




# Advances and challenges in the detection of academic stress and anxiety in the classroom: A literature review and recommendations

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## Abstract

In recent years, stress and anxiety have been identified as two of the leading causes of academic underachievement and dropout. However, there is little work on the detection of stress and anxiety in academic settings and/or its impact on the performance of undergraduate students. Moreover, there is a gap in the literature in terms of identifying any computing, information technologies, or technological platforms that help educational institutions to identify students with mental health problems. This paper aims to systematically review the literature to identify the advances, limitations, challenges, and possible lines of research for detecting academic stress and anxiety in the classroom. Forty-four recent articles on the topic of detecting stress and anxiety in academic settings were analyzed. The results show that the main tools used for detecting anxiety and stress are psychological instruments such as self-questionnaires. The second most used method is acquiring and analyzing biological signals and biomarkers using commercial measurement instruments. Data analysis is mainly performed using descriptive statistical tools and pattern recognition techniques. Specifically, physiological signals are combined with classification algorithms. The results of this method for detecting anxiety and academic stress in students are encouraging. Using physiological signals reduces some of the limitations of psychological instruments, such as response time and self-report bias. Finally, the main challenge in the detection of academic anxiety and stress is to bring detection systems into the classroom. Doing so, requires the use of non-invasive sensors and wearable systems to reduce the intrinsic stress caused by instrumentation.

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## 1 Introduction

“Stress is the biological and psychological response of the body to a stimulus (stressor) caused by an event, object, or person”, while, “anxiety is a state of agitation characterized by the anticipation of danger in which cognitive and physiological symptoms predominate” (Sierra, 2003). Anxiety can be a manifestation of stress and can also act as a stressor on the subject (Folkman, 2013; Owczarek et al., 2020). In psychology, a subject’s adaptive response determines their ability to predict upcoming stressful events and achieve self-control over the situation to cope with it adequately (Maturana & Vargas, 2015).

Stress and anxiety are present in daily life, and students are not exempt from experiencing these emotional states. Academic stress is “an adaptive systemic process, essentially psychological, on the part of students in school environments, to demands that in the subject’s assessment are considered stressful” (Toribio & Franco, 2016). Students at all educational levels deal with academic tasks that could generate stress during the teaching and learning process, such as a presentation, an exam, math exercises, among others.

Feelings of stress and anxiety are so prevalent that they have become normalized in students’ lives and, as a consequence, negatively affect academic performance (Baird, 2016; Wang et al., 2014). There exists a need to study the effects and consequences of stress and anxiety on students’ emotional state and academic performance (Berrío-García & Mazo-Zea, 2011).

In some subjects, the stress students are subjected to can serve as a driver to improve their results; however, performance in other subjects is negatively affected by stress (Leppavirta, 2011). Those who cannot adequately manage their stress response tend to show deficiencies in their grades and, in some cases, drop out (Corsini et al., 2012; Reyes-Carmona et al., 2017). For this reason, educational institutions must have tools and protocols to identify and manage the impact of stress on students and thus reduce the adverse effects on their academic performance.

UNESCO in their guide titled “Minding our mind during COVID-19” (Masod, 2020) specifies that students’ mental health must be a priority to provide an educational environment that meets basic human rights requirements. The authors decided to conduct this review because we did not identify any viable computing or technological platform which helps educational institutions to identify students with mental health problems when returning to face-to-face classes following COVID-19. In this way, this work identifies the challenges the academic community must face to propose practical and viable solutions to society.

The Organization for Economic Cooperation and Development (OECD) surveyed more than 500,000 students aged between 15 and 16 in 72 countries. Results indicate that more than 60% of the respondents feel stressed and anxious due to the fear of obtaining low grades, and more than 50% of the students suffer from anxiety when answering a test, even when they have studied and are prepared (Pascoe

et al., 2020). Other studies have shown that students with higher stress levels are more likely to suffer from poor academic performance that may even lead them to drop out (Roso-Bas et al., 2016). Although the results indicate that stress should be identified and assessed in students as early as possible, doing so is not easy.

