Acta Psychologica 259 (2025) 105324

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Mental illness risk prediction in high school students using artificial neural network

Samuel Encarnação [a,b,c,d], Paula Fortunato Vaz [e], Filipe Vaz [f,*], Álvaro Fortunato Vaz [g], António Miguel de Barros Monteiro [b,c]

[a] Department of Physical Activity and Sport Sciences, Universidad Autónoma de Madrid (UAM), Ciudad Universitaria de Cantoblanco, 28049 Madrid, Spain
[b] Department of Sport Sciences, Instituto Politécnico de Bragança (IPB), 5300-253 Bragança, Portugal
[c] Live Well Research Centre for Active Living and Wellbeing, Instituto Politécnico de Bragança, Portugal
[d] CI ISE, Instituto Superior de Ciências Educativas do Douro, 4560 547 Penafiel, Portugal
[e] Transdisciplinary Research Center in Education and Development (CITeD), Bragança Polytechnic University
[f] Unidade de Saúde Pública (USP), Unidade Local de Saúde do Nordeste (ULSNE), 5301-852 Bragança, Portugal
[g] Faculty of Medicine and Biomedical Sciences, University of Algarve, Campus da Penha, 8005-139 Faro, Portugal

A R T I C L E I N F O

Keywords:
Mental illness
Psychological distress
Deep learning
Quality of life
Well-being

A B S T R A C T

Introduction: The sustainable development goals of the United Nations 2030 agenda, goal number 3 – Good health and well-being- align with student mental health.
Objective: To conduct an artificial neural network (ANN) to predict the students' self-reported mental health dimensions.
Methods: A cross-sectional and observational study enrolling sociodemographic and health state data from 2050 university students aged (18–30 years). Results: The best algorithm's result was by predicting the students' depressive state with 97 % accuracy (weighted average = [precision = 0.79 %, recall = 0.79 %, F-1 score 0 0.79 %, cross-validation (73 %)]), while dimensions such overall mental health self-perception (validation accuracy = 60 %) and lack of interest in performing their activities of daily living [(ADLs), validation accuracy = 67 %], presented inferior predictions.
Conclusions: The ANN best predicted the university students' depressive state (73 %).

1. Introduction

Mental health is one of the most impacting global health issues, and it has been debated nowadays. The World Health Organization (WHO) describes mental health by “a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community” (WHO, 2023a). This subject has gained big scientific consideration over the years because suicide increased by 13 % in 2010 and become the fourth cause of death among those aged 15–29 years old (WHO, 2023a).

Within the sustainable development goals of the United Nations (UN) 2030 agenda, goal number 3 is highlighted – where good health and well-being specifically mention the need to ensure healthy lives and promote well-being for all at all ages (Martin, 2023). Moreover, students' mental health is a global goal because it has direct implications for an adequate learning process and professional preparation for the life in society (Mofatteh, 2020).

Even with the crescent incidence of psychological health issues in young persons, it keeps highly stigmatized by the society, which impairs people from looking for specialized help (Gaiha et al., 2020). Considering the importance of developing protective actions and minimizing the risks provoked by mental illness on a worldwide scale, in 2019, the WHO launched the WHO Special Initiative for Mental Health (2019–2023): Universal Health Coverage for Mental Health, which aims to provide accessible mental health care services in the primary health system of the low and high income countries (WHO, 2023b).

Despite the WHO efforts, mental health keeps being a serious global health issue at young age (WHO, 2023a). The latest neuroscience evidence has shown that chronic stress has been linked to the development of psychiatric disorders during adolescence 6. In a cross-sectional study performed with data collected from 2018 adolescents, Angelina et al. (2021) verified that dietary behavior and sleep quality were considered

* Corresponding author.
E-mail address: filipe.vaz@ulsne.min-saude.pt (F. Vaz).

https://doi.org/10.1016/j.actpsy.2025.105324
Received 12 December 2024; Received in revised form 19 April 2025; Accepted 21 July 2025
Available online 28 August 2025

protective factors against psychological distress, and variables such as not having a confidant, frequent argument with parents, feeling constantly worried about daily things, have a chronic illness and have some mental illness were significantly risk factors for psychologic distress.

Regarding environmental determination, the academic setting acknowledges a pivotal juncture in a students' life, as they begin to discover the daily life experiences, that can be both positive and challenging, which require regulated self-control and self-efficacy (Shengyao et al., 2024). Further to, during the degree scholarship, the students are also at higher risk of having the first contact with drug use and abuse, which poses a high mental health risk (Amaro et al., 2021). As a consequence, the possible aggressors to mental health at young ages can affect in the long-term the adequate functioning of the persons' physical, psychological/cognitive, and quality of life during the adult life (Zihl & Reppermund, 2023). The study of Park et al. showed that depressive symptoms during adolescence can significantly increase the cardiovascular disease risk at adulthood. Therefore, the study of Kim et al. (2024) showed that depressive symptoms in adolescence predicted memory performance in adulthood, which in turn is a risk factor for agraves in mental health during old age (Szymkowicz et al., 2023).

Considering that some adolescents cannot present an ideal brain structure formation, they may not be well prepared to adequately respond to distress during their academic time, especially in the early years of university, where the challenges and psychological pressure can exceed the capacity of adaptation of these individuals (Sisk & Gee, 2022). Then, identifying the most important factors that could help overall health and mental health professionals do underlying interventions to protect the youths' mental health is imperative (Gautam et al., 2024).

In a recent systematic review, Campbell et al. (2022) showed that United Kingdon (UK) students who experienced traumas in their childhood identified as LGBTQ, and those who had autism were the most liked group in risk of developing mental health issues. In addition, the authors noted that lack of engagement with learning and leisure activities and consequent poor literacy were considered the main behaviors associated with poor mental health (Campbell et al., 2022).

In a literature review, Mofatteh (2020) identified six risk factors (psychological, academic, biological, lifestyle, social and financial) that were associated with undergraduate students' stress, anxiety, and depression symptoms. In a recent observational study, Zhang et al. (2024) identified that positive interactions with the environment during adolescence are accumulated by the ventromedial e prefrontal cortex, which is related to outcomes of motivated behavior that contributes to improved value-based decision-making in adulthood, thus safeguarding against mental illness during adulthood and the next phases of the life.

The Individuals' brain functioning is very relevant to youths' mental health (Whittle et al., 2025). Despite the significant amount of research regarding the risk factors for the students' mental health (Gaiha et al., 2020; Sisk & Gee, 2022), the research that performs integrated analyses compiling external influencing factors and self-perception outcomes is very limited. Adding preliminary results on this topic, in a cross-sectional study, Ratanasiripong et al. (2018) found that four factors predicted depression in 441 undergraduate students being self-esteem, family economic status, resiliency, and year in school. Complementarily, in a recent systematic review Campbell et al. (2022) identified the factors most likely to mental illness risk were the experience of trauma in childhood, individuals identified as LGBTQ, and autist students.

In contrast to the actual evidence, mental health is a complex, theme determined by several interactions between social environment, such as sociodemographic conditions, behavioral and the properly individuals' psychological capabilities (Remes et al., 2021). In this way, approaches that can interpret and learn complex data can be very useful for deep comprehension of extended datasets and can allow to effective inferences to protect students' mental health during the course of their university studies (Arji et al., 2023; Squires et al., 2023).

Artificial intelligence (AI) has been widely used as a potent tool to make precise predictions and help professionals identify risks and treat patients with better precision and time-efficiently (Choudhury & Asan, 2020; Mohammed & Aljanabi, 2023). For example, artificial neural networks (ANN) are computational arranges that mimic very similarly the human brain functioning (Choudhury & Asan, 2020). ANN could work unsupervised (deep learning), meaning it can learn complex data patterns by its comprehension capacity and produce precise and applied outputs for the real-life (Taye, 2023). Then, ANN application could be very useful in neuroscience, enabling the development of better structured interventions and early treatment and protecting students against mental health risks (Badrulhisham et al., 2024).

In this sense, we aimed to apply a deep learning algorithm to understand how the weights from sociodemographic, behavioral, environmental, and self-reported mental health indicators predict some of the university students' mental health dimensions. In addition, this study intends to identify the variables that influence adolescents' mental health. We hypothesize that the self-reported mental health dimensions could better explain the university student's mental health than another variable.

2. Methods

2.1. Study design

This is a cross-sectional and observational study enrolling data collected from the application of a questionnaire comprising sociodemographic and health state variables from university students. The Scientific Board of the University of Porto, Portugal approved (Identification number: E18082). The approbation statement can be assed in the supplementary material (see S1). Before data collection, the objectives of this study were explained to all participants, and signed informed consent was obtained individually.

2.2. Participants

The dataset was collected from a project called "Characterizing access to health care: higher education students studying in the city of Bragança" that happened during the years of 2018–2019 (immediately before the start of the Coronavirus disease pandemic) at the Public Health Unit of Bragança, City in the North of Portugal. In total, 2050 young adults aged between 18 and 36 years, enrolling in the degree, master degree, and Higher Professional Technical Courses (HPTC) at the Instituto Politécnico de Bragança (IPB), participated in this study. With the support of a psychology professional, we selected three mental health metrics of interest as follows, 1st: overall self-reported mental health; 2nd: self-reported depressive state; and 3rd: self-reported lack of interest in performing the activities of daily living (ADLs). Table 1 describes the participants' characteristics by gender in absolute and percentual values. We performed a two simple proportions Chi-square test (X^2) to calculate the proportion of participants between sexes adopting the alpha <0.05 for statistical significance (Abadi et al., 2016; Haslwanter, 2016). The participants agreed to the research before reading and answering the questionnaire after the research explanation, which can be visualized in the following supplementary material (see S2).

