sustainability

MDPI

Article

What If Violent Behavior Was a Coping Strategy? Approaching a Model Based on Artificial Neural Networks

Juan Pedro Martínez Ramón [1] and Francisco Manuel Morales Rodríguez [2,*]

1 Department of Developmental and Educational Psychology, University of Murcia, Campus of Espinardo, C.P. 30100 Murcia, Spain; juanpedromartinezramon@um.es

2 Department of Developmental and Educational Psychology, University of Granada, Campus of Cartuja, C.P. 18071 Granada, Spain

* Correspondence: fmmorales@ugr.es

Received: 24 August 2020; Accepted: 6 September 2020; Published: 9 September 2020

check for updates

Abstract: The aggressor sets in motion dysfunctional and violent behaviors with others in the dynamic of bullying. These behaviors can be understood as misfit coping strategies in response to environmental demands perceived as stressful, putting at risk the quality of education. The aim of this study was to develop a predictive model based on artificial neural networks (ANN) to forecast a violent coping strategy based on perceived stress, resilience, other coping strategies and various socio-demographic variables. For this purpose, the Stress Coping Questionnaire (SCQ), the Perceived Stress Scale (PSS) and the Brief Resilient Coping Scale (BRCS) were administered to 283 participants from the educational field (71.5% women). The design was cross-sectional. An inferential analysis (multilayer perception ANN) was performed with SPSS version 24. The results showed a predictive model that took into consideration the subject's stress levels, personal assessment and strategies such as negative self-targeting or avoidance to predict open emotional expression (a coping strategy defined by violent behaviors) in approximately four out of five cases. The conclusions emphasis the need for considering problem solving, stress management and coping skills to prevent school violence and improve the social environment through sustainable psychological measures.

Keywords: artificial neural networks; bullying; school violence; social environment; psychological sustainability; prevention

1. Introduction

Coping strategies can be understood as a set of behaviors that the individual uses to manage a situation perceived as a problem [1]. The knowledge of the coping strategies put in place by the educational community is an essential aspect of implementing policies that will boost the quality of education, in line with the goal of sustainable development (OSD) number 3. In this line, the achievement of an inclusive and peaceful society (Goal 16) implies knowing how to detect violent behavior and the factors associated with it in order to prevent the emergence of school violence and to fight against bullying. These objectives are part of the United Nations Agenda 2030 [2] and are consistent with promoting the psychological wellbeing of the individual [3].

One of the main problems facing the education system and society as a whole is that of violence among members of the educational community [4,5]. The consequences of violent behavior are negative under all prisms and agents, both from the point of view of the aggressor and the attacked [6].

According to stress theory, the perception of certain environmental demands as stressful and the absence of other coping strategies can trigger a response to stress [1,7], e.g., high environmental demands [8,9] or unsafe conditions [10]. These stress levels, in turn, can feed back into the use of dysfunctional behaviors that put educational quality at risk, rather than others that are more beneficial to the social climate and personal adjustment [11].

Although the study of violence is not new, the desire to provide relevance and visibility to research into this behavior in the university environment is [12–15]. This means that there is a gap between the information accumulated in this stage when compared with previous educational stages [15–18]. The aggressor in the university environment is the one who sets in motion a series of behaviors with clear prejudice to other people, whether it be their property or their integrity [physical, psychological or emotional) [13,19]. These behaviors can be understood as maladaptive or dysfunctional coping strategies.

As a result of the theory of stress [1] and the factorial analysis of its components, various strategies have been found to manage the problems. It highlights the open emotional expression coping strategy (OEE), which is characterized by managing difficulties through insults, hostile behavior, moodiness, direct aggression, irritation, and hostile expression of emotions [20]. These are behavioral manifestations that can be classified as violent, even more so when there are other alternative ways to resolve the situation, such as through the use of the positive re-evaluation coping strategy (PRE) or the search for social support (SSS). The OEE, therefore, is a set of dysfunctional behaviors used to deal with a subjective threatening situation. Subjective elements, such as perception of the situation and self-perception of emotions, are involved in the choice of strategies [21,22].

Under this perspective, the use of a coping strategy in the educational field, even if it is dysfunctional, can be understood as a response set in motion when there is a situation perceived as stressful for the subject [23,24]. In relation to genesis, it is possible that the observation of other people who use certain strategies and their consequences in the environment may favor their learning or have a facilitating effect [12,25–30]. Regardless of its etiology, stress can be a trigger of a dysfunctional coping strategy (such as OEE) and can also function as a predictor of whether or not such a strategy will be used.

In another vein, resilience can be understood as a set of coping strategies aimed at solving in a functional way both the problems of daily life and those of a punctual but extremely intense nature, recovering satisfactorily from adversity [31]. This is a characteristic of people with emotional intelligence, which is related to good teaching performance [32–36] and with a greater ability to manage perceived stress [37]. Levels of resilience may predict the use of a violence-focused strategy (OEE) or others of a more prosocial nature.

The existence of differences in various socio-demographic aspects of resilience [38] and stress [39] justify the introduction of variables such as gender or age in the research.

To study the predictive capacity of stress, resilience, certain sociodemographic variables and other coping strategies in the use of OEE, it is considered appropriate to use artificial neural networks (ANNs). ANNs can be defined as systems capable of processing, structuring and predicting information. ANNs emulate human neural architecture and its distribution of neuron layers. Each information unit or node reproduces the functioning of a neuron. It is closely interconnected with other neurons in the network. The interconnections can be more or less intense depending on their contribution to the network through the synaptic weight of each one [40].

ANNs are based on the concept of artificial intelligence and are closely related to "big data", "machine learning" and how it is possible to reproduce systems capable of learning on their own [40]. ANNs have been used in many branches of science to predict data because of their usefulness in managing large databases. Neural networks have the ability to learn from incoming information and work with variables whose relationships are complex [41–43].

That said, the general objective of this study was to develop a predictive model based on artificial neural networks (ANNs) to predict the presence or absence of a violent coping strategy based on perceived stress, resilience, other coping strategies and various socio-demographic variables. This general objective was distributed into the following specific objectives: (1) to program an ANN using a predictive "backpropagation" model with neuron output OEE and inputs of stress, resilience, other coping strategies and sociodemographic variables with a hidden layer and three stages (training, validation and evaluation); (2) study the network architecture through the synaptic weights and the relationships that are generated between the neurons, based on their normalized importance, until reaching the signal to the output layer (OEE); evaluate the neuronal network through sensitivity, gain and elevation for the categorical dependent variable OEE.

With regard to the initial hypotheses, we expected to program an artificial neuronal network with learning capacity (H1); we expected to corroborate the existence of a network architecture composed of a series of predictive variables (coping strategies, stress and resilience) that would account for the use or non-use of OEE (H2); and we expected to obtain data that would psychometrically support the positive evaluation of the neuronal network obtained (H3).

2. Materials and Methods

2.1. Procedure

The design was cross-sectional and quantitatively focused. Once the objective was described and consent was obtained, the test battery was administered through a link sent to the educational community. With respect to the ethical aspects of the study, participation was anonymous, confidential and voluntary with all participants giving their consent. The guidelines of the Helsinki protocol were taken as a reference. The study protocol was approved by the Ethics Committee of the University of Granada (Spain).