The most commonly used tools to identify, measure, and evaluate anxiety and stress states are interviews, questionnaires, and self-reports. However, the disadvantage of these tools is that their results depend on the subject's response and the evaluator's interpretation, which can lead to debatable results (Balanza-Galindo et al., 2008). The scientific community has proposed using sensors, electronic measurement systems, and data processing algorithms to acquire and analyze different physiological signals and biological markers to overcome this obstacle. The signal values or levels can be related to the body's biological responses to stress and anxiety. Consequently, some authors have developed electronic diagnostic platforms that help experts identify stress and anxiety states in subjects in a quantifiable way, from a biological and psychological perspective, thus reducing subjectivity (García et al., 2016; Melillo et al., 2011; Rodríguez et al., 2020).

Papers on proposed biomarkers that correlate with the body's physiological response to states of stress and anxiety have been published. Morera et al. (2019) identified that heart rate (HR) and blood pressure (BP) are the most commonly used biomarkers in stress and anxiety detection. In the same year, a similar study was published by Giannakakis et al. (2019). They determined that skin conductance response (SCR) and skin conductance level (SCL) can be used to identify stress in subjects. SCR and SCL were obtained by way of an electrodermal activity signal (EDA) sensor, also called galvanic skin response (GSR). Alberdi et al. (2016), analyzed more than 40 articles on stress in the workplaces. They observed that the main challenges for identifying workplace stress are the subjects' privacy, ethical issues regarding the procedures, costs, efficiency, and the reliability of the systems, among others. Because of this, they propose improving sensors and measurement systems, emphasizing the advantages that monitoring and tele-assistance systems could bring over conventional stress and anxiety detection tools.

It is essential to mention that most of the studies conducted in order to identify stress and anxiety have been carried out in controlled environments, limiting the generalization of results. On the other hand, there are few studies on the measurement and evaluation of stress and anxiety in students in academic settings; therefore, there is no consensus among the scientific community on how to measure the impact stress and anxiety may have on students' performance and the results obtained thus far.

In order to establish a current perspective of the identification of academic stress and anxiety, it is necessary to review published works in the area whose purpose has been the identification of these in academic environments. As an initial result of the bibliographic search, no scientific work establishing the progress and challenges in detecting stress and anxiety in academic environments in recent years was found.

This work presents a review of the current state-of-the-art regarding academic stress and anxiety detection. This review aims to identify relevant studies in the area and to discuss the procedures used and results obtained in academic settings. Current challenges and limitations are established, outlining future lines of research. An

overview is provided to guide readers interested in the topic. The research questions that guided this work are:

1. Which psychological instruments, technological tools (data acquisition systems and sensors), and data processing techniques are most commonly employed in procedures to identify stress and anxiety in academic settings?
2. What are the limitations, challenges, and lines of research to be addressed in developing and implementing technological platforms to identify academic stress and anxiety in the classroom?

## 2 Method

Data were collected from four databases: *Google Scholar*, *Microsoft Academic*, *Science Direct*, and *PubMed*.

The search was performed manually using combinations of the following words: *stress*, *anxiety*, *academic*, *university students*, *undergraduate students*; *identification*, *detection*, and *recognition*. This search yielded 4, 762, 360 manuscripts. In order to provide an overview of the advances and identify the challenges in the detection of academic stress and anxiety in the classroom, this systematic review presents the most recent results on this topic. In consequence, the search was limited to papers published in recent years (between 2011 and 2022) and aimed at identifying or detecting stress and anxiety in a university setting, resulting in 774 papers. The titles and abstracts of the papers were checked to avoid duplication, and the papers that mentioned the participation of university students were selected, resulting in 65 articles.

Finally, only papers that met the following inclusion criteria were considered: a) research articles published in journals or congresses, b) the aim of the study was the detection and recognition of stress and anxiety in university settings (regardless of the number of participants in the studies, as long as the participants were university students); and c) the research focused on the use of psychological tools or biological signals in stress and anxiety detection procedures. A total of 44 articles were selected. Table 1 summarizes the procedure for selecting the sample of articles that was analyzed.