2.3. Data collection

We formed a group of interviewers who applied a questionnaire to all participants in person. Then, the students received the questionnaire from their professors at the end of their classes; thus, that moment was determined for the students to answer the questions. The students should ask for help if they are in doubt when answering the questionnaire. After preparation, the group of interviewees collected a large amount of data regarding sociodemographic and overall health aspects

Table 1
Targeted variables and participant's characteristics.

Variable	Mal. (*N* = 831)	%	Fem. (*N* = 1219)	%	X^2	*p*
Overall mental health						
Very good	384	46.2	378	31	1.0784e-30	1
Good	304	36.6	568	46.6	1.667	0.19
Reasonable	99	11.9	218	17.9	0.985	0.32
Bad	20	2.4	43	3.5	0.001	0.96
Too bad	13	1.6	6	0.5	0.004	0.94
Not reported	11	1.3	6	0.5	1.0883e-30	1
Felling down and depressed						
Never	422	50.8	405	33.2	5.656	**0.01**
Some days	318	38.3	644	52.8	3.674	0.05
Over than half the days	45	5.4	111	9.1	0.542	0.46
Almost always	24	2.9	44	3.6	7.7334e-31	1
Not reported	22	2.6	15	1.2	0.04	0.83
Lack of int. perf. the ADLs						
Never	199	23.9	185	15.2	1.884	0.16
Some days	484	58.2	845	69.3	2.207	0.13
Over than half the days	84	10.1	125	10.3	1.3004e-30	1
Almost always	43	5.2	48	3.9	0.010	0.91
Not reported	21	2.5	16	1.3	0.010	0.91
Age						
18–20 years	313	38	571	47	1.309	0.25
21–23 years	331	40	459	38	0.021	0.88
24–26 years	118	14	126	10	0.426	0.51
> de 26 years	69	8	63	5	0.329	0.56
Country						
Portugal	639	76.9	1019	83.5	0.987	0.32
Cabo Verde	84	10.1	102	8.4	0.029	0.86
Brazil	38	4.6	33	2.7	0.115	0.73
São Tomé and Príncipe	23	2.8	31	2.5	1.081e-30	1
Spain	15	1.8	4	0.3	0.120	0.72
Angola	12	1.4	5	0.4	1.394e-32	1
Mozambique	5	0.6	8	0.7	1.403e-30	1
Belarus	3	0.4	3	0.2	1.0581e-30	1
Guinea-Bissau	NA	NA	4	0.3	NA	NA
Pakistan	3	0.4	1	0.1	6.522e-31	1
China	NA	NA	2	0.2	NA	NA
India	2	0.2	NA	NA	NA	NA
Poland	2	0.2	2	0.2	0	1
France	1	0.1	NA	NA	NA	NA
Switzerland	NA	NA	1	0.1	NA	NA
South Africa	1	0.1	NA	NA	NA	NA
Armenia	1	0.1	NA	NA	NA	NA
Italy	1	0.1	1	0.1	0	1
East Timor	1	0.1	1	0.1	0	1
Nepal	NA	NA	1	0.1	NA	NA
Morocco	NA	NA	1	0.1	NA	A
Scholarly level						
HPTC	110	13	114	90.4	0.339	9.55
Degree student	614	74	956	78.4	0.318	0.57
Master's Degree student	107	13	149	12.2	1.2275e-30	1
Chronic illness						
Yes	68	8	158	13	0.851	0.35
No	739	89	1048	86	0.182	0.66
Not reported	24	3	13	1	0.255	0.61
Enrollment						
4–12 months	304	36.6	477	39.1	0.047	0.82
13–24 months	176	21.2	245	20.1	0.0003	0.98
25–36 months	136	16.4	222	18.2	0.022	0.88
>36 months	211	25.4	266	21.8	0.187	0.66

Table 1 (*continued*)

Variable	Mal. (*N* = 831)	%	Fem. (*N* = 1219)	%	X^2	*p*
Not reported	4	0.5	9	0.7	0.187	1
Father's scholarly						
Incomplete First cycle	6	1	7	1	0	1
First cycle	194	23	370	30	0.924	0.33
Third cycle	222	27	379	31	0.218	0.64
High school	218	26	234	19	1.032	0.30
Degree	106	13	116	10	0.196	0.65
MDegree or DrDegree	40	5	38	3	0.130	0.71
Not reported	45	5	75	6	2.9644e-32	1
Mother's scholarly						
Incomplete First cycle	8	1	11	1	0	1
First cycle	137	16	283	23	1.146	0.28
Third cycle	210	25	377	31	0.620	0.43
High school	273	33	324	27	0.595	0.44
Degree	129	16	142	12	0.373	0.54
MDegree or DrDegree	39	5	34	3	0.130	0.71
Not reported	35	4	48	4	0	1
Current smoke habits						
Never smoked	473	57	764	63	0.520	0.47
Former smoker	22	3	34	3	0	1
Smoke occasionally	114	14	152	12	0.044	0.83
1–10 cigarettes per day	137	16	195	16	0	1
11–20 cigarettes per day	58	7	45	4	0.384	0.53
>21 cigarettes per day	10	1	NA	NA	NA	NA
Not reported	17	2	29	2	0	1
Drink beer or cider						
Never	126	15	378	31	6.352	**0.01**
Drink occasionally	239	29	447	36.7	1.017	0.31
1–2× week	240	29	276	22.6	0.761	0.38
3–4× week	137	16	90	7.4	2.795	0.09
5–6× week	53	6	23	1.9	1.266	0.26
Every day	36	4	5	0.4	1.570	0.21
Drink wine						
Never	326	39	679	55.7	4.943	**0.02**
Drink occasionally	312	38	400	32.8	0.385	0.53
1–2× week	142	17	109	8.9	2.235	0.13
3–4× week	28	3	26	2.1	2.3275e-31	1
5–6× week	13	2	1	0.1	0.398	0.53
Every day	10	1	4	0.3	1.063e-30	1
Drink white spirit beverages						
Never	184	22	290	23.8	0.018	0.89
Drink occasionally	334	40	536	44	0.184	0.66
1–2× week	207	25	310	25.4	2.5244e-31	1
3–4× week	79	10	64	5.3	0.968	0.32
5–6× week	14	2	16	1.3	1.084e-30	1
Every day	13	2	3	0.2	0.294	0.58
Cannabis before enrolling						
Never	573	69	989	81.1	3.29	0.06
Use occasionally	136	16	162	13.3	0.115	0.73
1–2× week	37	4	34	2.8	0.006	0.93
3–4× week	34	4	18	1.5	0.420	0.51
5–6× week	13	2	4	0.3	0.171	0.67
Every day	38	5	12	1	1.546	0.21
Ecstasy						
Never	797	95.9	1200	98.4	0.406	0.52
Use occasionally	33	4	15	1.2	0.639	0.42

(*continued on next page*)

Table 1 (*continued*)

Variable	Mal. (N = 831)	%	Fem. (N = 1219)	%	X^2	p
1–2× week	1	0.1	3	0.2	0.255	0.61
Every day	NA	NA	1	0.1	NA	NA
Amphetamines						
Never	821	98.8	1213	99.5	9.4895e-29	1
Use occasionally	7	0.8	6	0.5	1.0591e-30	1
1–2× week	3	0.4	NA	NA	NA	NA
Cocaine						
Never	813	97.8	1211	99.3	0.087	0.76
Use occasionally	17	2	7	0.6	0.062	0.80
1–2× week	NA	NA	1	0.1	NA	NA
3–4× week	1	0.1	NA	NA	NA	NA
LSD						
Never	822	98.9	1215	99.7	1.5246e-28	1
Use occasionally	9	1.1	4	0.3	1.0632e-30	1

Data are reported in absolute and percentual (%) values. MAL, male, FEM, female, X^2, p, 95 % confidence interval for statistical significance level at $p < 0.05$, NA, not available, e-, scientific notation. Significant values are highlighted in bold.

