual cyberbullying:</i>			
I have edited photos of colleagues in offensive manner	0.879		
I have forced to talk about sexual issues on the Internet	0.756	17.053	0.000
I have defamed on sex-related issues on the Internet	0.794	15.351	0.000
I have shared images with sexual content on the Internet	0.800	15.759	0.000
I have made comments with sexual content about colleagues	0.760	13.915	0.000

direct and indirect paths [65]. Table 4 shows the positive and significant relationship of high level of psychopathy and sexual cyberbullying behaviour (0.196*; $p = 0.048$) and the positive and significant relationship of high level of Machiavellianism and sexual cyberbullying behaviour (0.391***; $p = 0.001$), supporting hypotheses H1 and H2. However, there is not significant relationship between narcissism and sexual cyberbullying behaviour (0.098^{ns}; $p = 0.446$); thus, H3 is not supported.

3.2. Artificial intelligence to explore sexual cyberbullying behaviours: ensemble classification trees

In this section, we aim to provide a tool based on artificial intelligence, using ensemble classification trees, in order to explore the relationship between Dark Triad traits (i.e., psychopathy, Machiavellianism and narcissism) and potential sexual cyberbullying behaviours.

Compared to other methods, the ensemble classification trees are one of the most intuitive and transparent classification algorithms [66], representing a powerful alternative to the traditional statistical models [67]. According to Homaie-Shandizi et al. [68], these models were presented in the 1960s (see [69]) and two decades later the first modern and comprehensive algorithm was developed (see [70]). In the tree structure, leaves represent classifications and branches conjunctions of features that lead to the above categories [67,71]. The objective is to perform a recursive partition of the training data in homogeneous subsets to minimize the diversity of members within each new partition [72]. Decision trees require few assumptions, no domain knowledge and a minimum of parameters, contributing to make them more flexible and attractive for researches in management [66]. In addition, ensemble classification trees detect non-linear relationships and show a good performance for qualitative information analysis [67].

Table 2. Reliability and validity. Correlation coefficients and chi-square difference test.

Cronbach's alpha	Composite reliability	AVE	Construct	Psychopathy	Machiavellianism	Narcissism	Sexual cyberbullying
0.895	0.892	0.674	Psychopathy	0.821			
0.896	0.897	0.687	Machiavellianism	0.695*** (176.970***)	0.829		
0.902	0.902	0.698	Narcissism	0.544*** (96.693***)	0.590*** (125.2***)	0.835	
0.896	0.898	0.640	Sexual cyberbullying	0.543*** (96.404***)	0.608*** (134.3***)	0.461*** (125.2***)	0.800

Note: n = 374; ***p < 0.001; **p < 0.001; square root of AVE is shown on the diagonal; Off-diagonal elements are the correlation coefficients and values in the brackets show the Chi-square difference statistics with df = 1.

Table 3. Measures of the model fit.

Number of observations Used 374		
Estimator	Maximum likelihood	Robust
Minimum Function Test Statistic	373.560	256.834
Degrees of freedom	113	113
p-value (Chi-square)	0.000	0.000
Scaling correction factor or the Satorra-Bentler correction		1.454
Model test baseline model		
Minimum Function Test Statistic	4654.151	2717.402
Degrees of freedom	136	136
p-value	0.000	0.000
User model versus baseline model		
Comparative Fit Index (CFI) ^a	0.942	0.944
Tucker-Lewis Index (TLI) ^b	0.931	0.933
RMSEA ^c	0.079	0.058
SRMR ^d	0.045	0.045

^a Recommended value ≥ 0.90 [53,63].

^b Recommended value ≥ 0.90 [53].

^c Recommended value ≤ 0.08 [54].

^d Recommended value ≤ 0.1 [64].