**Table 1** Articles identified and included in the review of databases

Database	Docs. initially retrieved after applying key words and period	Docs. after title and abstract review	Docs. meeting inclusion criteria
Google Scholar	688	7	6
Microsoft Academic	68	54	35
Science Direct	13	3	2
PubMed	5	1	1
Total	774	65	44

**Table 2** Featured of the reviewed articles

Features
Tool used for the evaluation of subjects
Psychological instruments
Biological measurements
Combined systems
Application of detection system
Sample characteristics
Stressors
Data analysis for stress and anxiety recognition
Detected phenomenon

Cooper's method (Randolph, 2009) was used to formulate the research questions, the search methodology, the criteria to select the literature, and abstract the collected data to address current limitations. The characteristics of the anxiety and stress detection systems reported in the articles were identified; these characteristics are as follows: the primary tool employed in the stress and anxiety identification procedure (use of biological signal measurements, use of psychological tools, or a combination of both); the tasks and situations considered as stress generators (stressors); the tools used to perform the data analysis; and the phenomenon detected (stress, anxiety, stressful situations, and academic stress). These characteristics are summarized in Table 2.

### 3 Results

44 scientific articles were reviewed; 41.00% of them (18 articles) were written in the Americas, 29.50% (13 articles) in Europe, 25.00% (11 articles) in Asia, and 4.50% (2 articles) in Africa. The year with the fewest publications on the topic was 2014 with two publications, and the year with the most publications was 2020 with six published articles.

#### 3.1 Tools used for the evaluation of subjects

Due to the psychological and biological components that prevail in stress and anxiety states, the detection procedures for these states can generally be classified into two groups: a) those based on the use of psychological instruments and b) those that rely on biological markers. It was found that psychological instruments were used to assess subjects in 20 articles (45.50%). In 15 articles (34.00%), measurements of physical signs, physiological signals, and biological markers were used. In 9 articles (20.50%), a combination of both tools (psychological instruments in combination with biological markers) was used.

### 3.1.1 Psychological instruments

The most commonly used psychological instruments are self-reports and interviews. In the first two articles, the responses were evaluated by using scales or indexes previously validated in the population. The disadvantage of this method is that the responses depend on the subject's perception. Some studies conducted interviews to reduce bias in the results as a result of the respondent's perception. The test responses were validated through concordance indexes such as Cronbach's index ( $\alpha_c$ ) (Cronbach, 1951). Table 3 shows the number of times (N) that each