listed with their respective categories: 1st: Age [18–20, 21–23, 24–26, >26 years], 2nd. gender [male, female], 3rd: to be foreign [native or foreign], 4th: level of scholarly [degree, master degree or HPTC], 5th: city before enroll in the IPB [city's name, Bragança's district or other district], 6th: live out of Portugal [other district, Bragança's district, or to be an exchanger], 7th: father's scholarly [first cycle, third cycle, high school, degree, master degree, doctor degree], 8th: mother's scholarly [first cycle, third cycle, high school, degree, master degree, doctor degree], 9th: smoke habits before enroll on IPB [never smoked before, smoke occasionally, 1–10 cigarettes per day, 11–20 cigarettes per day, >21 cigarettes per day, former smoker, not reported], 10th: current smoke habits [never smoked before, smoke occasionally, 1–10 cigarettes per day, 11–20 cigarettes per day, >21 cigarettes per day, former smoker, not reported], 11th: drink cider on the last 6 months [never, drink occasionally, 1–2× week, Never, 3–4× week, 5–6× week, every day], 12th: drink wine on the last 6 months [never, drink occasionally, 1–2× week, Never, 3–4× week, 5–6× week, every day], 13th: drink white/spirit beverages on the last 6 months [never, drink occasionally, 1–2× week, Never, 3–4× week, 5–6× week, every day], 14th: drink more than 6 drinks in a day on the last 6 months [never, drink occasionally, 1× month, 2–3× month, 1–2× week, >3× week, not reported], 15th: drink and use drugs before enroll on IPB [yes, never, or not reported], 16th: use cannabis before enroll on IPB [never, use occasionally, 1–2 week, 3–4 week, 5–6 week, every day], 17th: use ecstasy before enroll on IPB [never, use occasionally, 1–2× week, every day], 18th: amphetamines before enroll on IPB [never, use occasionally, 1–2 week], 19th: use cocaine before enroll on IPB [never, use occasionally, 1–2× week, 3–4× week]m 20th: heroin before enroll on IPB [never, 3–4], 21st: LSD before enroll on IPB [never, use occasionally], 22nd: use other type of drug before enroll on IPB [never, used occasionally, 1–2× week, 3–4× week, every day], 23rd: number of sexual relation partners in the last 6 months [0, 1, 2, 3, 4, >5], 24th: vaginal sex with partner in the last 6 months [yes, no, not reported, not applicable], 25th: anal sex with partner in last 6 months [yes, no, not reported, not applicable], 26th: oral sex with partner in the last 6 months [yes, no, not reported, not applicable], 27th: vaginal sex with occasional partner in the last 6 months [yes, no, not reported, not applicable], 28th: anal sex with occasional partner in the last 6 months [yes, no, not reported, not applicable], 29th: oral sex with occasional partner in the last 6 months [yes, no, not reported, not applicable],30th: no condom sex in the last 6 months [not reported, stable and/or long-term relationship, use of another contraceptive method, do not have a condom, did not remember or devalued the use of a condom, trying to get pregnant], 31st: overall health self-perception [good, very good, reasonable, bad, too bad, not reported], 32nd: mental health self-perception [good, very good, reasonable, bad, too bad, not reported], 33rd: lack of interest in the activities of daily living [never, some days, more than half the days, almost always, not reported], 34th: feeling down, depressed [never, some days, more than half days, almost always, not reported], 35th: felling tired, with lack of energy [never, some days, more than half days, almost always, not reported], 36th: feeling bad with yourself [never, some days, more than half days, almost always, not reported], 37th: feeling nervous, anxious [never, some days, more than half days, almost always, not reported], 38th: trouble concentration [never, some days, more than half days, almost always, not reported], 39th: chronic illness [yes, no, not reported], 40th: health care services [yes, no, not reported], 41st: times that used hospital attendance during enrollment [0, 1–2×, 3–4×, >5×, not reported], 42nd: times that used health center attendance during enrollment [0, 1–2×, 3–4×, >5×, not reported], 43rd: times that locked for a private doctor [0, 1–2×, 3–4×, >5×, not reported], 44th: searched by other alternative health attendances [0, 1–2×, 3–4×, >5×, not reported], 45th: difficult to get healthcare during enrollment [yes, no, not reported], 46th: hardest attendances in healthcare [hospital, health center, lack of doctor, other reasons, not reported], 47th: difficulties cause inhibition to use healthcare [yes, no, not reported], 48th reasons to have difficulties in health care [lack of specialists, do not know the place, delayed attendance, economic reasons, lack of organization, not reported], 49th: level of satisfaction with the health services [too unsatisfied, unsatisfied, satisfied, to satisfied, not reported]. Initially, there was less than 5 % missing data; thus, as most codes were categorical, we preferred to clean the dataset, excluding the missing observations. The dataset used in this study is available to download on the GitHub platform, with the link present in the data availability statement session.

2.4. Artificial neural network implementation

We stored the data in a Microsoft EXCEL 365® spreadsheet. After this, we performed all analyses in PythonTM, a computational programming language (Python, 2023). Initially, we cleaned the data to find missing data or irregularities in the dataset. In the next step, to prepare the data to be inserted into the ANN, we applied a one-hot encoding technique to transform each answer category into binary classes that could be adequately identified and learned by the ANN (Haslwanter, 2016). After preparing data, we conducted a best-featuring selection analysis to identify better predictors of the targeted outcomes (Taye, 2023). To calculate the best features for the target mental health dimensions, we used the Chi-square test for goodness of fit (X^2), which tests if a real frequency of determined categoric variables differs from a hypothesized frequency (Unpingco, 2016). Then, we reallocated all independent variables into an array X (predictive array) and the target variable into an array y (predicted or target variable); then, we split the data into 30 % and 70 % for testing. After performing the model training, aiming to model the ANN structure, we performed hyperparameter tunning using "Early Stopping" technique to identify the best batch size and number of epochs in ANN hyperparameters for three different model optimizers (Adam, SGD, or RMSprop) (Yang & Shami, 2020). "Early Stopping" finds the best accuracy for prediction between all batch sizes and the number of epoch combinations, maximizing the algorithms' learning performance (Bartlett et al., 2023; Prechelt, 2012). Thus, we developed an ANN with three convolutional layers. In the first layer, using the "relu" (Rectified Linear Unit) function for activation of non-linear learning patterns in the ANN, the function "input_dim" to insert the number of independent variables (inputs) (n = 50). We also added the weights (W) or (number of initial neurons) of the matrix in the first hidden layer, described in Eq. (1), as follows:

$$W = \frac{k\ indepdent\ variables \pm dependent\ variable}{2} \tag{1}$$

Then, we added the "kernel_initializer" activating the function uniform, thus determining that the neurons in the first layer were drawn from a uniform distribution of the provided dataset. The Eq. (2) summarizes the first convolutional layer:

$$h1 = ReLU(W1*X + b1) \tag{2}$$

Where $W1$ is the weight matrix of the first hidden layer with dimensions (k independent variables x W), and $b1$ is the bias vector with dimensions (1 x W). In the second layer, we also applied the "relu" function for activation and inserted k units in the second layer, corresponding to the sum of the k independent variables plus the dependent variable, with "kernel_initializer" activating uniform function for learning pattern (Miotto et al., 2017). Then, Eq. (3) summarizes the second convolutional layer:

$$h2 = ReLU(W2*h1 + b2) \tag{3}$$

$W2$ is the weight matrix of the second hidden layer with dimensions (26 × 51), and $b2$ is the bias vector with dimensions (1 × sum of k independent and dependent variables). In the third convolutional layer (the output layer), we inserted the "softmax" activation, which regulates the outputs' probability, to sum up to 1, making the algorithm interpretation more adequate (Montesinos López et al., 2022). Next, we added the number of categories corresponding to each predicted mental health variable and repeated the "kernel_initializer" to activate the function uniform, then standardizing the ANN pattern for all layers (Miotto et al., 2017). Eq. (4) summarizes the third convolutional layer structure:

$$y_{pred} = Softmax(W3*h2 + b3) \tag{4}$$

Where $W3$ is the weight matrix of the output layer with dimensions (k independent variables × k classes for dependent variable), and $b3$ is the bias vector with dimensions (1 × k classes for dependent variable). After arranging the model architecture, we compile the model, adjusting the best optimizer according to the "Early Stopping" results (Adam, SGD, or RMSprop) (Prechelt, 2012), defining the model loss to "categorical_crossentropy" to improve the models' performance to identify the level of similarity between the predicted probabilities and the true positive in the one-hot encoded target categories. Finally, we defined the accuracy to determine the models' learning performance (Montesinos López et al., 2022). Table 2 shows the full ANN's architecture.

Additionally, we calculated three models' performance metrics: precision, recall, and F-1 score. Eq. (5) exemplifies precision:

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \tag{5}$$

Eq. (6) ***exemplifies recall:***

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \tag{6}$$

Eq. (7) ***exemplifies F-1 score:***

$$F1 - score = \frac{2*(Precision*Recall)}{(Precision + Recall)} \tag{7}$$

To summarize the precision, recall, and F-1 score in each predicted category, we calculated the weighted average, which verifies the average of each class considering the imbalances (weights) in the total number frequency of subjects (Montesinos López et al., 2022). Finally, we performed the models' cross-validation using the "Early Stopping" function, where the "keras.callbacks.EarlyStopping" function and monitor = "val_loss" were activated to measure when the accuracy loss during the models' validation training. The mode = "min" was monitored when the model training validation loss stopped decreasing, indicating the peak of performance during the validation. The patience = "10" indicated no increases in the validation loss during training. The model fit adopted a callback = "es" that listed callbacks for training, signalizing to stop the validation if there was no increase during 10 consecutive epochs. We set up the epochs number to 8,000,000 (a large number) to ensure that the validation model can run until the "Early Stopping" be activated 19,27. The best batch size for validation was 100. The shuffle = "True" ensured that the data were shuffled before each epoch, ensuring no bias occurrence during training. The training was set to 30 % of the model, and verbose = "1", set up progress bars during training to help the data scientist to accompany the model during model evaluation (Montesinos López et al., 2022). The ANN and its validation outputs are shown in graphs and tables. The entire codes are organized and available in the GitHub platform and are available in the data availability statement session. In addition, Fig. 1 helps to better understand and visualize the ANN implementation in our study.

3. Results

We started the ANN with only the best features for each targeted variable to verify the models' performance with these isolated variable panels. However, the first ANN did not exceed an accuracy of 65 % for the three targeted variables. Then, we kept fitting the model hierarchically, adding features considering their scores. After starting to add variables, the ANN's accuracy kept constantly increasing. Then, we noted that the best ANN's performances (>90 %) were reached when all features were present in the ANN. In deep learning models, including less critical features can help the model learn the information of the best features more completely (Taye, 2023). Thus, in the next session, we will report the ANN results and validation metrics for each target mental health dimension.