We used RandomForest and Adabag package in R, which allow the bagging and boosting techniques, for the ensemble of classification trees. For the analysis, the 75% of the sample was used for training, and the remaining 25% was established to test it. It is noteworthy that different thresholds for classification were implemented, with values ranging were

from 0.00 to 1.00, and increments of 0.05. For each of these thresholds, 1000 iterations were made. For each iteration, it was chosen which random elements of the database would be in the training group and which one in the test group. We assessed each of these groups (training and test) with the bagging and the boosting techniques. For each threshold level, the means and the standard deviation obtained with the aforementioned 1000 iterations were calculated. In addition, the percentile 0.025 and 0.975 were determined. This was intended to make a similar test to which is performed with the bootstrap test (to reference). We also calculated the t-value and compared it with a two-tailed t-Student of 998 degrees of freedom.

The ensemble of individual classifiers is used to improve the precision of the classifiers. Random Forest, bagging and boosting are widely used methods [47]. These methods generate a diverse set of classifiers through manipulation of the training data with a learning algorithm [49]. Bagging is a method to generate multiple versions of a predictor and get an aggregated predictor. Such multiple versions are obtained by bootstrap replicates of the learning set [67]. Thus, based on a training set with M examples, new training sets are obtained uniformly with replacement. Boosting focuses on generating a series of classifiers. The training set for each member of the series is chosen based on the previous classifier performance. So, examples are extracted with replacement with probability proportional to their weights [49]. According to Breiman [73] (p.5), “Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently”. In addition, two more results were obtained by assembling the predictions made with these three previously mentioned methods. For the first, the final value used was the result of that method in which the absolute difference in probabilities between the two possible classification values was greater (ensembled1). In the second, the result was calculated as the mean value obtained in the three methods (ensembled2). Finally, we used logistic regression as the baseline to compare the performance of previous methods.

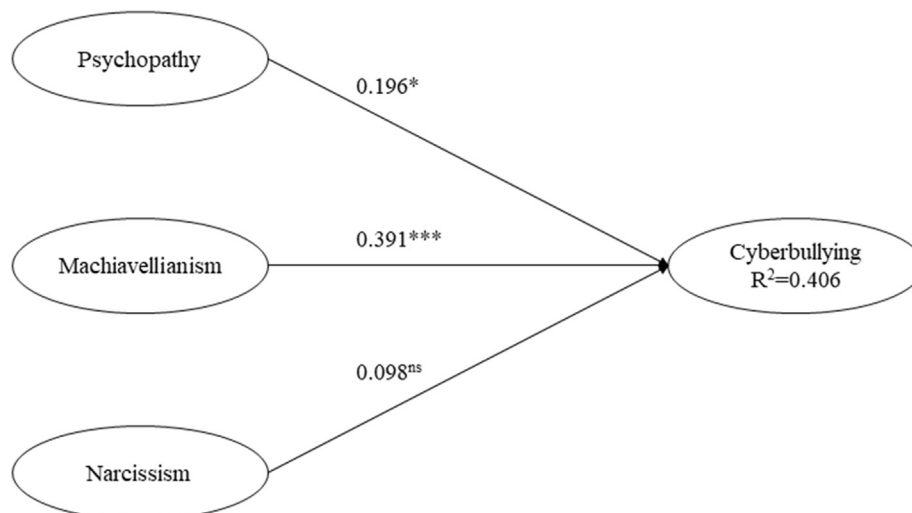


Figure 1. Research model. The structural equation modelling for testing the hypotheses is displayed.

Table 4. Results of path analysis.

Direct Effect	Estimate	Standard error	Z-value	p-Value	Percentile Bootstrap 95% confidence interval	Remarks
Psychopathy→ Sexual cyberbullying	0.196*	0.099	1.082	0.048	[0.023; 0.413] Sig	Supported
Machiavellianism→ Sexual cyberbullying	0.391***	0.120	3.255	0.001	[0.147; 0.623] Sig	Supported
Narcissism→ Sexual cyberbullying	0.098 ^{ns}	0.058	1.677	0.446	[-0.015; 0.213] NS	Not supported

Significance level: ***p < 0.001; **p < 0.01; *p < 0.05; ^{ns} non-significant.
 Sig: Significant; NS: Non-significant.