2.2. Participants

The study was composed of N = 283 participants belonging to the university community of the southeast area of Spain. Concretely, 71.5% (203) were women and 28.2% (80) were men. The mean age was 31.07 years (SD = 12.02). With respect to marital status, 69.7% (198) were single, 26.4% (75) were married, 3.2% (9) were divorced, and 0.4% (1) widowed. A large majority of them had a Bachelor's degree (52.8%) or a Master's degree (38.7%). With regard to the roles they played within the educational community, 57% (162) were students; 30.6% (87) were professors or worked in a related position; 4.9% (14) were defined as the mother, father or legal guardian of a student; and the remaining 7.5% belonged to other category (for example, administrative and service personnel).

The dependent variable was initially continuous and was dichotomized using the 50th percentile as the cut-off point (non-use versus use of OEE). It was found that 163 subjects were not using OEE (57.6%) and 120 were using OEE (42.4%). Table 1 shows the descriptive analysis of the continuous variables that acted as independent variables in the network and the analysis of the dependent variable when it was continuous and once was dichotomized.

Table 1. Descriptive analysis of the continuous independent variables and of the dependent variable of the neural network (N = 283).

	Min	Max	*M*	*SD*	Asymmetry		Kurtosis	
					Value	Standard Error	Value	Standard Error
IV								
FSP	4	24	16.06	4.704	−0.265	0.14	−0.716	0.289
NSF	0	21	7.96	3.907	0.567	0.145	0.131	0.289
PRE	4	24	16.04	4.119	−0.425	0.145	−0.290	0.289
AVD	0	24	12.55	4.472	0.075	0.145	0.070	0.289
SSS	0	24	14.36	6.390	−0.215	0.145	−0.943	0.289
RLG	0	24	3.73	5.602	1.713	0.145	2.288	0.289
Stress	5	52	25.75	9.097	0.257	0.145	0.036	0.289
Resilience	4	20	15.01	3.281	−0.605	0.145	0.092	0.289
DV								
OEE	0	21	8.19	3.777	0.468	0.145	0.433	0.289
OEE (non-use/use)	1	3	1.90	0.876	0.468	0.145	0.433	0.289

Note. DV: Dependent variable; IV: Independent variable; Min.: Minimum; Max.: Maximum; M: Mean; SD: Standard Deviation; FSP: Focusing on the solution of the problem; NSF: Negative self-focus; PRE: Positive re-evaluation; AVD: Avoidance; SSS: Search for social support; RLG: Religion. Source: Own elaboration.

2.3. Instruments

The questionnaires used in the study were as follows:

Stress Coping Questionnaire (SCQ) or (CAE in the original version) [20]. It consists of 7 dimensions and 42 items in Spanish with a Likert type scale from 0 to 4, where 0 was “Never” and 4 “Almost always”. Each dimension corresponds to a coping strategy: focus on the solution of the problem or FSP (items 1, 8, 15, 22, 29 and 36), negative self-focus or NSF (items 2, 9, 16, 23, 30 and 37), positive re-evaluation or PRE (items 3, 10, 17, 24, 31 and 38), open emotional expression or OEE (items 4, 11, 18, 25, 32 and 39), avoidance or AVD (items 5, 12, 19, 26, 33 and 40), seeking social support or SSS (items 6, 13, 20, 27, 34 and 41) and religion or RLG (items 7, 14, 21, 28, 35 and 42). All are direct items. The sum of each scale reflects greater use of that coping strategy. The OEE, which is the dependent variable of the predictive model of this research, was made up of the items “I unloaded my bad mood on others” (item 4), “I insulted certain people” (item 11), “I behaved in a hostile manner towards others” (item 18), “I assaulted some people” (item 25), “I became irritated with some people” (item 32) and “I struggled and vented my feelings” (without reference to a filter or empathy) (item 39). Cronbach’s internal consistency coefficients Alpha for each scale in the original study were greater than or equal to 0.85 for SSS, FSP and RLG, between 0.71 and 0.76 for OEE, AVD and PRE, and 0.64 for NSF [20]. The internal consistency obtained in this investigation is shown in Table 2.

Table 2. Internal consistency obtained in coping strategies.

Strategy	Cronbach’s Alpha
FSP	0.86
NFS	0.72
PRE	0.78
OEE	0.68
AVD	0.71
BAS	0.94
RLG	0.93

Note. OEE: Open emotional expression; FSP: Focusing on the solution of the problem; NSF: Negative self-focus.; AVD: Avoidance; SSS: Search for social support; RLG: Religion; PRE: Positive re-evaluation. Source: Own elaboration.

Perceived Stress Scale (PSS) [44]. The Spanish adaptation was used [45]. It consists of 14 items and a 5-point Likert scale where 0 is "Never" and 5 is "Very often". Items 4, 5, 6, 7, 9, 10, and 13 are indirect. Once they are inverted, the summation is done. The higher the score, the greater the perceived stress. Example of a direct item: "In the last month, how often have you been affected by something that has happened unexpectedly? (Item 1). Example of indirect item: "In the last month, how often have you felt that things are going well for you?" (Item 7). In the adapted version, an internal consistency in Cronbach's Alpha of 0.81 was obtained [44]. In the current investigation, an Alpha of 0.86 was obtained.

Brief Resilient Coping Scale (BRCS) [46], adapted to Spanish [47]. It consists of 4 direct items that assess the subject's ability to cope with stressful situations in a positive way, through five response options from 1 to 5 where 1 means "Doesn't describe me at all" and 5 corresponds to "Describes me very well", with scores ranging from 4 to 20. A total score is obtained based on the sum of the items. Once the sum is obtained, the scores are distributed into three levels of resilience. In particular, the intervals proposed by [46] were 4–13 points for low resilience, 14–16 points for medium resilience and 17–20 points for high resilience. Example of item: "I am looking for creative ways to change difficult situations" (item 1) The BRCS has reached in its Spanish version a Cronbanch's Alpha of 0.87 [48]. In this study it reached 0.78.

Socio-demographic questionnaire. This is an ad hoc elaboration tool for the collection of the following variables: sex, marital status, training and role in the educational field (mainly student, teacher or family).

2.4. Data Analysis

A multilayer perceptron (MLP) algorithm was designed. This is a special type of ANN architecture, with a backward error propagation-learning algorithm (or backpropagation), very useful for analyzing deep and complex data relationships. For the creation of the ANN, the total number of participants was randomly assigned to three groups: training group (60%), validation group (30%) and test group (10%). An input layer, a hidden layer and an output layer formed the architecture. A random seed was established and, to optimize the network results, continuous variables were used in the trigger function for the "backpropagation" algorithm in the covariates and the hyperbolic tangent function for the hidden layer [49]. The SPSS statistical package version 24.0 was used [50].

3. Results

3.1. Neural Network Programming

Prior to the training phase, a random seed was generated, setting the value 9,191,972 as a starting point to encourage replication of the results. Next, the factors, covariates and the variable dependent on multilayer perceptual ANN were selected. We proceeded to assess which change of scale of covariates allowed a more adjusted model, obtaining that the percentage of incorrect prognoses in the test phase was lower when the change of scale was not applied. With regard to the scores, the relative number 7 was established in training (70%), 2 in the testing (20%) and 1 in the reserve (10%). Regarding the architecture, the automatic selection of the architecture established a minimum and maximum number of units of the hidden layer that varied between 1 and 50, respectively. The type of network training was: online. The optimization algorithm was: gradient slope. The training options are shown in Table 3.