Table 2
ANN basic structure.

```
# MODEL TRAINING
  x_train,x_test,y_train, y_test = train_test_split(x,y,test_size = 0.3, random_state = 0)
# X ARRAY PREPROCESSING
  from sklearn.preprocessing import standardscaler
  sc = standardscaler()
  x_train = sc.fit_transform(x_train)
  x_test = sc.transform(x_test)
# MODEL ARCHITECTURE
  model = sequential()
  model.add(dense(activation = "relu", input_dim = k independent variable, units = k classes, kernel_initializer = "uniform"))
  model.add(dense(activation = "relu", units = total k variable, kernel_initializer = "uniform"))
  model.add(dense(activation = "softmax", units = k units, kernel_initializer = "uniform"))
# MODEL COMPILATION
  model.compile(optimizer = 'adam or sgd or rmsprop', loss = 'categorical_crossentropy', metrics = ['accuracy'])
  history = model.fit(x_train, y_train, batch_size = k units,epochs = k units)
```

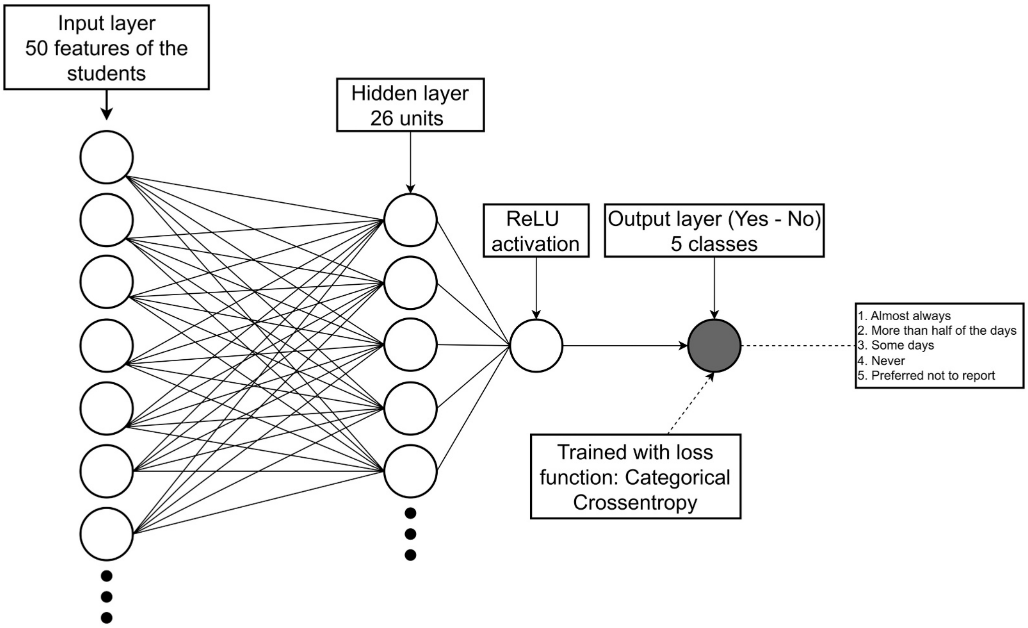

Fig. 1. Schematic representation of the implemented ANN.

3.1. Overall mental health state

3.1.1. Featuring selection

The featuring selection analysis showed that the most associated variables with self-reported overall mental health perception were hierarchically 1st: feeling bad about yourself, 2nd: trouble concentrating, 3rd: overall health perception, 4th: feeling tired, with lack of energy, 5th: having a chronic illness, 6th: feeling nervous, anxious, 8th: feeling down, depressed, 9th: lack of interest in performing ADLs, 10th: to use other drugs before enrolling on IPB, as described on Fig. 2.

Most of the variables presented a significant difference between the answer category concerning the variable overall mental health self-perception, $p < 0.01$. Some variables must be highlighted; for instance, a significant number of participants who felt bad about themselves some days, and more than half the days, $p < 0.001$; that had trouble concentrating on some days, $p < 0.001$, were feeling tired and with lack of energy in dome days and more than half the days, $p < 0.001$, that were feeling nervous and anxious in some days and more than half the days, $p < 0.001$, that were feeling down and depressed in some days and more than half the days, $p < 0.01$, and those that were feeling lack of interest in performing their ADLs in some days and more than half the days, $p < 0.001$.

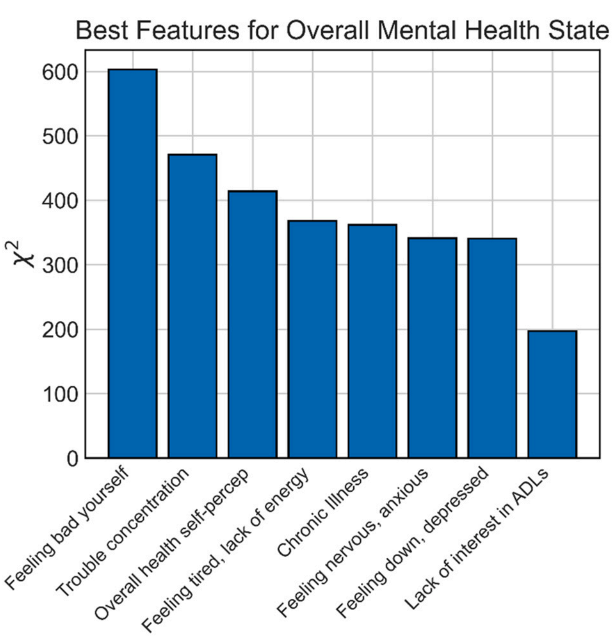

Fig. 2. Best features for overall mental health state. X^2, chi-square for goodness of fit statistics.

3.1.2. ANN results

The ANN showed an accuracy of 94 % regarding the students' overall health perception, showing a high capacity to learn the data patterns when targeting this variable. Combining a batch size of 8 units and 100 epochs using the Adam optimizer found the best learning performance. The model expended 30 s and started the learning with a loss of accuracy 1.09 and finished with 0.18 units.

3.1.3. Precision, recall, and F-1 score

To predict the students' overall mental health state, the ANN presented the following weighted average metrics: precision = 0.67 %, recall = 0.67 %, F-1 score = 0.67 %, Table 3. (See Tables 4 and 5.)

3.1.4. Cross-validation

After training 30 % of the learned data, we found 73 % training accuracy and 60 % (reasonable) validation accuracy. The analysis reached the peach performance with 70 epochs, as shown in Fig. 3.

Table 3
Precision, recall, and F-1 score for overall mental health state's prediction.

Category	Precision	Recall	F1-score	N
Good	0.67	0.72	0.70	872
Very good	0.75	0.74	0.74	762
Reasonable	0.54	0.44	0.49	317
Bad	0.67	0.32	0.43	19
Too bad	0.42	0.48	0.45	63
Not reported	0.71	0.88	0.79	17
Accuracy			0.67	2050
Macro average	0.63	0.60	0.60	2050
Weighted average	0.67	0.67	0.67	2050

Note. N, total sample for each category and the sum of all categories.

Table 4
Precision, recall, and F-1 score for lack of interest in performing their ADLs prediction.

Category	Precision	Recall	F1-score	Support
Never	0.69	0.59	0.63	384
Some days	0.82	0.89	0.85	1329
Over half the days	0.64	0.45	0.53	209
Almost always	0.54	0.60	0.57	91
Not reported	0.72	0.70	0.71	37
Accuracy			0.77	2050
Macro Average	0.76	0.65	0.66	2050
Weighted Average	0.69	0.77	0.76	2050

N, total sample for each category and the sum of all categories.

Table 5
Precision, recall and F-1 score for depressive state's prediction.

Category	Precision	Recall	F1-score	N
Some days	0.82	0.80	0.81	962
Never	0.80	0.84	0.82	827
Over than half the days	0.64	0.54	0.59	156
Almost always	0.60	0.65	0.62	68
Not reported	0.69	0.65	0.67	37
Accuracy			0.79	2050
Macro Average	0.71	0.70	0.70	2050
Weighted Average	0.79	0.79	0.79	2050

N, total sample for each category and for the sum of all categories.

3.2. Lack of interest in performing the ADLS

3.2.1. Featuring selection

The featuring selection analysis showed that the most associated variables with self-reported overall mental health perception were hierarchically 1st: feeling bad about yourself, 2nd: feeling tired, with lack of energy, 3rd: trouble concentrating, 4th: feeling down, depressed, 5th: feeling nervous, anxious, 6th: overall mental health self-perception, 7th: having a chronic illness, 8th: overall health self-perception, and 9th: country, as described on Fig. 4.

Similar to the variable overall mental health self-perception and depressive state, most of the variables presented significant differences between answer categories concerning the variable lack of interest in performing the ADLs, $p < 0.01$. For instance, there were a significant number of students who feel bad about themselves on some days and more than half the days, $p < 0.0001$; that were feeling tired and lacked energy on some days and more than half the days, $p < 0.0001$, that had trouble concentration some days and in more than half the days, $p < 0.001$; that were feeling down and pressed in some days and more than half the days, $p < 0.001$; that were feeling nervous and anxious some days and in more than half the days.

3.2.2. ANN results

The ANN showed an accuracy of 94 % regarding the students' overall health perception, showing a high capacity to learn the data patterns when targeting this variable. Combining a batch size of 16 units and 100 epochs using Adam optimizer found this best learning performance. The model expended 15.6 s and started the learning with a loss of accuracy of 1.25 and finished with 0.12 units.

3.2.3. Precision, recall, and F-1 score

To predict the students' lack of interest in their daily living activities, the ANN presented the following weighted average metrics: precision =

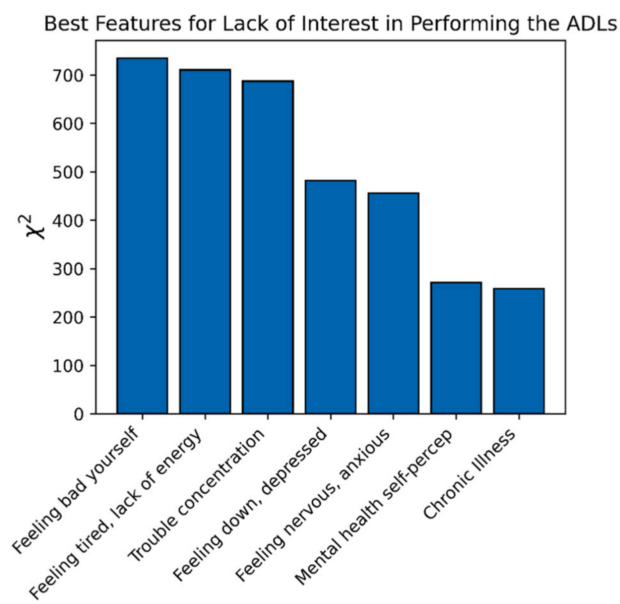

Fig. 4. The best features are due to a lack of interest in performing the ADLs. X^2, chi-square for goodness of fit statistics.