Considering an error of 75% train (see Figure 2), the best method is Random Forest (error near 5.6%). The second method with the best result was the assembly through mean values (ensembled2) of the other three methods based on trees (8.1%). The third was bagging with an error close to 9.1%. In fourth position can be placed the method of assembly by differences (ensembled1) with 9.5% error. Finally, it appears boosting with 22.6% error and logistic regression (logit) with 29.6%.

Figure 3 shows false positives and false negatives. Both issues are considered negative, although the second one remains a major concern. In order to reduce the serious inconveniences of these two issues, a comparison has been made between the different techniques applied in this study. As a result, the methods that performed better with respect to false positives are ensembled1 and Random Forest, while for false negatives Random Forest and bagging obtained better results.

Figure 4 shows the sensitivity and the specificity of the methods. Sensitivity and specificity analysis is used to evaluate a test performance. On the one hand, sensitivity is the proportion of positive cases that are

well detected by the method used; in other words, it is the true positive rate. The method will be better the closer the sensitivity is to 1, because it will be detecting better the real positive cases. On the other hand, specificity shows the proportion of negative cases that are well detected by the method; therefore, it is the true negative rate. The method will be better the closer the specificity is to 1, because it will be detecting better the real negative cases. Consistent with the results showed in previous analysis (see Figure 3), Random Forest presents a much better sensitivity than the rest of the methods and a similar specificity than ensembled1 (see Figure 4). Consequently, the Random Forest seems to be the best method to explore the relationship between Dark Triad traits and sexual cyberbullying behaviours.

Considering the receiver operating characteristic (ROC) curves, Figure 5 shows that the area under the curve (AUC) in the Random Forest method (AUC = 0.983) presents a better result than the other methods. It is followed by the esembled2 method (0.978), bagging (AUC = 0.964), esembled2 method (0.962), boosting (AUC = 0.862) and logistic