Table 3. ANN training options.

Option	Value
Initial learning rate	0.4
Lower learning rate limit	0.001
Reduction of the learning rate, at times	10
Drive	0.9
Center of interval	0
Interval shift	±0.5

Source: Own elaboration.

Finally, in the configuration of the ANN options, it was decided to include the missing values in the categorical factors and dependent variables (DV) due to the fact this is viable. With respect to the stop rules, the order of verification and the associated values were as follows: (1) maximum number of steps without a decrease in error: 1; (2) data to use for calculating prediction error: choose automatically; (3) maximum training time: 15 min; (4) maximum number of training times: calculate automatically; (5) minimum relative change of training error: 0.0001; (6) minimum relative change of training error rate: 0.001.

The summary of the model, as well as the final distribution of the cases taken by the network for each phase, is shown in Table 4. During the training phase the network learned to catalogue the subjects. The testing phase was used to validate the network, detecting any errors in it and perfecting the algorithm. Finally, the reserve phase allows us to evaluate the model and make sure that the network really has a predictive value, exposing it to cases not used before.

Table 4. Summary of artificial neural network case processing.

Phase	Model Summary [(a)]		Distribution	
			N [(b)]	Proportion (Scale 0–1)
Training	Cross entropy error	116.92	193	0.7
	Percentage of incorrect forecasts	29		
	Stop rule used	OCS		
	Set-up time	0:00:00.14		
Testing	Cross entropy error	26.64	49	0.18
	Incorrect forecast percentage	22.4		
Reserve	Incorrect forecast percentage	22.9	35	0.13

Note. [(a)] Dependent variable OEE (open emotional expression); [(b)] N = 277; missing cases: 7. OCS: One consecutive step without discrimination of the error—Error calculations are based on the test sample. Source: Own elaboration.

3.2. Neural Network Architecture

The network generated was made up of three layers. Firstly, an input layer formed by four factors of a nominal or ordinal nature (marital status, studies, educational role and sex) and nine continuous covariates (age, focus on the solution of the problem, self-focus, avoidance, search for social support, religion, positive re-evaluation, stress and resilience), adding up to 25 units excluding bias (see Table 5). The covariates did not undergo a change of scale. Secondly, a hidden layer composed of three neurons or units and whose activation function was by hyperbolic tangent. Thirdly, the output layer was composed of two units being softmax the activation function used, and cross entropy, the error function.

Table 5. Parameter estimates.

Predictor [Node Value] *Variable*		Predicted				
		Hidden Layer			Output Layer	Output Layer
		H(1:1)	H(1:2)	H(1:3)	OEE = −1	OEE = 1
Input layer	(Bias)	0.38	−0.04	−0.01		
	[Marital status = 1] *Married*	−0.29	−0.09	−0.31		
	[Marital status = 2] *Divorced*	−0.46	0.39	−0.04		
	[Marital status = 3] *Single*	0.46	0.49	−0.26		
	[Marital status = 4] *Widow*	0.35	−0.32	0.15		
	[Studies = 1] *Primary*	0.15	0.27	0.12		
	[Studies = 2] *Secondary*	0.23	0.22	0.04		
	[Studies = 3] *Vocational*	0.15	−0.16	0.46		
	[Studies = 4] *Bachelor*	−0.47	0.27	−0.24		
	[Studies = 5] *Master*	0.1	−0.13	−0.57		
	[Studies = 6] *PhD*	0.05	−0.47	−0.16		
	[Role = 1] *Family*	0.03	−0.14	0.18		
	[Role = 2] *Student*	0.49	−0.11	0.15		
	[Role = 3] *Professor*	0.19	−0.31	−0.39		
	[Role = 4] *Staff*	0.13	0.19	−0.06		
	[Sex = 1] *Male*	0.39	−0.08	0		
	[Sex = 2] *Female*	−0.12	−0.24	0.37		
	Age (years)	−0.14	−0.16	−0.02		
	FSP	0.41	−0.34	−0.55		
	NSF	−0.47	0.01	0.48		
	AVD	−0.25	−0.19	0.51		
	SSS	−0.02	0.17	0.43		
	RLG	−0.13	−0.48	0.43		
	PRE	−0.28	−0.22	−0.2		
	Stress	−0.34	−0.16	−0.11		
	Resilience	−0.5	−0.47	−0.14		
Hidden layer	(Bias)				0.1	0.23
	H(1:1)				−0.45	−0.09
	H(1:2)				−0.31	0.24
	H(1:3)				−0.56	0.42

Note. OEE: Open emotional expression; FSP: Focusing on the solution of the problem; NSF: Negative self-focus; AVD: Avoidance; SSS: Search for social support; RLG: Religion; PRE: Positive re-evaluation. Source: Own elaboration.

The importance of the independent variables is defined by their synaptic weights, i.e., the contribution of each predictor to the network. It is extracted from the analysis of the results of the participants in the training and test phases (Table 6).

Table 6. Importance of the independent variables.

Independent Variables	Importance	Standard Importance
Marital status	0.008	4.1%
Studies	0.016	8.9%
Role	0.010	5.2%
Sex	0.006	3.4%
Age	0.016	8.9%
FSP	0.155	84.6%
NSF	0.153	83.4%
AVD	0.183	100%
SSS	0.155	84.5%
RLG	0.124	67.8%
PRE	0.060	32.7%
Stress	0.076	41.4%
Resilience	0.037	20.1%

Note. FSP: Focusing on the solution of the problem; NSF: Negative self-focus.; AVD: Avoidance; SSS: Search for social support; RLG: Religion; PRE: Positive re-evaluation. Source: Own elaboration.

The graphic relationship that the above variables have with each other can be analyzed in Figure 1. Coping strategies have a greater standardized importance in the model, highlighting avoidance. Stress is the only variable that stands above one of the coping strategies, in this case, positive re-evaluation. The sociodemographic variables have a lesser normalized importance for the network, especially in the case of sex and marital status.