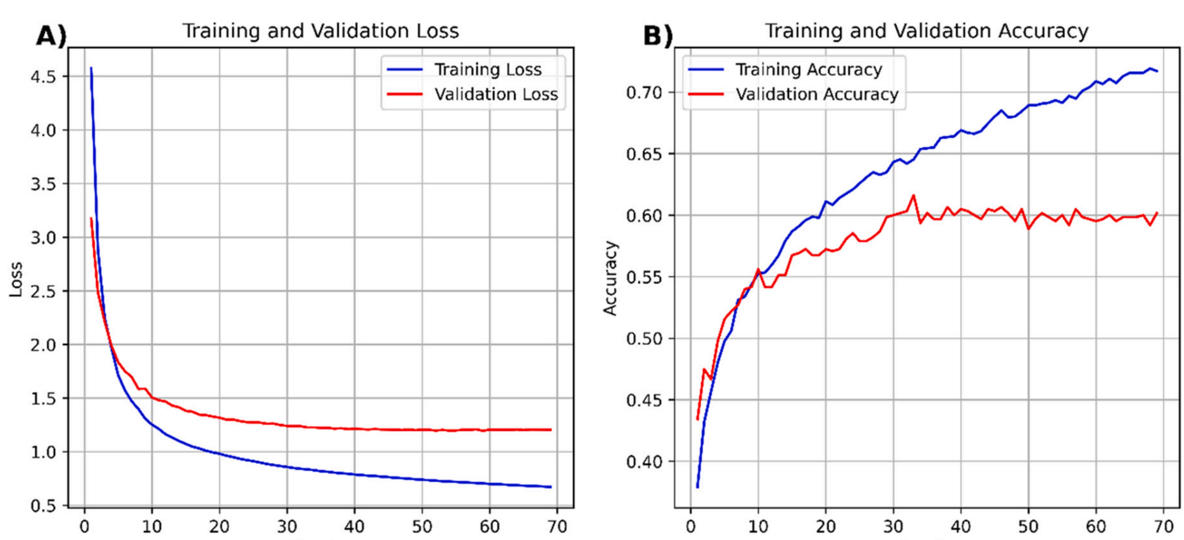

Fig. 3. Accuracy score and loss during ANN cross-validation within the students' mental health set as the target variable.

precision = 0.76 %, recall = 0.77 %, F-1 score = 0.77 %.

3.2.4. Cross-validation

After training 30 % of the learned data, we found 82 % training accuracy and 67 % (reasonable) validation accuracy. The analysis reached the peach performance with 30 epoch, as shown in Fig. 5.

3.3. Depressive state

3.3.1. Featuring selection

The featuring selection analysis showed that the most associated variables with the self-reported depressive state were hierarchically 1st: feeling bad about yourself, 2nd: feeling tired, with lack of energy, 3rd: trouble concentrating, 4th: feeling nervous and anxious, 5th: mental health self-perception, 6th: lack of interest in performing the ADLs, 7th: chronic illness, and 8th: overall health self-perception, as described on Fig. 6.

Similar to the variable overall mental health self-perception, most of the variables presented a significant difference between the answer category and the variable depressive state, $p < 0.01$. For instance, there were a significant number of students who feel bad about themselves on some days and more than half the days, $p < 0.001$; that were feeling lack of energy on some days and in more than half the days, $p < 0.001$; that were feeling trouble concentration in some days and in more than the half the days, $p < 0.001$; that were feeling nervous and anxious in some days and in more than half the days, $p < 0.001$; and those that were feeling lack of interest in perform their ADLs in some days, $p < 0.0001$.

3.3.2. ANN results

The ANN showed an accuracy of 97 % regarding the students' depressive state and exhibited a high capacity to learn these data patterns when targeting this variable. Similar to the students' overall mental health self-perception, this best learning performance was found with a batch size of 8 units and 100 epochs using the Adam optimizer. The model presented a similar processing time, expending 30 s to finish the analysis, and started the learning with a loss of accuracy of 1.14 and finished with 0.10 units.

3.3.3. Precision, recall, and F-1 score

To predict the students' depressive state, the ANN presented the following weighted average metrics: precision = 0.79 %, recall = 0.79 %, and F-1 score = 0.79 %.

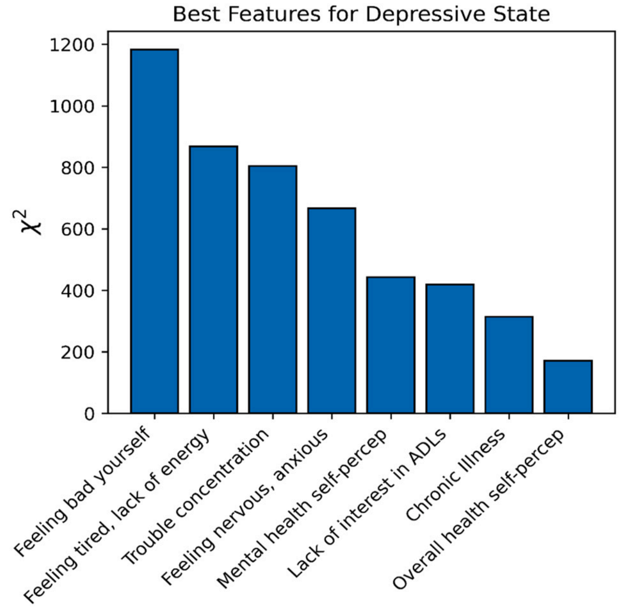

Fig. 6. Best features for depressive symptoms. X^2, chi-square for goodness of fit statistics.

3.3.4. Cross-validation

After training 30 % of the learned data, we found 82 % training accuracy and 73 % (good) validation accuracy. The analysis reached the peach performance with 25 epochs, as shown in Fig. 7.

4. Discussion

The objective of this study was to conduct an ANN to predict the students' self-reported mental health dimensions. Our hypothesis was proved when we found that different mental health dimensions were the most important predictive features of the university students' self-reported mental health state, with a special highlight on the students who feel bad about themselves standing at the top of the ranking. These findings were very well learned (accuracy >90 %). Additionally, the ANN presented its best validation performance when tested for depressive state being strongly associated with the negative feelings about themselves.

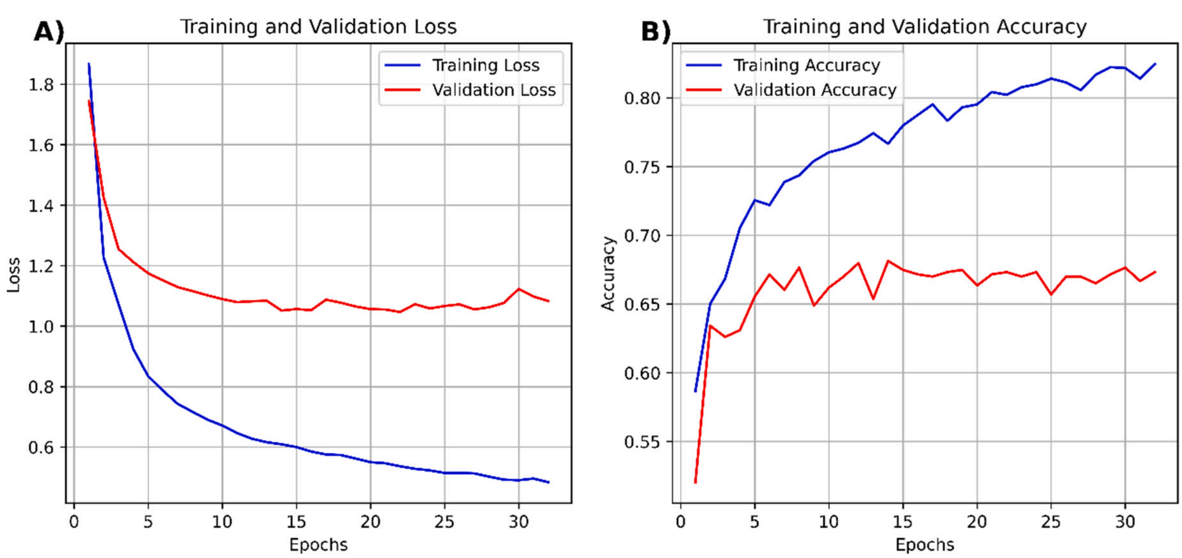

Fig. 5. Accuracy score and accuracy loss during ANN cross-validation due to the student's lack of interest in performing their ADLs are set as the target variable.

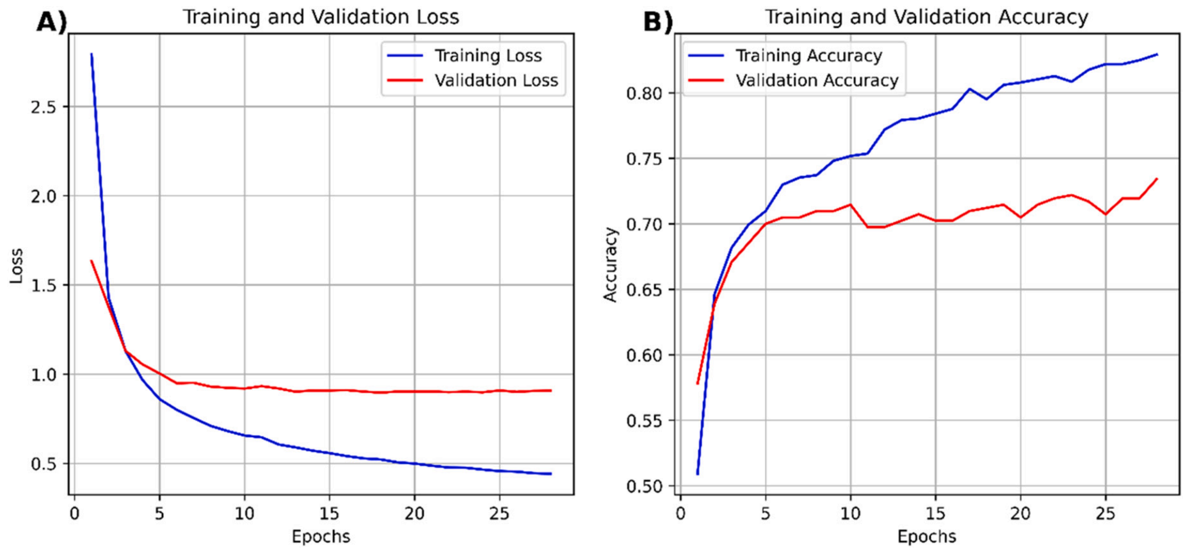

Fig. 7. Accuracy score and accuracy loss during ANN cross-validation within the students' depressive set as the target variable.