**Table 3** Psychological instruments used in reviewed articles

Psychological instrument	Acronym	N
State-Trait Anxiety Inventory (Spielberger et al., 1968)	STAI	6
SISCO Inventory of Academic Stress (Manrique-Millones et al., 2019)	SISCO	4
Inventario de Ansiedad Rasgo-Estado (Spielberger & Díaz, 1975)	IDARE	4
Academic Stress Inventory (Rafael García-Ros & Natividad, 2012)	ASI	2
Depression, Anxiety and Stress Scale (Akin & Çetin, 2007)	DASS	2
Beck's Anxiety Inventory (Steer & Beck, 1997)	BAI	1
Beck's Depression Inventory (Beck et al., 1996)	BDI	1
Cambridge Brain Sciences Cognitive Tool (Wynn, 1991)	CBSCT	1
Chinese Maudsley Personality Inventory (Chen et al., 2020)	C-MPI	1
Concise Mental Health Checklist (Chen et al., 2020)	CMHC	1
Coping Flexibility Scale (Sánchez et al., 2019)	CFS	1
Demographic Questionnaire (Karaman et al., 2019)	DQ	1
Framingham's Type A Behaviour Scale (Sánchez et al., 2019)	FBS-A	1
General Health Questionnaire (Hankins, 2008)	GHQ-12	1
Hindrance and Challenge Stress Scale (Lin et al., 2019)	HCSS	1
Life Engagement Test (Sánchez et al., 2019)	LET	1
Maslach Burnout Inventory (Maslach et al., 1986)	MBI	1
NEO Five Factor Inventory (Sánchez et al., 2019)	NEO-FFI	1
Patient Health Questionnaire (Manea et al., 2015)	PHQ-9	1
Perception of Academic Stress Scale Modified (Bedewy & Gabriel, 2015)	PASS-M	1
Perceived Control of Internal States Scale (Lin et al., 2019)	PCOISS	1
Perceived Stress Scale (Sánchez et al., 2019)	PSS	1
Pittsburgh Sleep Quality Index (Smyth, 1999)	PSQI	1
Rost Test modified by Moraschi (Moraschi, 1990)	RT-M	1
Rotter's Internal External Scale (Rotter, 1966)	I-E	1
Satisfaction with Life Scale (Diener et al., 1985)	SLS	1
Self-rating Depression Scale (Zung, 1965)	SDS	1
Stress Symptom Inventory (Pozos-Radillo et al., 2014)	SSI	1
Student Life Stress Inventory (Gadzella & Masten, 2005)	SSI-R	1
Subjective Units of Distress Scale (Sánchez et al., 2019)	SUDS	1
UCLA Loneliness Scale (Sánchez et al., 2019)	UCLA-LS	1
University Stress Screening Tool (Chen et al., 2020)	USST	1
Psychological Stress Measure (Desai et al., 2021)	PSM-9	1

N: number of articles in which psychological instruments were used

psychological instrument was found in the reviewed literature. In some studies, two or more psychological instruments were used to identify stress and anxiety states. In addition, Tables 4 and 5 summarize previous studies focused on the psychological-tool-based systems for academic stress and anxiety detection.

Table 3 demonstrates that, the most used psychological instrument is the State-Trait Anxiety Inventory (STAI). This test is popular because it is easy to apply and the results are easy to interpret. The STAI test was used in 9 (33.33%) of the 27 articles in which a psychological instrument was used. It is important to consider that one disadvantage of the use of psychological instruments is that each tool must be appropriate and valid for the population surveyed due to cultural, social, environmental, educational, and demographic differences between countries (Tsang et al., 2017). Then, it is reasonable to state that the instruments used in the literature should have been validated and appropriate for each case, explaining the lack of generalization and consensus regarding the use of the same instrument by the scientific community.

### 3.1.2 Biological measurements

Anxiety manifests itself by activating the autonomic, motor and central, endocrine, and immune, nervous systems (Kaniusas, 2011). On the other hand, stress activates the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). These manifestations modify the values and characteristics of various biomarkers and biosignals.

*Physical signs* are described as a measure of body alteration that can be directly perceived by an expert, evaluator, or medic; for example: muscle activity, pupil size, eye movements, blinking, semi-involuntary limb movements, facial expression, head movements and voice characteristics, volume, pitch and rate of speech (Giannakakis et al., 2019). On the other hand, *physiological signals* are directly related to vital bodily functions, and most of them respond to the SNS and the PNS of the human body. Some examples are electroencephalography (EEG), electrocardiography (ECG), heart rate (HR), heart rate variability (HRV), galvanic skin response (GSR), electromyography (EMG), photoplethysmography (PPG), blood volume per pulse (BVP), skin temperature (ST), oxygenation (SpO<sub>2</sub>), and respiration or breathing rate (Br). Finally, *biomarkers* measure hormone levels, such as cortisol and catecholamine (Sharma & Gedeon, 2012). In other words, *physical signs and physiological signals* are considered *biological signals (biosignals)*. Hormone levels, and other biochemical measures are called *biomarkers* (Giannakakis et al., 2019; Morera et al., 2019). Tables 4 and 5 summarize the systems based on biological signals and biomarkers for academic stress and anxiety detection.