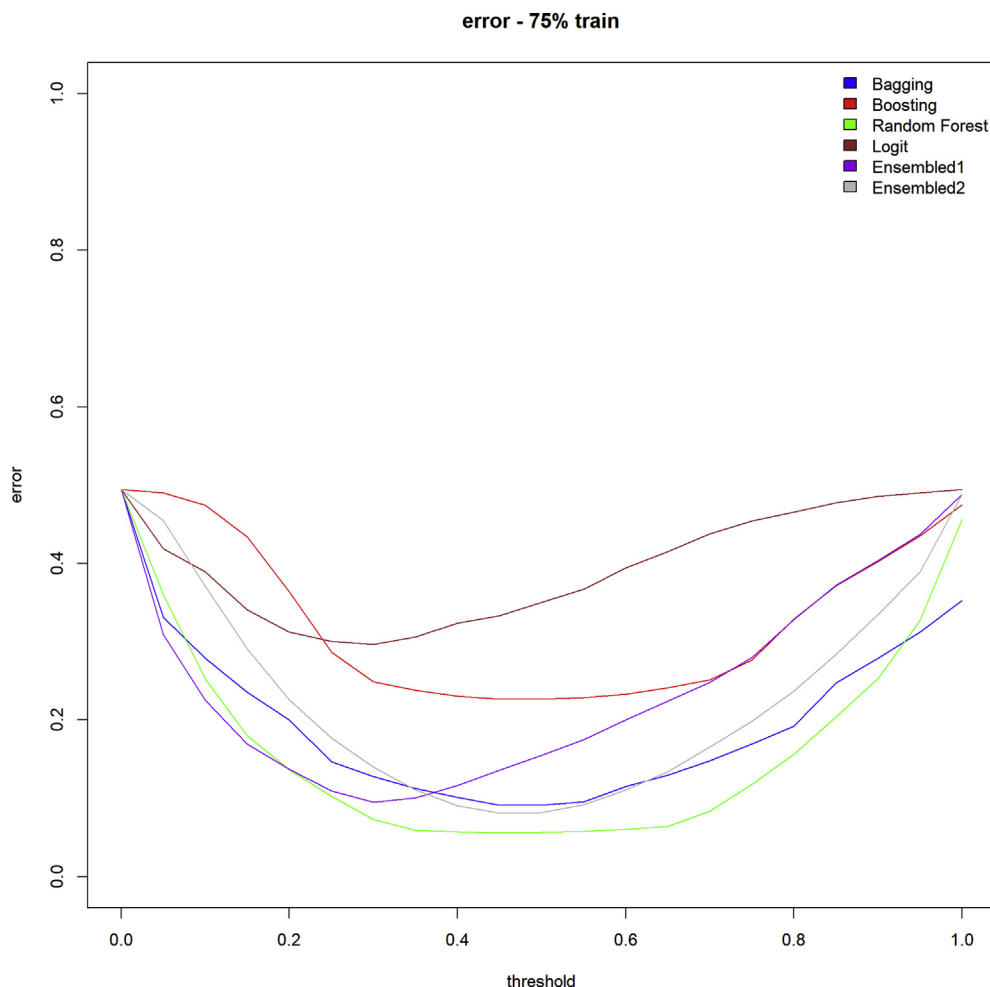


Figure 2. Total error with 75% train.

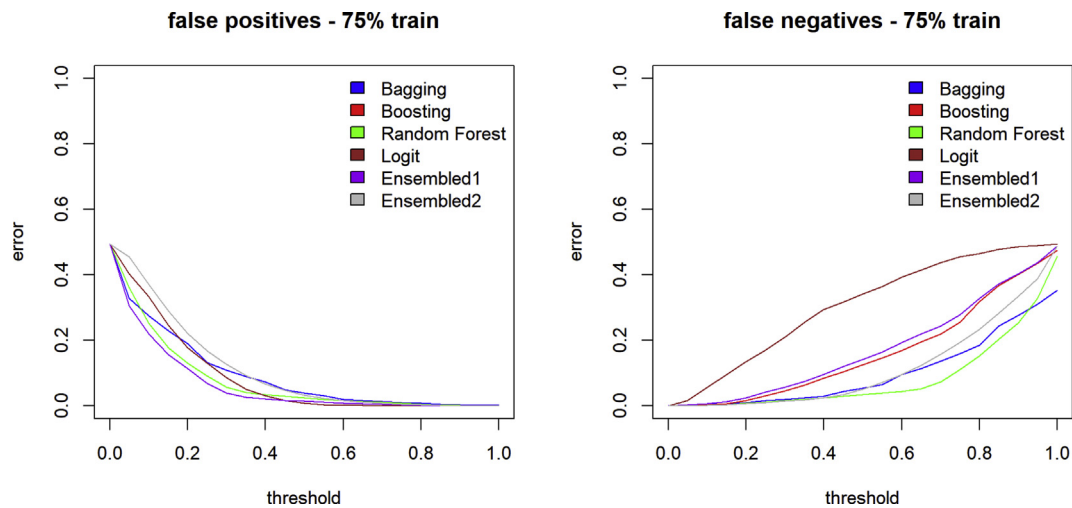


Figure 3. False positives and false negatives with 75% train.