We obtained these final outputs after applying the algorithm considering the entire dataset. Despite some features not presenting big weights to predict the target-dependent variables, we noted that the best performance (both in training and validation sets) occurred when we considered these less weighted variables. In some cases, considering fewer determining features could help avoid overfitting and help algorithms better understand the data (Mamdouh Farghaly & Abd El-Hafeez, 2023). In neurosciences, the data about real-life related topics is usually very complex, and even when some variables appear less important in determining some phenomena, it still could be important to help artificial intelligence understand these deep interactions within the data patterns and help to make accurate predictions (Bohr & Memarzadeh, 2020). In addition, featuring selection techniques like machine learning algorithms or even statistical models used in our present study will likely add clarity to deep learning models, which sometimes can be considered "black boxes" due to their complexity levels during the inferences (Hassija et al., 2024).We found that the variable regarding the state of the students who feel bad about themselves was the most important feature to predict the participants' overall mental health self-perception, followed by other seven variables, hierarchically (trouble concentration, overall health self-perception, feeling tired, and with lack of energy, have a chronic illness, feeling nervous and anxious, feeling down and depressed, and feeling lack of interest in performing the ADLs).

Mental health is complex, and better predicting this type of outcome is a challenging task for researchers (Koutsouleris et al., 2022). Mental health could be determined by several factors, such as country, culture, scholarly and income level, which are considered relevant external factors, which in turn can influence internal parameters related to mental health (Öngür & Paulus, 2025) such as self-resilience and self-capacity to deal with daily issues and challenges, think about these questions and consciously find logic ways to better facing up and solve these daily problems (Ungar & Theron, 2020).

In line with our findings, Zhu et al. (2016) analyzed cross-sectional data from 508 Chinese university students and noted that self-concept, mental health, and social adaptation significantly correlated with each other, which indicates the importance of having a good self-concept to reach a good social and mental development during the students ́degree time. These previous results from Zhu et al. (2016) agree with our previous findings, but our dataset was formed by a more robust set of variables when considering real-life representation. In a more recent observational study, Cassaretto et al. (2024) identified that variables such as resilience, academic self-efficacy and digital inclusion significantly impacted the generalized distress levels of 3147 undergraduate students. Similarly, the fact that the students who feel bad about themselves was also the most correlated feature with the students' lack of interest in performing their ADLs, hierarchically followed by the seven variables (feeling tired and lacking energy, having trouble concentrating, feeling down or depressed, feeling nervous and anxious, mental health self-perception and have a chronic illness). The psychology field considers feeling discouraged in performing ADLs, also known as anhedonia, a huge factor associated with major depressive disorders (Serretti, 2023). Anhedonia is the lack of satisfaction and interest in performing all interesting and pleasurable ADLs (Watson et al., 2020). This condition is the most common major depressive disorder symptom and is characterized by a diminished interest or pleasure in performing some or even all ADLs during some days, or in the gravest cases, and it could manifest daily in a persons' daily life (Watson et al., 2020). In addition, anhedonia is also reported to be correlated with suicide ideation in adolescents with major depressive disorders (Cai et al., 2023).

In complement with the outputs of our study, Fan et al. (2024) performed a cross-sectional study with 35 patients with major depressive disorders and 35 healthy controls aged 16–55 years, where the anhedonia dimensions like desire, motivation, effort, and consummatory pleasure were reduced in the prefrontal cortex of the individuals with major depressive disorders accompanied by reduced prefrontal cortex activity, marked by reduced oxygenation and hemoglobin concentration. These findings revealed the impact of negative mood regulations and lack of engagement in the ADLs for the mental illness risk of young individuals (Fan et al., 2024).

Finally, the students ́depressive state was the best predicted mental health outcome after cross-validation (79 %), also higher correlated with the feature regarded the students feeling about themselves, and hierarchically followed by seven variables (feeling tired and lack of energy, trouble concentrating, feeling nervous and anxious, mental health self-perception, lack of interest in performing ADLs, have a chronic illness and the overall health self-perception) and in the same way that the students' mental health and lack of interest in performing their ADLs, these variables were most associated with the students' self-esteem.

A depressive state, when presented in a determined time, could be a risk factor for major depressive disorders (Bains & Abdijadid, 2023). Not only a person with depressive symptoms could have depression, but if some individuals chronically present symptoms, they are considered at elevated risk for major depressive disorders than those with only acute cases of depressive feelings (WHO, 2023a). This risk is because chronic depressive symptoms are linked to several factors, such as deregulation in serotonin, which impacts mood regulation (WHO, 2023a), and alterations in dopamine and norepinephrine that impact motivation, pleasure, and arousal in performing daily activities (Baik, 2020), increased chronic inflammation which impairs neuronal synapses (Zhang et al., 2023).

In addition, prolonged depressive symptoms are correlated to reduced neuroplasticity, meaning that the brain presents reduced synaptic connections, which in turn provokes reduced brain capacity to adapt to stress in daily life (Price & Duman, 2020). In this way, the combination of these molecular alterations makes a person with prolonged depressive feelings lose the capacity to overcome life challenges and, in the worst, it can start causing negative and suicidal ideation, which could put these persons' lives at risk (Harmer et al., 2023).

For instance, Lin (2015) analyzed data from 235 Taiwanese university students and found that gratitude and self-esteem directly influenced the participants' depressive symptoms. These findings agree with our findings, which showed that students who feel bad about themselves were at higher risk of more frequent depressive symptoms. In addition, Chow and Berenbaum (2016) collected data from 136 undergraduate students (65 % female), and these authors found that the group engaged in activities that increased their sense of usefulness were significantly better than the placebo group in controlling their depressive symptoms. Recent evidence has shown that cognitive components such as social support, resilience, and self-esteem protect mental health onset during adolescence (Cui et al., 2024; Liu et al., 2021). In a cross-sectional study with 689 Chinese university students, Cui et al. identified that self-esteem, personality traits, and resilience correlated with the students' well-being levels.

Despite the strong trend between self-esteem dimensions and mental health states shown in the current literature (Bains & Abdijadid, 2023; Cai et al., 2023; Cassaretto et al., 2024; Cui et al., 2024; Fan et al., 2024; Harmer et al., 2023; Hassija et al., 2024; Koutsouleris et al., 2022; Liu et al., 2021; Öngür & Paulus, 2025; Price & Duman, 2020; Ungar & Theron, 2020; Watson et al., 2020; Zhang et al., 2023), the actual evidence about this topic still does not present a consensus. It can be seen in the study of Harrison et al. (2022), where they found a significant correlation between worthlessness and hopelessness but did not find any influencing effect of anhedonia in self-worth parameters. In contrast, Fernández-Castillo and Fernández-Prados (2022) analyzed data from 1547 university students (21.8 % men and 77.3 % women), and they found that reduced self-esteem and resilience best-predicted burnout syndrome in the students. Our study presents evidence in favor of a positive association of poor self-esteem with a lack of interest in performing the ADLs in the analyzed students, then strengthens the level of evidence in favor of self-esteem could determine the students ́ mental dimension related to their levels of vigor in performing their daily activity. From a physiological perspective, there is an a priori hypothesis that self-stem-related features will recurrently be associated with anhedonia (Demir-Kassem et al., 2025). However, literature sometimes shows the opposite, as can be seem in the systematic review of Campbell et al. (2022) where only variables such as childhood trauma, LGBTQ and students with autism were significant factors for worse mental health. A plausible explanation of these discrepancies within the current literature is because health states are complex, and its outcomes can be significantly variable over time, or else; therefore some features that are commonly strongly correlated with others can be not in specific adaptative periods, or important confounding factors, such as parental and family history are not included in the models (Kirkbride et al., 2024). Finally, this study highlights the importance of preventing the risks associated with poor mental health in university students. The late screening and interventions put students at risk of developing major depressive disorders, which in turn, in the long term, can increase cardiovascular risk (Park et al., 2023), diabetes, and obesity (Melin et al., 2022), reduce memory, and consequent learning capacity (Kim et al., 2024). Thus, not preventing mental health complications at a young age can globally harm the persons' quality of life in adulthood (Weinmann et al., 2025). In addition, long-term damage to mental health can cause dementia onset in older ages (Voros et al., 2020). This knowledge must be had in count to the professional working with mental health within the scholarly environment, which can use it as a base to identify and intervene with those students at higher risk for mental health issues.

4.1. Study limitations and strengths

Our study presents limitations that must be acknowledged, such as the cross-sectional design that did not allow causality analyses. Another limiting point was the lack of data collection of variables like income level, screen time, nutritional behavior, sleep quality, physical activity levels, and sedentary behavior, which are potential mental health influencing factors (Al-Amin et al., 2025; Hasan et al., 2023) therefore parental variables (Kirkbride et al., 2024), childhood history of trauma, autism and being LGBTQ could be potential confounding factors and were not included in the ANN model. On the other hand, this study presents important strengths, such as the fact we developed a deep learning model, which helps to validate more practical evidence for real-life scenarios. This study was a novelty, being the first research to implement an ANN in this knowledge field for this specific research question. This way, our findings can stimulate other researchers to implement similar approaches or even optimize our coding to produce diversified evidence and make possible comparations with our study and the current literature to open new steps for future research.