Tables 6 and 7 summarize the reviewed literature related to the use of biological signals and biomarkers to identify stress in academic settings. The sensors and electronic data acquisition systems are primarily commercial and were used to perform data acquisition, conditioning, and storage. In 18 papers, commercial sensors and platforms were used as data acquisition systems along with audiovisual software for task presentation (stressors); in 4 papers, the use of custom-made GSR sensors is reported, and in 1 paper, a portable device (LG Smartwatch) was used for biosignal

**Table 4** Psychological-tool-based systems for stress and anxiety detection (part I)

Author, year	Sample size	Instrument	Stressor label	Contribution
(Mejía-Rubalcava et al., 2012)	73	SISCO	S2	Age, salivary flow rate and academic stress level are related a higher propensity to dental caries
(Backović et al., 2012)	755	GHQ-12, MBI	S2, S10, S12, S19	The first findings on academic distress and burnout among medical students in Serbia are presented
(Corsini et al., 2012)	269	IDARE	S1	Anxiety levels increase with curricular advancement. No relationship is found with gender. Low correlation between age and anxiety level
(Martínez et al., 2012)	114	RT-M	S1	The poor execution of study and learning strategies leads to and inefficient meta cognitive condition that leads to anxiety
(Bati et al., 2013)	570	STAI	S10	High levels of trait anxiety regardless of gender. To reduce the anxiety provoked by the first study of a cadaver, preparatory sessions should be planned
(Pozos-Radillo et al., 2014)	527	ASI, SSI	S1	Classroom intervention, mandatory work and doing an exam predict high levels of chronic stress, were chiefly observed in 18-, 23- and 25- year-old females
(Rivas-Acuña et al., 2014)	106	STAI	S1	An increasingly anxiogenic context, negatively affect adaptation, academic performance, interpersonal relationships, and maturation
(Martínez-Otero, 2014)	137	SISCO	S1	Low frequency of moderate academic stress observed. Most reported stressors were homework overload and evaluations. Most reported effects were drowsiness, restlessness, and variations in eating
(Waqas et al., 2015)	251	PSS-14, PSQI	S1, S3	High prevalence of academic stress and poor sleep quality among medical students, use of sedatives more than once a week
(Bedewy & Gabriel, 2015)	100	PASS-M, $\alpha_c=0.7$	S3	Brief self-report scale to measure academic stress sources was developed. Most reported sources were competition with peers, work load, career expectations, and little rest time
(Hernández et al., 2015)	116	IDARE	S1	The evaluated population presented constant mid-level state and trait anxiety
(Castillo-Pimienta et al., 2016)	327	STAI, ASI	S1	Higher levels of anxiety in Nursing students than in Medical Technology students. The main stressors were academic overload, lack of time to complete assignments, and taking exams

For questionnaire acronyms, see Table 3. For stressor labels, see Table 10. Statistical data analysis was used in all cases



**Table 5** Psychological-tool-based systems for stress and anxiety detection (part II)

Author, year	Sample size	Instrument	Stressor label	Contribution
(Reyes-Carmona et al., 2017)	479	IDARE	S9	No correlation was found between anxiety and grade point average of medical interns
(Mahroon et al., 2017)	307	BDI, BAI	S1	Alarming prevalence of depression and anxiety symptoms among medical students were reported. High correlation of symptoms with ethnicity, female gender, relationship with peers, career progress, and academic performance
(Dube et al., 2018)	19	DASS	S3	Academic problems were the main source of stress. Females had comparatively higher stress levels than their male counterparts
(Romo-Nava et al., 2019)	814	PHQ-9, SISCO	S20	Major depressive disorder (MDD) is strongly associated with current and past abuse and increasingly correlated with academic stress along with the academic progress
(Liu et al., 2019)	1401	DASS	S1	Chinese college students suffer from higher-than-normal anxiety levels in the first three years. 20 to 40% of students suffered from different degrees of depression, anxiety, and stress
(Karaman et al., 2019)	307	SSI-R	S1, S3	Higher academic stress levels were associated with higher levels of locus of control and lower life satisfaction. Female college students had higher physiological stress than male students
(Lin et al., 2019)	55	HCSS, PCOISS	S7	For students with high or mean levels of perceived control, academic stress does not influence working memory. For low levels of perceived control, academic stress was negatively associated with students' task performance
(Chen et al., 2020)	857	CMHC, USIT, $\alpha_c = 0.63$ , C- MPI, $\alpha_c = 0.87$	S1, S3	Socio-demographic stress sources, self-rated mental health, neurotic personality, and academic curricula correlated with stress-induced suicide risk among Chinese students