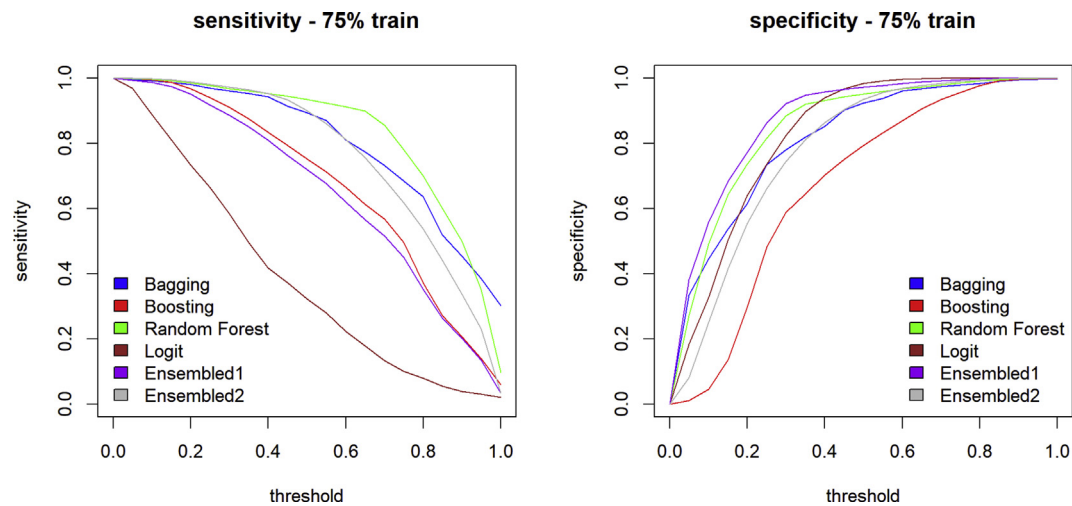


Figure 4. Sensitivity and specificity of the models with 75% train.

regression (AUC = 0.774). All these results, together with those presented above, make it clear that the Random Forest method can be considered superior to boosting and logit.

Table 5 shows the average values obtained through the 1000 logistic regressions carried out, as well as their standard deviations, t-values and significance. Results evidence that Machiavellianism is the variable with greater importance in the classification.

Finally, Table 6 shows the importance of each of the Dark Triad traits to explore sexual cyberbullying behaviours by using bagging, boosting and Random Forest methods. Mean value of importance, standard deviation, and t-value are displayed. Considering the results obtained, Machiavellianism presents higher level of relationship to potential sexual cyberbullying behaviours by using bagging and Random Forest. Using the boosting method, a high level of psychopathy seems to be the most important variable associated to sexual cyberbullying behaviours.

4. Discussion

Considering the main aim of the study, this paper actually contributes to the research on the Dark Triad and sexual cyberbullying behaviour. In this regard, the present work used artificial intelligence to establish which are the relations that can occur between the Dark Triad traits and sexual cyberbullying behaviours. Specifically, the theoretical contribution of the study refers to the relationship of two dimensions of the Dark

Triad (psychopathy and Machiavellianism) with sexual cyberbullying behaviours. These results support earlier findings [37].

Workplace harassment and especially sexual harassment are already legally regulated in Europe requiring organizations to take adequate precautions and to include these bad practises in their Occupational Risk Prevention Manuals. The World Health Organisation (WHO) and the International Labour Office (ILO) have developed a proposal for a new Occupational Safety and Health (OSH) indicator for the United Nations' Sustainable Development Goals (SDGs), relating to Goal 8: "Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all". To achieve a decent work the organization's management should not be improvised, but protocolized. One condition to obtain a respectful workplace is to avoid any kind of harassment. The prevention of the risk of cyber harassment at work, whatever its modality -sexual, sexist, moral, discriminatory-must therefore form part of the protocol for managing harassment and other psychosocial risks. It should be remembered that in the recent and very important Spanish Constitutional Court Decision 56/2019, of 6 May, the decisive relevance is given to the effective activation of the protocol to avoid the responsibility derived from the possible risk of harassment. Therefore, it is crucial to develop protocols to prevent the risk of cyberbullying in the workplace, in any of its forms.