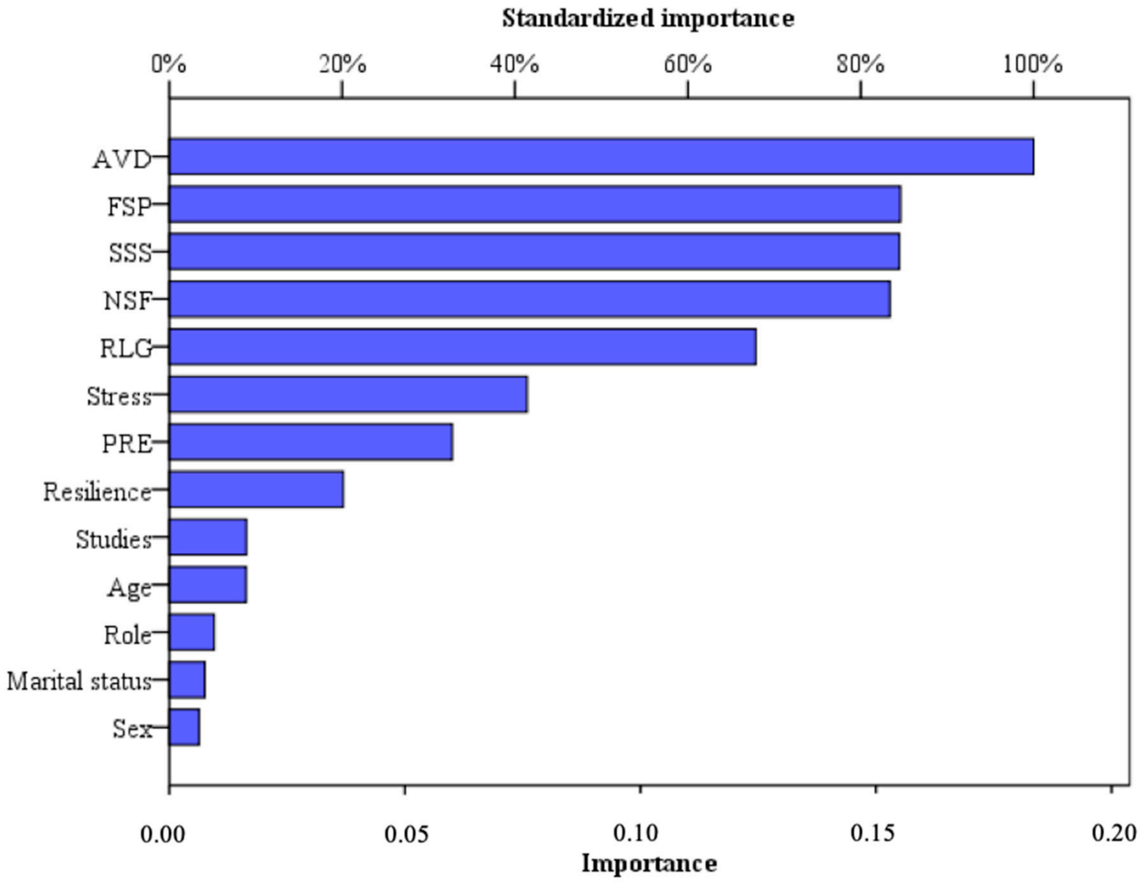

Figure 1. Importance of the variables of the "input" layer in the network. Source: Own elaboration.

The graphic representation of the parameter estimates for the interconnections between the input, hidden and output layer neurons is shown in Figure 2. The hidden layer activation function was hyperbolic tangent and the resultant layer activation function was softmax. The line that connects the nodes of the layers of the neural network represents the synaptic weighting. A lighter colored line represents synaptic weights below 0 and a darker colored line represents synoptic weights above 0.

Table 7 shows the classification of cases. If we analyze the global correct percentage for each of the phases, we can see how during the training the model acquires a predictive capacity of 71% of the cases. In the testing phase the network continues to learn with new cases, feeding back and improving its classification capacity up to 77.6% probability of success. It also improved its ability to predict between the use or non-use of OEE. In the testing phase the network was adjusted in a more balanced way. Finally, in the reserve phase, the network checks its operation using cases that were not treated in the two previous phases. It is checked how the network manages to maintain similar levels in its predictive capacity with a correct percentage of 77.1% so that approximately four out of five cases are predicted. In the reserve phase, the balance between the percentage of cases that did not use the OEE and those that were correctly predicted reached a greater balance than in the previous phases, reflecting the good fit of the model.

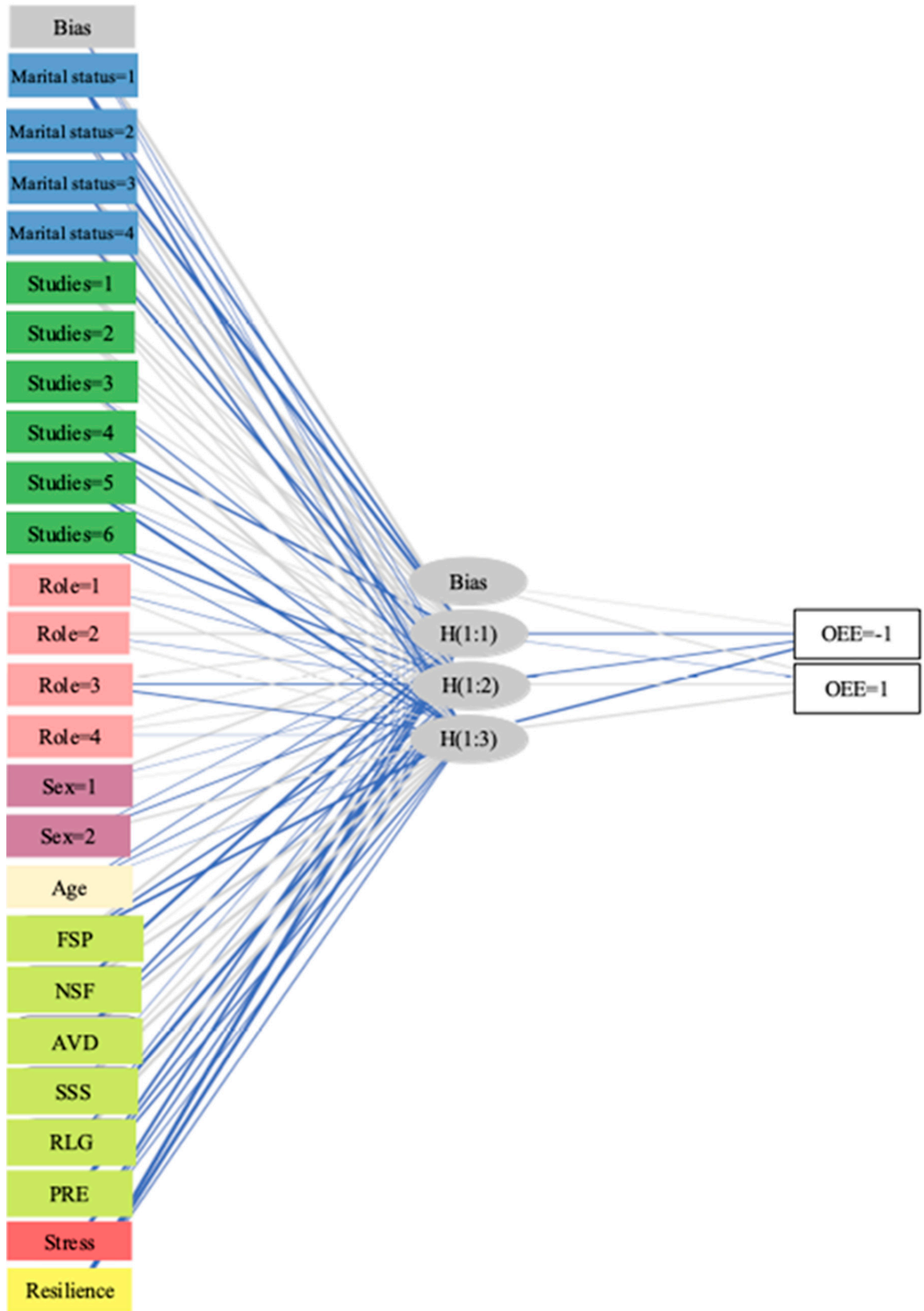

Figure 2. Artificial neural network of the OEE strategy composed of input, hidden and output layers. Source: Own elaboration.

Table 7. Classification of correctly predicted cases for each phase.