For questionnaire acronyms, see Table 3. For stressor labels, see Table 10. Statistical data analysis was used in all cases

**Table 6** Systems based on biological signals and markers for academic stress and anxiety detection

Author, year	Sample size	Signal/Marker	Acquisition system	Stressor	Data Analysis	Accuracy
(Santos et al., 2011)	80	HR, GSR	Physiolab and I-330 C2 Module	S4, S14	Fuzzy logic	99.50%
(Melillo et al., 2011)	42	HRV	ECG Pocket	S2	Statistical, LDA analysis	90.00%
(Melillo et al., 2013)	42	HRV	ECG Pocket	S2	Decision tree	87.00%
(Castaldo et al., 2016)	42	HRV	ECG Pocket	S8	Decision tree	79.00%
(González & Jiménez, 2016)	16	ECG, GSR	EDA100C, ECG100C Biopac	S7, S9	Statistical	NR
(Assaf et al., 2017)	35	Cortisol, cytokines	Heparinized vacutainers	S1, S2	Statistical	NR
(Ramteke & Thool, 2017)	30	HRV	Biopac electrocardiograph 3-bias	S2, S8	Statistical	NR
(Egímez et al., 2017)	7	HR, GSR	Custom made GSR, LG Smart-watch	S9, S12, v	Random forest	78.80%
(Nepal et al., 2018)	60	GSR	NR	S4	Statistical	NR
(Castaldo et al., 2019)	42	HRV	ECG Pocket	S2	KNN	94.00%
(Desai et al., 2020)	6	BEG	EasyCap	S4	Gaussian process	94.00%
(Ramírez-Adrados et al., 2020)	110	HRV	Polar V800 HR monitor	S6	Statistical	NR
(Ramírez-Adrados et al., 2020)	110	Cortisol, HRV	Polar V800 HR monitor; Lafayette Instrument Flicker, Fusion Control Unit Model 12,021	S6, S18	Statistical	NR

GSR = Galvanic Skin Response; HR = Heart Rate; HRV = Heart Rate Variability; ECG = Electrocardiography; LDA = Linear Discriminant Analysis; KNN = K-Nearest Neighbor; NR = Not Reported. For stressor labels, see Table 10

**Table 7** Systems based on biological signals and markers for academic stress and anxiety detection

Author, year	Sample size	Signal/Marker	Acquisition system	Stressor	Data analysis	Accuracy
(Durán Acevedo et al., 2021a)	25	GSR, EMG, ECG	ADS1015, ADS1298ECG, Studio GSR Seed	S2	LDA, SVM	90.00%
(Durán-Acevedo et al., 2021b)	25	GSR, e-nose	Seed Studio GSR, e-nose	S2	LDA, KNN, SVM	96.00%

GSR = Galvanic Skin Response; HR = Heart Rate; HRV = Heart Rate Variability; ECG = Electrocardiography; EMG = electromyography; LDA = Linear Discriminant Analysis; SVM = Support Vector Machine; KNN = K-Nearest Neighbor. For stressor labels, see Table 10

measurement. Some of the most commonly used electronic devices are: Ates Medical Easy ECG Pocket, Biopac EDA100C, Biopac ECG100C, Respiration Monitor Belt, Easycap EEG Recording Cap, Polar V800 HR monitor, Lafayette Instrument Flicker Fusion Control Unit Model 12021, Sallivette sampling devices for cortisol, and PAXgene blood RNA tubes for collecting blood samples.