In this regard, the main practical contribution of the paper refers to using artificial intelligence to explore personality traits more likely to be

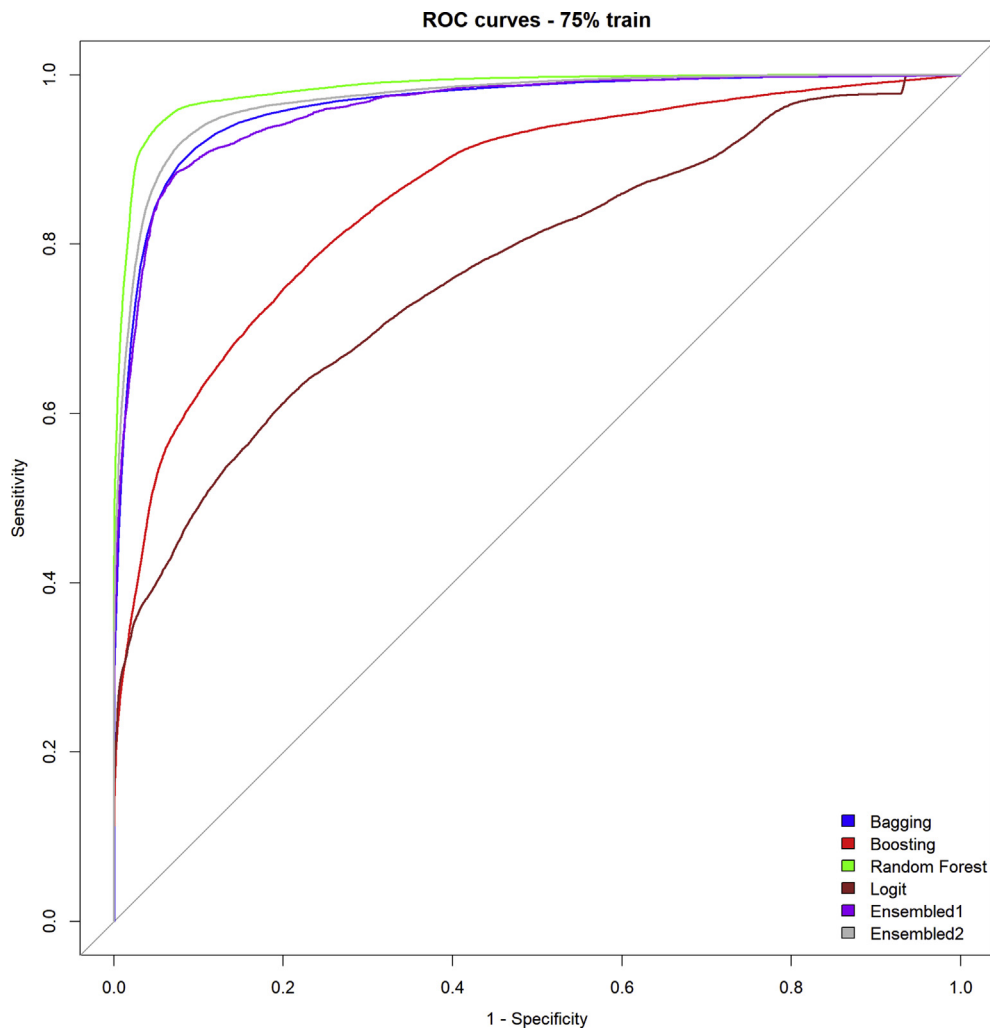


Figure 5. ROC curves.

related to sexual cyberbullying behaviour. The methodology is based on the use of structural equation modelling and ensemble classification tree (specifically with Random Forest, bagging and boosting methods). Results evidence that Random Forest is superior to the other methods, and also have a high sensitivity value, showing a better performance regarding false negatives. Thus, the research provides a method with a low false negative rate to detect potential sexual cyberbullying behaviour. In that sense, our research proposes the Random Forest method as the best solution to correctly treat false negatives. In addition, the results

Table 5. Results of logistic regressions (75% train).