Phase	Observed	Predicted (Dependent Variable: OEE)		
		Non-Use	Use	Correct Percentage
Training	Non-use	86	26	76.8%
	Use	30	51	63%
	Overall rate	60.1%	39.9%	71%
Testing	Non-use	23	8	74.2%
	Use	3	15	83.3%
	Overall rate	53.1%	46.9%	77.6%
Reserve	Non-use	14	4	77.8%
	Use	4	13	76.5%
	Overall rate	51.4%	48.6%	77.1%

Note. OEE: Open emotional expression. Source: Own elaboration.

3.3. Network Assessment

The evaluation of the network was carried out through the analysis of sensitivity, gain and elevation for the categorical dependent variable (DV) OEE. Sensitivity was measured using the Receiver Operating Characteristic (ROC) curve of the DV. The area under the curve for the use and non-use of the OEE was 0.723, which meant that the predictive ability was superior to random, as can also be seen in Figure 3. In relation to the accumulated gain (Figure 4), the area is also above the diagonal or baseline for OEE = −1 and OEE = 1. Finally, the elevation allowed us to examine the results of the accumulated gains located this time on the *y*-axis, in relation to the baseline in Figure 5. The reserve phase set out in Table 7 with the classification of correctly predicted cases and was also a tool for evaluating the network.

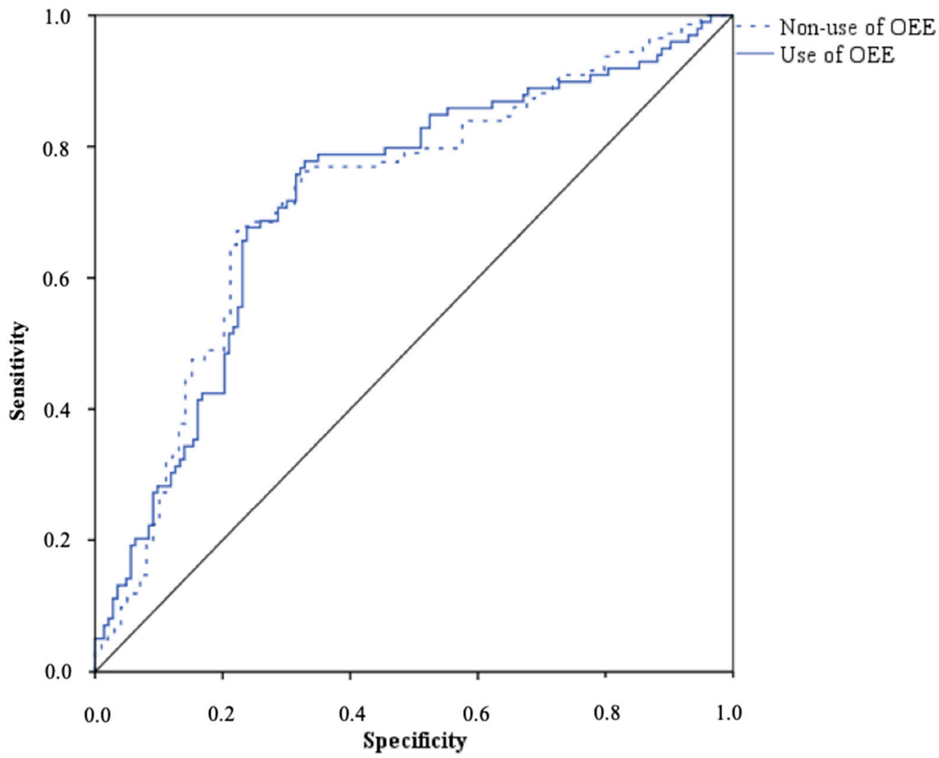

Figure 3. Sensitivity of the dependent variable Open Emotional Expression (OEE). Source: Own elaboration.

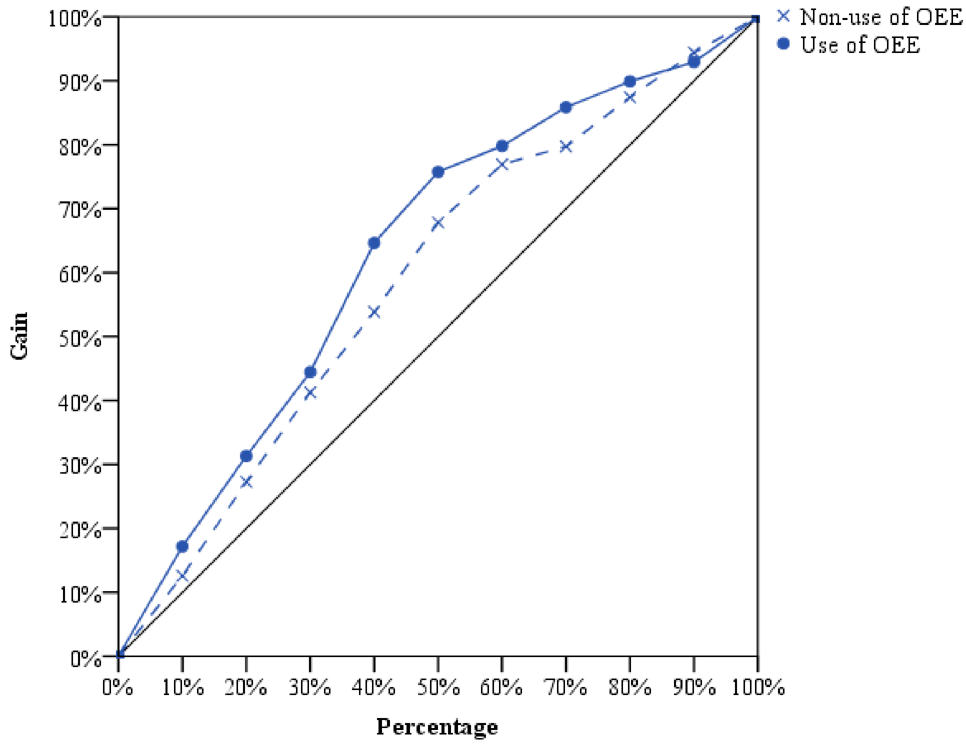

Figure 4. Gain of the dependent variable Open Emotional Expression (OEE). Source: Own elaboration.