For future studies, based on the current evidence, we suggest the optimization of ANN models, with larger sample size and more complex datasets, which will significantly enrich the body of evidence in this research field. In addition, in complement to ANN implementation, the realization of decomposition analysis and if possible, in longitudinal designs can add on evidence about the causal influence of a diversity of factors in the mental health dimensions of students of different degrees (Martínez-Sánchez et al., 2024).

4.2. Clinical applications

This present study ranked and validated an ANN of the best predictors of self-reported mental health dimensions. Therefore, the self-esteem category was the best predictive feature of the student's mental health dimensions. In addition, the best target for forecasting was the depressive state, showing good replicability in real life (overall accuracy = 97 %, validation accuracy = 73 %). This information could be used and adopted by mental health professionals, who can use these initial steps to individualize their therapy sessions and help students, thus preventing mental illness and its complications during university studies. Proper universities could use these results to build new interventive strategies and prevent damage to the students' mental health and quality of life.

4.3. Conclusions

We conclude that The ANN presented excellent learning performance (>90 %) for all targeted variables, within reasonable to good generalization capacity (60–73 %). Finally, the university students' depressive state was the best-predicted variable (overall accuracy = 97 %, validation accuracy = 73 %). Our findings suggest a possibility of education institutions can use AI-based algorithms to early identify mental illness risk, enabling rapid preventive intervention with the academic community.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actpsy.2025.105324.

CRediT authorship contribution statement

Samuel Encarnação: Writing – review & editing, Methodology, Software, Writing – original draft, Conceptualization. **Paula Fortunato Vaz:** Writing – review & editing, Methodology. **Filipe Vaz:** Project administration, Formal analysis, Writing – review & editing, Methodology. **Álvaro Fortunato Vaz:** Formal analysis, Writing – review & editing. **António Miguel de Barros Monteiro:** Conceptualization, Writing – review & editing, Data curation.

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this work, the author(s) used Grammarly® in its Premium version to assist with English grammar refinements, clarity, and style corrections. After using this tool, the author (s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Funding

This research was not supported by any funder.

Declaration of competing interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgments

We gratefully acknowledge the financial support from The Scientific Board of the University of Porto, Portugal, approved (Identification number: CE18082). We also thank the Public Health Unit of Bragança, a City in the North of Portugal, and the Instituto Politécnico de Bragança (IPB).

Data availability

We make the full dataset available in the following GitHub link (see here). All the data were processed and analyzed using Python TM, programming language (Python, 2023).

References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., … Zheng, X. (2016). TensorFlow: A system for large-scale machine learning (no. arXiv:1605.08695). arXiv. 10.48550/arXiv.1605.08695.

Al-Amin, M., Rinky, F., Bhuiyan, M. N. H., Yeasmin, R., Akter, T., Hoque, N., & Reza, S. (2025). Factors influencing mental health outcomes among university students: A cross-sectional study in Bangladesh. *BMJ Open, 15*(3), Article e097745. https://doi.org/10.1136/bmjopen-2024-097745

Amaro, H., Sanchez, M., Bautista, T., & Cox, R. (2021). Social vulnerabilities for substance use: Stressors, socially toxic environments, and discrimination and racism. *Neuropharmacology, 188*, Article 108518. https://doi.org/10.1016/j.neuropharm.2021.108518

Angelina, S., Kurniawan, A., Agung, F. H., Halim, D. A., Wijovi, F., Jodhinata, C., … Hamdoyo, A. (2021). Adolescents' mental health status and influential factors amid the coronavirus disease pandemic. *Clinical Epidemiology and Global Health, 12*, Article 100903. https://doi.org/10.1016/j.cegh.2021.100903

Arji, G., Erfannia, L., alirezaei, S., & Hemmat, M. (2023). A systematic literature review and analysis of deep learning algorithms in mental disorders. *Informatics in Medicine Unlocked, 40*, Article 101284. https://doi.org/10.1016/j.imu.2023.101284

Badrulhisham, F., Pogatzki-Zahn, E., Segelcke, D., Spisak, T., & Vollert, J. (2024). Machine learning and artificial intelligence in neuroscience: A primer for researchers. *Brain, Behavior, and Immunity, 115*, 470–479. https://doi.org/10.1016/j.bbi.2023.11.005

Baik, J.-H. (2020). Stress and the dopaminergic reward system. *Experimental and Molecular Medicine, 52*(12), Article 12. https://doi.org/10.1038/s12276-020-00532-4

Bains, N., & Abdijadid, S. (2023). Major depressive disorder. Em StatPearls. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK559078/.

Bartlett, C. W., Bossenbroek, J., Ueyama, Y., McCallinhart, P., Peters, O. A., Santillan, D. A., … Ray, W. C. (2023). Invasive or more direct measurements can provide an objective early-stopping ceiling for training deep neural networks on non-invasive or less-direct biomedical data. *SN Computer Science, 4*(2), 161. https://doi.org/10.1007/s42979-022-01553-8

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. In *Artificial intelligence in healthcare* (pp. 25–60). https://doi.org/10.1016/B978-0-12-818438-7.00002-2

Cai, H., Li, Z.-L., He, F., Li, S.-Y., Zhao, Y.-J., Zhang, W.-Y., Zhang, Y., Su, Z., Jackson, T., & Xiang, Y.-T. (2023). Suicide ideation and anhedonia among clinically stable adolescents with the recurrent depressive disorder during the COVID-19 pandemic: A network perspective. *Journal of Affective Disorders, 324*, 317–324. https://doi.org/10.1016/j.jad.2022.12.052

Campbell, F., Blank, L., Cantrell, A., Baxter, S., Blackmore, C., Dixon, J., & Goyder, E. (2022). Factors that influence mental health of university and college students in the UK: A systematic review. *BMC Public Health, 22*(1), 1778. https://doi.org/10.1186/s12889-022-13943-x

Cassaretto, M., Espinosa, A., & Chau, C. (2024). Effects of resilience, social support, and academic self-efficacy, on mental health among Peruvian university students during the pandemic: The mediating role of digital inclusion. *Frontiers in Psychology, 15*. https://doi.org/10.3389/fpsyg.2024.1282281

Choudhury, A., & Asan, O. (2020). Role of artificial intelligence in patient safety outcomes: Systematic literature review. *JMIR Medical Informatics, 8*(7), Article e18599. https://doi.org/10.2196/18599

Chow, P. I., & Berenbaum, H. (2016). The relation between depression and appreciation: The role of perceptions of emotional utility in an experimental test of causality. *Cognition and Emotion, 30*(4), 797–806. https://doi.org/10.1080/02699931.2015.1022511

Cui, Z., Lin, Z., Ren, J., Cao, Y., & Tian, X. (2024). Exploring self-esteem and personality traits as predictors of mental wellbeing among Chinese university students: The mediating and moderating role of resilience. *Frontiers in Psychology, 15*. https://doi.org/10.3389/fpsyg.2024.1308863

Demir-Kassem, S., Frey, A.-L., & McCabe, C. (2025). Meaning in life mediates the effects of sense of self and prosocial behaviours on anhedonia: A path analysis. *Journal of Affective Disorders, 368*, 503–512. https://doi.org/10.1016/j.jad.2024.09.106

Fan, H., Li, Q., Du, Y., Yan, Y., Ni, R., Wei, J., Zhao, L., Yang, X., & Ma, X. (2024). Relationship of prefrontal cortex activity with anhedonia and cognitive function in major depressive disorder: An fNIRS study. *Frontiers in Psychiatry, 15*. https://doi.org/10.3389/fpsyt.2024.1428425

Fernández-Castillo, A., & Fernández-Prados, M. J. (2022). Burnout, resilience and self-esteem in school teaching university students. *Behavioral Sciences, 12*(11), Article 422. https://doi.org/10.3390/bs12110422

Gaiha, S. M., Taylor Salisbury, T., Koschorke, M., Raman, U., & Petticrew, M. (2020). Stigma associated with mental health problems among young people in India: A systematic review of magnitude, manifestations and recommendations. *BMC Psychiatry, 20*, 538. https://doi.org/10.1186/s12888-020-02937-x

Gautam, S., Jain, A., Chaudhary, J., Gautam, M., Gaur, M., & Grover, S. (2024). Concept of mental health and mental well-being, it's determinants and coping strategies. *Indian Journal of Psychiatry, 66*(Suppl. 2), S231–S244. https://doi.org/10.4103/indianjpsychiatry.indianjpsychiatry_707_23

Harmer, B., Lee, S., Duong, T. vi H., & Saadabadi, A. (2023). Suicidal ideation. Em StatPearls. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK565877/.

Harrison, P., Lawrence, A. J., Wang, S., Liu, S., Xie, G., Yang, X., & Zahn, R. (2022). The psychopathology of worthlessness in depression. *Frontiers in Psychiatry, 13*. https://doi.org/10.3389/fpsyt.2022.818542

Hasan, A. B. M. N., Sharif, A. B., & Jahan, I. (2023). Perceived barriers to maintain physical activity and its association to mental health status of Bangladeshi adults: A quantile regression approach. *Scientific Reports, 13*(1), Article 1. https://doi.org/10.1038/s41598-023-36299-7

Haslwanter, T. (2016). An introduction to statistics with python. In *With applications in the life sciences*. Switzerland: Springer International Publishing.