	(Intercept)	Psychopathy	Machiavellianism	Narcissism
Coefficients	0.137	0.352	0.724	0.272
SD coefficients	0.040	0.090	0.110	0.070
<i>t</i>	3.455	3.912	6.597	3.886
Significance	***	***	***	***
Percentile interval 2.5%	0.063	0.176	0.509	0.136
Percentile interval 97.5%	0.220	0.546	0.946	0.405

T-Bootstrap (based on t(998) two-tailed test); t(0.05; 998) = 1.962; t(0.01; 998) = 2.581; t(0.001; 998) = 3.300; **p* < 0.05; ***p* < 0.01; ****p* < 0.001; ^{ns} Non-significant.

Table 6. Means of the importance, standard deviations, and Student-t for bagging, boosting and Random Forest.

	Machiavellianism	Narcissism	Psychopathy
Bagging - 75% train			
Mean Importance	41.300	24.601	34.100
SD Importance	5.239	3.953	4.227
<i>t</i>	7.883	6.224	8.067
Significance	***	***	***
Boosting - 75% train			
Mean Importance	33.408	28.479	38.113
SD Importance	2.275	2.175	2.270
<i>t</i>	14.685	13.096	16.791
Significance	***	***	***
Random Forest - 75% train			
Mean Importance	36.633	30.334	30.034
SD Importance	2.476	2.237	2.035
<i>t</i>	14.792	13.559	16.232
Significance	***	***	***

T-Bootstrap (based on t(998) two-tailed test); t(0.05; 998) = 1.962; t(0.01; 998) = 2.581; t(0.001; 998) = 3.300; **p* < 0.05; ***p* < 0.01; ****p* < 0.001; ^{ns} Non-significant.

obtained propose the ensemble classification tree as a powerful and more efficient method, because it could continue learning with new cases. Therefore, as the sample expands with new individuals and the number of iterations increases, the results obtained through the ensemble classification tree method will improve.

According to the above, this study provides a relevant tool for improving organizational management by taking into account social responsibility policies. Regarding the internal dimension of Corporate Social Responsibility, organizations must consider psychosocial health in the workplace. Therefore, within their corporate social responsibility companies should be concerned to maintain policies and develop procedures that generate an organizational culture of zero tolerance to harassment, bullying and cyberbullying. Moreover, considering the profile of respondents, they would be middle and top managers in the future, who would interact not only face-to-face, but also through electronic devices. With this tool, companies could prevent undesirable behaviours in terms of sexual cyberbullying, by implementing training activities or prevention actions, to promote an organizational culture, which avoids any behaviour of sexual cyberbullying. The proper and preventive management of the risk of cyberbullying at work must include a policy of training, information and awareness on the subject, in order to help all employees of the organization to prevent it or, if necessary, to stop it.

Combined efforts of the firm are needed to prevent, reduce, or eliminate potential cyberbullying behaviours. The organization could use the tool proposed in this study to develop internal policies and procedures for identifying and deterring potential cyberbullying behaviour. By using this questionnaire in training courses, the organization can foster an organizational culture based on a respectful workplace free of sexual cyberbullying behaviours. Afterwards, the organization could propose policies and strategies addressed to promote healthy use of the Internet in order to prevent possible overuse and addiction. In addition, it is important to reduce involvement in cyberbullying, in all roles, by reducing risk factors in order to create a greater sense of safety at workplace. It must be an important task to solve or to take care about it, because the worst consequence of such situations could also lead employees (as victims) to suicide risk [72].

Finally, concerning future research, it would be interesting to analyse how variables such as gender, age or social status may affect the relationship between dark personality and sexual cyberbullying behaviours.

Declarations

Author contribution statement

Agustín Sánchez-Medina: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Inmaculada Galván-Sánchez, Margarita Fernández-Monroy: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

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