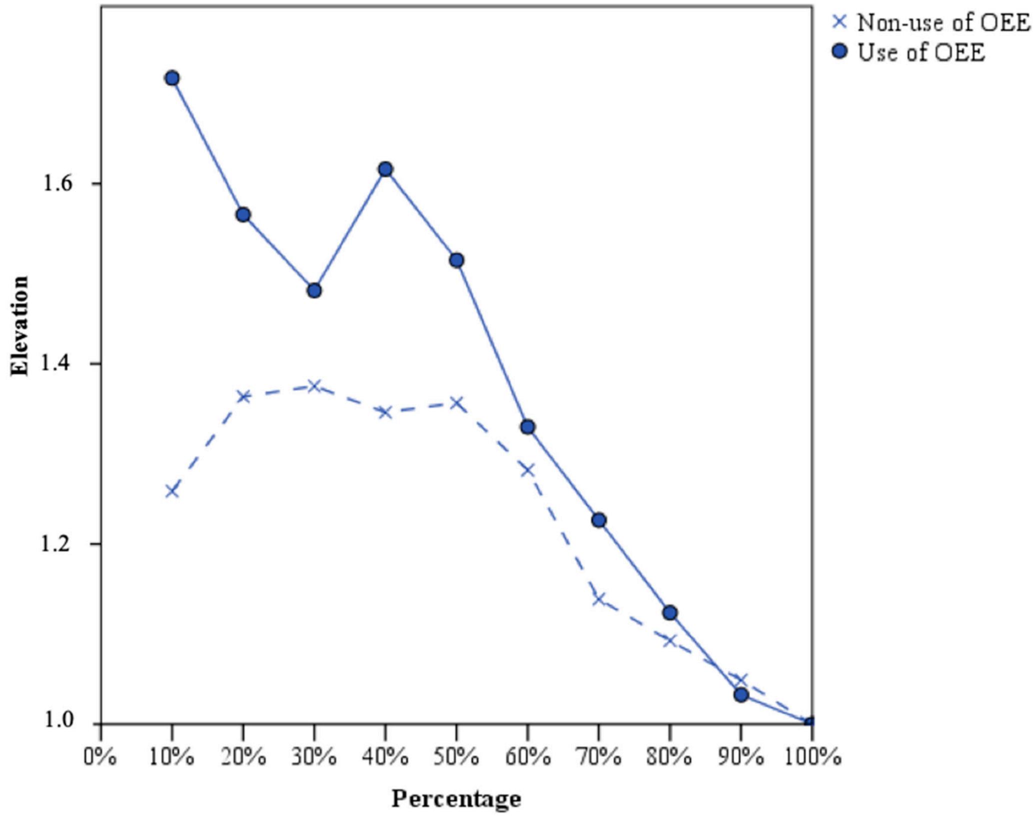

Figure 5. Elevation of the dependent variable Open Emotional Expression (OEE). Source: Own elaboration.

4. Discussion

The main objective of this study was to design an ANN predictive model with the ability to predict FES (defined by violent or maladaptive behaviors) based on certain sociodemographic variables, coping strategies, levels of perceived stress and resilience.

First, the results indicated that the predictive model "backpropagation" with three layers (input, hidden and output) was fully functional as expected [49]. H1 is confirmed, i.e., it is possible to program an ANN with learning capability [49] placing the initial learning rate value at 0.4, in line with previous results [51]. In order to optimize the learning capacity, three phases were included, two of which were for learning. In relation to this, the first one used approximately 70% of the cases to learn to predict the results of the neuron output OEE (training phase) and 20% to adjust the network (test phase) [49].

Secondly, the study of synaptic weights and standardized significance confirms the existence of variables capable of predicting the use or non-use of OEE (H2). The variables that had the greatest contribution to the network through the input neurons were coping strategies. The avoidance coping strategy was the one that contributed most to the predictive value of the network. Coping strategies are mostly more important for the network than stress levels or resilience, although the latter two variables also contribute 41.4% and 20.1%, respectively. It seems that coping strategies are composed of complex systems of reaction to certain situations perceived as stressful [49], so that when you evaluate the contribution of a strategy to the network, you may also be implicitly assessing a stress component. According to ANN, those who implement the avoidance strategy are more likely to behave violently. This only reflects the complexity of violent behavior in the educational field [17,29].

Contrary to what might be assumed, sociodemographic variables hardly played a relevant role in the prognosis of violent behavior, interpreted as a greater use of the OEE coping strategy. Thus, for example, although there may be gender differences in stress levels [39] or resilience [32], this does not substantially affect the predictive capacity of the network. These variables could have been eliminated. The network would have gained in simplicity and processing speed, but would have decreased in predictive capacity, which is why it was decided to include these variables as well [40]. On the other hand, the synaptic weights of the different types of roles in the network invite reflection on the relevance of teachers as positive models [12,27–29,36,37].

Regarding stress, it is proven that it is a predictive variable, coinciding with the stress model [1] and with further studies [3,34,52,53]. It is necessary to learn to use the most functional coping strategies and to manage emotions and stress [25,26,28,29]. The allocation of different synaptic weights according to the coping strategy supports its factorial structure [23,24,31].

Thirdly, we evaluated the usefulness of ANN through sensitivity, gain and elevation, obtaining a positive evaluation of its predictive capacity, confirming H3. The reserve phase, consisting of approximately 10% of cases, was also used to evaluate the functioning of the network using new cases to avoid contamination following the guidelines of Schiller et al. [22]. The evaluation of the network confirms that the results are not due to chance and that, under certain parameters (input and hidden layer), the educational community can make aggressive or violent use of its emotions by reacting violently (output layer) or in a dysfunctional way in line with expectations [12,13,25,29,37,49].

4.1. Applicability

With regard to the applicability of this study, it is clear how artificial neural networks represent a feasible psychometric strategy to assess the complex relationships between variables in the educational field. The interpretation of the synaptic weights goes beyond the capacity to maintain covariant relationships between the variables, but manages to introduce the predictive capacity into the model. This is very useful for society and, even more so, for the school environment, where the use of neural networks to study educational phenomena is currently in a phase of expansion, together with "machine learning" and artificial intelligence [41,42,54].

The psychological and emotional conditions of the educational community and stressors impact on their health and wellbeing [13,15], hence the need to detect and prevent associated factors. Since it has been shown in this research that stress and avoidance play a relevant role in the genesis of violent behavior as a coping strategy, these variables should be the focus of attention when designing programs and fitted interventions to improve the social environment and thus contribute to a sustainable psychology of the educational community.

Having said that, the ability to predict violent behavior in the educational community, thanks to the ANNs, has profound practical implications. For example, this model could be a key factor within the vocational and employment environment, specifically in recruitment processes for new professors. Along these lines, it should be studied the possibility of including psychological variables in the processes of competitive examinations for accessing to the teaching profession. Knowing which variables best predict an individual's future functioning, and always assuming a bias, it would be feasible to look for those desired traits in the aspirants.

Besides, if the variables that predict violent behavior can be measured, as is in this case, stress levels and other variables could be monitored to detect peaks, avoid major problems, prevent conflicts and teach those strategies that encourage the usage of other strategies more appropriate to improve the coexistence of the educational community. The training developed for professors, families and students should include instruction in resilience, emotional management, seeking social support and strategies to stop perceiving certain stimuli as a threat (related to stress). It could be organized as a subject implemented from primary education to university, and an essential aspect of the curriculum that qualifies to teach.

4.2. Limitations and Future Lines of Research

As for limitations, the name given to the religious coping strategy today could be adapted by that of spirituality since it does not have to be associated with a particular religion. In fact, some authors use it as the equivalent [9]. The participation of families was low in the sample but statistically sufficient for network calculations.

With regard to future lines of research, it is considered appropriate to add more variables to the predictive equation, trying not to overload the neural network. It would also be interesting to increase the number of participants and countries in order to foster the generalization of the results to other contexts, promoting comparative studies. More research is needed to understand the complex relationship between the variables.

5. Conclusions

Throughout this paper we illustrate how violent behavior can be seen as a coping strategy that works as a variable dependent on other factors such as resilience (or lack thereof), stress levels and the implementation of other coping strategies through a model based on artificial neural networks. Considering violent behavior as a coping strategy in the face of certain variables (personal and environmental), it is possible to develop an ANN by means of a predictive "backpropagation" model with three layers. The model was able to correctly predict the absence or presence of violent behavior in four out of five cases not previously seen or studied by the network, thus demonstrating the learning capacity of the network and the good fit of the model. In order for the measures proposed in the future to be sustainable, it will be necessary to have a holistic vision of the phenomenon and to rely on predictive models.