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., … Hussain, A. (2024). Interpreting black-box models: A review on explainable artificial intelligence. *Cognitive Computation, 16*(1), 45–74. https://doi.org/10.1007/s12559-023-10179-8

Kim, J., Park, G.-R., & Jang, H. (2024). Adolescent depressive symptoms and memory performance in young adulthood: Testing critical period, accumulation, and pathway models using a sibling comparison design. *Social Science & Medicine, 360*, Article 117328. https://doi.org/10.1016/j.socscimed.2024.117328

Kirkbride, J. B., Anglin, D. M., Colman, I., Dykxhoorn, J., Jones, P. B., Patalay, P., … Griffiths, S. L. (2024). The social determinants of mental health and disorder: Evidence, prevention and recommendations. *World Psychiatry, 23*(1), 58–90. https://doi.org/10.1002/wps.21160

Koutsouleris, N., Hauser, T. U., Skvortsova, V., & Choudhury, M. D. (2022). From promise to practice: Towards the realisation of AI-informed mental health care. *The Lancet Digital Health, 4*(11), e829–e840. https://doi.org/10.1016/S2589-7500(22)00153-4

Lin, C.-C. (2015). Gratitude and depression in young adults: The mediating role of self-esteem and well-being. *Personality and Individual Differences, 87*, 30–34. https://doi.org/10.1016/j.paid.2015.07.017

Liu, Q., Jiang, M., Li, S., & Yang, Y. (2021). Social support, resilience, and self-esteem protect against common mental health problems in early adolescence. *Medicine, 100*(4), Article e24334. https://doi.org/10.1097/MD.0000000000024334

Mamdouh Farghaly, H., & Abd El-Hafeez, T. (2023). A high-quality feature selection method based on frequent and correlated items for text classification. *Soft Computing, 27*(16), 11259–11274. https://doi.org/10.1007/s00500-023-08587-x

Martin. (2023). The sustainable development goals. In *United nations sustainable development*. https://www.un.org/sustainabledevelopment/health/.

Martínez-Sánchez, Á., Arranz, G., & Lozano-Durán, A. (2024). Decomposing causality into its synergistic, unique, and redundant components. *Nature Communications, 15*(1), 9296. https://doi.org/10.1038/s41467-024-53373-4

Melin, E. O., Wanby, P., Neumark, T., Holmberg, S., Neumark, A.-S. N., Johansson, K., … Thunander, M. (2022). Depression was associated with younger age, female sex, obesity, smoking, and physical inactivity, in 1027 patients with newly diagnosed type 2 diabetes: A Swedish multicentre cross-sectional study. *BMC Endocrine Disorders, 22*(1), 273. https://doi.org/10.1186/s12902-022-01184-3

Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2017). Deep learning for healthcare: Review, opportunities and challenges. *Briefings in Bioinformatics, 19*(6), 1236–1246. https://doi.org/10.1093/bib/bbx044

Mofatteh, M. (2020). Risk factors associated with stress, anxiety, and depression among university undergraduate students. *AIMS Public Health, 8*(1), 36–65. https://doi.org/10.3934/publichealth.2021004

Mohammed, S. Y., & Aljanabi, M. (2023). Human-centric IoT for health monitoring in the healthcare 5.0 FrameworkDescriptive analysis and directions for future research. *EDRAAK, 2023*, 21–26. https://doi.org/10.70470/EDRAAK/2023/005

Montesinos López, O. A., Montesinos López, A., & Crossa, J. 2022. Fundamentals of artificial neural networks and deep learning. Em O.A. Montesinos López, A. Montesinos López, & J. Crossa (Eds.), Multivariate statistical machine learning methods for genomic prediction (379–425). Springer International Publishing. https://doi.org/10.1007/978-3-030-89010-0_10.

Öngür, D., & Paulus, M. P. (2025). Embracing complexity in psychiatry—From reductionistic to systems approaches. *The Lancet Psychiatry, 12*(3), 220–227. https://doi.org/10.1016/S2215-0366(24)00334-1

Park, H., Kim, T., & Kim, J. (2023). Longitudinal pathways from adolescent depressive symptoms to cardiovascular disease risk in adulthood. *Social Science & Medicine, 318*, Article 115657. https://doi.org/10.1016/j.socscimed.2023.115657

Prechelt, L. 2012. Early stopping—But when? Em G. Montavon, G. B. Orr, & K.-R. Müller (Eds.), Neural networks: Tricks of the trade: Second Edition (pp. 53–67). Springer. https://doi.org/10.1007/978-3-642-35289-8_5.

Price, R. B., & Duman, R. (2020). Neuroplasticity in cognitive and psychological mechanisms of depression: An integrative model. *Molecular Psychiatry, 25*(3), 530–543. https://doi.org/10.1038/s41380-019-0615-x

Python. (2023, March 8). *Welcome to Python.org*. Python.Org. https://www.python.org/.

Ratanasiripong, P., China, T., & Toyama, S. (2018). Mental health and well-being of university students in Okinawa. *Education Research International, 2018*, Article e4231836. https://doi.org/10.1155/2018/4231836

Remes, O., Mendes, J. F., & Templeton, P. (2021). Biological, psychological, and social determinants of depression: A review of recent literature. *Brain Sciences, 11*(12), Article 1633. https://doi.org/10.3390/brainsci11121633

Serretti, A. (2023). Anhedonia and depressive disorders. *Clinical Psychopharmacology and Neuroscience: The Official Scientific Journal of the Korean College of Neuropsychopharmacology, 21*(3), 401–409. https://doi.org/10.9758/cpn.23.1086

Shengyao, Y., Salarzadeh Jenatabadi, H., Mengshi, Y., Minqin, C., Xuefen, L., & Mustafa, Z. (2024). Academic resilience, self-efficacy, and motivation: The role of parenting style. *Scientific Reports, 14*, 5571. https://doi.org/10.1038/s41598-024-55530-7

Sisk, L. M., & Gee, D. G. (2022). Stress and adolescence: Vulnerability and opportunity during a sensitive window of development. *Current Opinion in Psychology, 44*, 286–292. https://doi.org/10.1016/j.copsyc.2021.10.005

Squires, M., Tao, X., Elangovan, S., Gururajan, R., Zhou, X., Acharya, U. R., & Li, Y. (2023). Deep learning and machine learning in psychiatry: A survey of current progress in depression detection, diagnosis and treatment. *Brain Informatics, 10*(1), 10. https://doi.org/10.1186/s40708-023-00188-6

Szymkowicz, S. M., Gerlach, A. R., Homiack, D., & Taylor, W. D. (2023). Biological factors influencing depression in later life: Role of aging processes and treatment implications. *Translational Psychiatry, 13*(1), 1–16. https://doi.org/10.1038/s41398-023-02464-9

Taye, M. M. (2023). Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions. *Computation, 11*(3), Article 3. https://doi.org/10.3390/computation11030052

Ungar, M., & Theron, L. (2020). Resilience and mental health: How multisystemic processes contribute to positive outcomes. *The Lancet Psychiatry, 7*(5), 441–448. https://doi.org/10.1016/S2215-0366(19)30434-1

Unpingco, J. (2016). *Python for probability, statistics, and machine learning* (Vol. 1). Springer.

Voros, V., Fekete, S., Tenyi, T., Rihmer, Z., Szili, I., & Osvath, P. (2020). Untreated depressive symptoms significantly worsen quality of life in old age and may lead to the misdiagnosis of dementia: A cross-sectional study. *Annals of General Psychiatry, 19*, 52. https://doi.org/10.1186/s12991-020-00302-6

Watson, R., Harvey, K., McCabe, C., & Reynolds, S. (2020). Understanding anhedonia: A qualitative study exploring loss of interest and pleasure in adolescent depression. *European Child & Adolescent Psychiatry, 29*(4), 489–499. https://doi.org/10.1007/s00787-019-01364-y

Weinmann, T., Wibowo, R., Forster, F., Gerlich, J., Wengenroth, L., Weinmayr, G., Genuneit, J., Nowak, D., Vogelberg, C., Radon, K., & Herbig, B. (2025). Association of chronic stress during studies with depressive symptoms 10 years later. *Scientific Reports, 15*(1), 2379. https://doi.org/10.1038/s41598-025-85311-9

Whittle, S., Zhang, L., & Rakesh, D. (2025). Environmental and neurodevelopmental contributors to youth mental illness. *Neuropsychopharmacology, 50*(1), 201–210. https://doi.org/10.1038/s41386-024-01926-y

WHO. (2023a). Mental health. https://www.who.int/health-topics/mental-health.

WHO, W. H. (2023b). Regional framework for the future of mental health in the Western Pacific 2023–2030. https://apps.who.int/iris/handle/10665/369120.

Yang, L., & Shami, A. (2020). On hyperparameter optimization of machine learning algorithms: Theory and practice. *Neurocomputing, 415*, 295–316. https://doi.org/10.1016/j.neucom.2020.07.061

Zhang W. Xiao D. Mao Q. Xia H. 2023 Role of neuroinflammation in neurodegeneration development Signal Transduction and Targeted Therapy 8 1 Artigo 1 https://doi.org/10.1038/s41392-023-01486-5.

Zhang, Y., Li, B., Zhang, L., Cheng, A., Long, S., Wang, J., Wen, M., Li, K., & Liu, C. (2024). Prefrontal brain activity and self-injurious behavior in adolescents with major depressive disorder: A functional near-infrared spectroscopy (fNIRS) study. *Journal of Psychiatric Research, 176*, 248–253. https://doi.org/10.1016/j.jpsychires.2024.06.001

Zhu J. Wang X. Liu Z. Liu T. Wei G. Chen X. 2016 The relationship between self-concept and mental health among Chinese college students: The mediating effect of social adjusting Open journal of Social Sciences 4 12 Artigo 12 https://doi.org/10.4236/jss.2016.412011.

Zihl, J., & Reppermund, S. (2023). The aging mind: A complex challenge for research and practice. *Aging Brain, 3*, Article 100060. https://doi.org/10.1016/j.nbas.2022.100060

Further Reading

Pfeifer, J. H., & Berkman, E. T. (2018). The development of self and identity in adolescence: Neural evidence and implications for a value-based choice perspective on motivated behavior. *Child Development Perspectives, 12*(3), 158–164. https://doi.org/10.1111/cdep.12279