Author Contributions: Conceptualization, F.M.M.R. and J.P.M.R.; methodology, F.M.M.R. and J.P.M.R.; software, J.P.M.R.; validation, F.M.M.R. and J.P.M.R.; formal analysis J.P.M.R.; investigation, F.M.M.R. and J.P.M.R.; resources, F.M.M.R.; data curation, F.M.M.R. and J.P.M.R.; writing—original draft preparation, J.P.M.R. and F.M.M.R.; writing—review and editing, F.M.M.R. and J.P.M.R.; visualization, F.M.M.R.; supervision, F.M.M.R. and J.P.M.R.; project administration, F.M.M.R. and J.P.M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Lazarus, R.; Folkman, S. *Estrés y Procesos Cognitivos*; Editorial Martínez Roca: Madrid, Spain, 1986.
2. Naciones Unidas. *Informe de los Objetivos de Desarrollo Sostenible*; Naciones Unidas: New York, NY, USA, 2019.
3. Turner, A.I.; Smyth, N.; Hall, S.J.; Torres, S.J.; Hussein, M.; Jayasinghe, S.U.; Ball, K.; Clow, A. Psychological stress reactivity and future health and disease outcomes: A systematic review of prospective evidence. *Psychoneuroendocrinology* **2020**, *114*, 104599. [CrossRef] [PubMed]
4. Cerezo, F.; Sánchez, C.; Ruiz, C.; Arense, J.J. Adolescents and preadolescents' roles on bullying, and its relation with social climate and parenting styles. *Rev. Psicodidact.* **2015**, *20*, 139–194. [CrossRef]
5. Cerezo, F.; Méndez, I. Agresores en bullying y conductas antisociales. *Eur. J. Investig. Health Psychol. Educ.* **2015**, *3*, 5–14. [CrossRef]
6. Ribeiro, I.J.; Pereira, R.; Freire, I.V.; De Oliveira, B.G.; Casotti, C.A.; Boery, E.N. Stress and quality of life among university students: A systematic literature review. *Health Prof. Educ.* **2018**, *4*, 70–77. [CrossRef]
7. Morales Rodríguez, F.M. Estrategias de afrontamiento en una muestra de estudiantes universitarios. *Int. J. Dev. Educ. Psychol. INFAD Rev. Psicol.* **2018**, *2*, 289–293. [CrossRef]
8. Sutcliffe, J.H.; Greenberger, P.A. Identifying psychological difficulties in college athletes. *J. Allergy Clin. Immunol. Pract.* **2020**, *8*, 2216–2219. [CrossRef] [PubMed]
9. Lal, A.; Tharyan, A.; Tharyan, P. The prevalence, determinants and the role of empathy and religious or spiritual beliefs on job stress, job satisfaction, coping, burnout, and mental health in medical and surgical faculty of a teaching hospital: A cross-sectional survey. *Rev. Med. Interne* **2020**, *41*, 232–240. [CrossRef]
10. Giunchi, M.; Vonthron, A.M.; Ghislieri, C. Perceived job insecurity and sustainable wellbeing: Do coping strategies help? *Sustainability* **2019**, *11*, 784. [CrossRef]
11. Morales, F.M. Relaciones entre afrontamiento del estrés cotidiano, autoconcepto, habilidades sociales e inteligencia emocional. *Eur. J. Educ. Psychol.* **2018**, *10*, 41. Available online: https://formacionasunivep.com/ejep/index.php/journal/article/view/121 (accessed on 23 August 2020). [CrossRef]
12. Erschens, R.; Loda, T.; Herrmann-Werner, A.; Keifenheim, K.E.; Stuber, F.; Nikendei, C.; Zipfel, S.; Junne, F. Behaviour-based functional and dysfunctional strategies of medical students to cope with burnout. *Med. Educ. Online* **2018**, *24*, 1554876. [CrossRef]
13. Martínez, J.P.; Méndez, I.; Ruiz-Esteban, C.; Cerezo, F. Validación y fiabilidad del Cuestionario sobre Acoso entre Estudiantes Universitarios (QAEU). *Rev. Fuentes* **2020**, *22*, 88–104. [CrossRef]
14. Anjum, A.; Muazzam, A.; Manzoor, F.; Visvizi, A.; Nawaz, R. Mediating bullying and strain in higher education institutions: The case of pakistan. *Sustainability* **2019**, *11*, 2244. [CrossRef]
15. Méndez, I.; Jorquera, A.B.; Ruiz-Esteban, C.; Martínez, J.P.; Fernández-Sogorb, A. Emotional intelligence, bullying, and cyberbullying in adolescents. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4837. [CrossRef] [PubMed]
16. Martínez, J.P. Cómo se defiende el profesorado de secundaria del estrés: Burnout y estrategias de afrontamiento. *Rev. Psicol. Trab. Organ.* **2015**, *31*, 1–9. [CrossRef]
17. Martínez, J.P.; Méndez, I.; Ruiz-Esteban, C.; Fernández-Sogorb, A.; García-Fernández, J.M. Profiles of Burnout, Coping Strategies and Depressive Symptomatology. *Front. Psychol.* **2020**, *11*, 591. [CrossRef] [PubMed]
18. Alhija, F.N.A. Teacher stress and coping: The role of personal and job characteristics. *Procedia Soc. Behav. Sci.* **2015**, *185*, 374–380. [CrossRef]
19. Méndez, I.; Ruiz-Esteban, C.; Martínez, J.P.; Cerezo, F. Bullying in higher education. *Behav. Psychol. Conduct.* **2019**, *27*, 55–68.
20. Sandín, B.; Chorot, O. Cuestionario de aprontamiento del estrés (CAE): Desarrollo y validación preliminar. *Rev. Psicopatol. Psicol. Clin.* **2003**, *8*, 39–54. [CrossRef]
21. De La Rosa-Rojas, G.; Chang-Grozo, S.; Delgado-Flores, L.; Oliveros-Lijap, L.; Murillo-Pérez, D.; Ortiz-Lozada, R.; Vela-Ulloa, G.; Yhuri, C.N. Levels of stress and coping strategies in medical students compared with students from other schools. *Gac. Med. Mex.* **2015**, *4*, 443–449. Available online: https://bit.ly/3fbMMLb (accessed on 11 August 2020).
22. Schiller, J.H.; Stansfield, R.B.; Belmonte, D.C.; Purkiss, J.A.; Reddy, R.M.; House, J.B.; Santen, S.A. Medical students' use of different coping strategies and relationship with academic performance in preclinical and clinical years. *Teach. Learn. Med.* **2018**, *30*, 15–21. [CrossRef]

23. Xu, N.; Liu, Y. Coping strategy mediates the relationship between body image evaluation and mental health: A study with Chinese college students with disabilities. *Disabil. Health J.* **2020**, *13*, 100830. [CrossRef] [PubMed]
24. Richardson, C.M.E.; Hoene, T.H.M.; Rigatti, H.L. Self-critical perfectionism and daily drinking to cope with negative emotional experiences among college students. *Pers. Individ. Differ.* **2020**, *156*, 109773. [CrossRef]
25. Arias-Gundín, O.; Vizoso, C.M. Relationship between approach coping, burnout and engagement in future educators. *Estud. Sobre Educ.* **2018**, *35*, 409–427. [CrossRef]
26. Enrique, A.; Mooney, O.; Salamanca-Sanabria, A.; Lee, C.T.; Farrell, S.; Richards, D. Assessing the efficacy and acceptability of an internet-delivered intervention for resilience among college students: A pilot randomised control trial protocol. *Internet Interv.* **2019**, *17*, 100254. [CrossRef]
27. Kyriakou, K.; Petinou, K.; Phinikettos, I. Risk factors for voice disorders in university professors in cyprus. *J. Voice* **2018**, *32*, 643.e1–643.e9. [CrossRef] [PubMed]
28. Puigbó, J.; Edo, S.; Rovira, T.; Limonero, J.T.; Fernández-Castro, J. Influencia de la inteligencia emocional percibida en el afrontamiento del estrés cotidiano. *Ansiedad Estrés* **2019**, *25*, 1–6. [CrossRef]
29. Enns, A.; Eldridge, G.D.; Montgomery, C.; Gonzalez, V.M. Perceived stress, coping strategies, and emotional intelligence: A cross-sectional study of university students in helping disciplines. *Nurse Educ. Today* **2018**, *68*, 226–231. [CrossRef]
30. Alvarado, R. Duelo y alexitimia. *Rev. Digit. Med. Psicosom. Psicoter.* **2013**, *3*, 1–13.
31. Hoffmann, C.F.A.; Geisler, F.C.M. Accept what you observe: A conditional process model linking mindfulness facets, threat appraisal, and perceived stress in German college students. *Pers. Individ. Differ.* **2020**, *156*, 109752. [CrossRef]
32. Jonason, P.K.; Talbot, D.; Cunningham, M.L.; Chonody, J. Higher-order coping strategies: Who uses them and what outcomes are linked to them. *Pers. Individ. Differ.* **2020**, *155*, 109755. [CrossRef]
33. Herrero, R.; Mira, A.; Cormo, G.; Etchemendy, E.; Baños, R.; García-Palacios, A.; Ebert, D.D.; Franke, M.; Berger, T.; Schaub, M.P.; et al. An Internet based intervention for improving resilience and coping strategies in university students: Study protocol for a randomized controlled trial. *Internet Interv.* **2019**, *16*, 43–51. [CrossRef] [PubMed]
34. Erdogan, E.; Ozdogan, O.; Erdogan, M. University students' resilience level: The effect of gender and faculty. *Procedia Soc. Behav. Sci.* **2015**, *186*, 1262–1267. [CrossRef]
35. Chmitorz, A.; Kunzler, A.; Helmreich, I.; Tüscher, O.; Kalisch, R.; Kubiak, T.; Wessa, M.; Lieb, K. Intervention studies to foster resilience—A systematic review and proposal for a resilience framework in future intervention studies. *Clin. Psychol. Rev.* **2018**, *59*, 78–100. [CrossRef]
36. Cantero-García, M.; Alonso-Tapia, J. Brief resilience scale in front children's behavior problems (BRS-BP). *An. Psicol.* **2018**, *34*, 531–535. [CrossRef]
37. Mérida-López, S.; Extremera, N. Cuando la falta de compromiso ocupacional del profesorado novel no es suficiente para explicar la intención de abandono: ¡la inteligencia emocional importa! [When pre-service teachers' lack of occupational commitment is not enough to explain intention to quit: Emotional intelligence matters!]. *Rev. Psicodidáctica* **2020**, *25*, 52–58. [CrossRef]
38. Lehrer, H.M.; Steinhardt, M.A.; Dubois, S.K.; Laudenslager, M.L. Perceived stress, psychological resilience, hair cortisol concentration, and metabolic syndrome severity: A moderated mediation model. *Psychoneuroendocrinology* **2020**, *113*, 104510. [CrossRef]
39. Ge, Y.; Xin, S.; Luan, D.; Zou, Z.; Bai, X.; Liu, M.; Gao, Q. Independent and combined associations between screen time and physical activity and perceived stress among college students. *Addict. Behav.* **2020**, *103*, 106224. [CrossRef]
40. Buscema, P.M.; Massini, G.; Breda, M.; Lodwick, W.A.; Newman, F.; Asadi-Zeydabadi, M. Artificial Neural Networks. In *Artificial Adaptive Systems Using Auto Contractive Maps*; Springer: New York, NY, USA, 2018; Volume 131, pp. 11–35. [CrossRef]
41. Qin, S.J.; Chiang, L.H. Advances and opportunities in machine learning for process data analytics. *Comput. Chem. Eng.* **2019**, *126*, 465–473. [CrossRef]
42. Kolachalama, V.B.; Garg, P.S. Machine learning and medical education. *NPJ Digit. Med.* **2018**, *1*, 54. [CrossRef]
43. Hahn, G.; Ponce-Álvarez, A.; Deco, G.; Aertsen, A.; Kumar, A. Portraits of communication in neuronal networks. *Nat. Rev. Neurosci.* **2019**, *20*, 117–127. [CrossRef]

44. Cohen, S.; Kamarck, T.; Mermelstein, R. A global measure of perceived stress. *J. Health Soc. Behav.* **1983**, *24*, 385–396. [CrossRef] [PubMed]
45. Remor, E. Psychometric properties of a European Spanish version of the Perceived Stress Scale (PSS). *Span. J. Psychol.* **2006**, *9*, 86–93. [CrossRef]
46. Sinclair, V.G.; Wallston, K.A. The development and psychometric evaluation of the brief resilient coping scale. *Assessment* **2004**, *11*, 94–101. [CrossRef] [PubMed]
47. Moret-Tatay, C.; Fernández, J.J.; Civera, C.; Navarro-Pardo, E.; De la Hera, C.M.A. Psychometric properties and Factor structure of the BRCS in an elderly Spanish sample. *An. Psicol.* **2015**, *31*, 1030–1034. [CrossRef]
48. Caycho-Rodríguez, T.; Ventura-León, J.; García-Cadena, C.H.; Tomás, J.M.; Domínguez-Vergara, J.; Daniel, L.; Arias-Gallegos, W.L. Psychometric evidence of a brief measure of resilience in non-institutionalized Peruvian older adults. *Psychosoc. Interv.* **2018**, *27*, 73–79. [CrossRef]
49. International Business Machines. *IBM SPSS Neural Networks 20*; Microsoft: New York, NY, USA, 2011.
50. IBM Corp. *IBM SPSS Statistics for Windows*; IBM Corp: New York, NY, USA, 2016.
51. Zhang, S.; Liu, Q.; Chen, W.; Wang, Q.; Huang, Z. Interactive networks and social knowledge construction behavioral patterns in primary school teachers' online collaborative learning activities. *Comput. Educ.* **2017**, *104*, 1–17. [CrossRef]
52. Hinds, E.; Jones, L.B.; Gau, J.M.; Forrester, K.K.; Biglan, A. Teacher distress and the role of experiential avoidance. *Psychol. Sch.* **2015**, *52*, 284–297. [CrossRef]
53. Ferguson, K.; Frost, L.; Hall, D. Predicting teacher anxiety, depression, and job satisfaction. *J. Teach. Learn.* **2012**, *8*, 27–42. [CrossRef]
54. Dillenbourg, P. The evolution of research on digital education. *Int. J. Artif. Intell. Educ.* **2016**, *26*, 544–560. [CrossRef]