Since stress and anxiety generate a biological response due to the subject's primary instinct for survival and well-being, biosignals and biomarkers are reliable indicators of the presence of anxiety and stress. Technological developments have improved the accuracy of subject measurements, data extraction, and analysis of signal characteristics. Moreover, it is feasible to use portable and wearable devices or mobile applications (Egilmez et al., 2017).

According to the literature review, HRV analysis using ECG is the most commonly used physiological indicator of stress, followed by the GSR signal. In third place, measurements of hormone levels such as cortisol and cytokines were taken (see Table 6). The raw ECG signal and HR values were minimally used. The least used signals were EEG, SpO<sub>2</sub>, and Br. Some authors reported HRV signals and cortisol levels as reliable indicators of stress states (Morera et al., 2019). In addition, the use of the time and frequency of HRV signals as biomarkers for stress detection was analyzed due to their reliability (Castaldo et al., 2015). Other signals have also been analyzed as stress indicators, physical signs such as changes in pupil size, voice, or physiological signals such as temperature, respiration rate, and photoplethysmography (Giannakakis et al., 2019).

Thus, it can be summarized that the previously mentioned biological measurements are relevant in the context of academic stress identification given that they quantify neuroautonomic changes associated with the onset of stress, such as physiological time series (e.g., HRV and GSR) (Dalmeida & Masala, 2021; Pop-Jordanova & Pop-Jordanov, 2020). Additionally, changes in the concentration of biomarkers such as hormones and cytokines are also relevant since they are related to neuroendocrine-immune modifications produced by stress (Menard et al., 2017).

### 3.1.3 Combined systems

Tables 8 and 9 show systems based on biological signals, biomarkers and psychological tools for academic stress and anxiety detection. In these studies, the authors propose using a combination of psychological tools and biosignals to correlate scores of the indices and questionnaires of the psychological tools with the behavior of the biosignals in anxiety and stress situations. A positive correlation between questionnaire scores and biosignal statistical values was reported (Honda et al., 2013; Hoskin et al., 2013; Barbic et al., 2020). However, although some authors report favorable results for stress and anxiety detection, in most cases, their experiments were conducted in controlled environments using laboratory activities (stressors), limiting the possibility to generalize their results to academic environments. Also, it is impossible to have a perspective of the impact of stress and anxiety on students' performance.

**Table 8** Systems based on biological signals, biomarkers and psychological tools for academic stress and anxiety detection

Author, year	Sample size	Signal/parameter	Sensor	Stressor label	Data analysis	Contribution
(Kurokawa et al., 2011)	26	STAI, SDS, Cortisol	Sallivette sampling devices	S5	Statistical	No significant correlation between psychological measurements and salivary cortisol level. GR $\beta$ isoform may be involved in physiological stress regulation
(Honda et al., 2013)	25	microRNAs, STAI	Sallivette, PAXgene	S5	Statistical	Maximum correlation between miR-16 and STAI-state scores: 0.375. Identified miRNAs may participate in integrated stress response
(Hoskin et al., 2013)	70	Hearing, STAI	Laptop audiovisual A-SDT	S13	Statistical	More anxious participants presented auditory hallucinations
(García et al., 2016)	45	GSR, SISCO	GSR proto-type	S15	Genetic algorithm	the importance of the use of biosignals along with psychological instruments is discussed
(Sánchez et al., 2019)	18	HRV, SUDS, LET, CFS, PSS, FBS-A, NEO-FFI, UCLA-LS	Polar V800 HR monitor	S11	Statistical	Anticipatory anxiety response increased, absence of habituation process, positive relation between loneliness and stress response
(Barbic et al., 2020)	12	ECG, CBSCT	MR-D Pulse, ECG portable	S7, S17	Statistical	Cognitive performance improved in a cooler environment, ECG modulation also increased

For questionnaire acronyms, see Table 3. For stressor labels, see Table 10. GSR = Galvanic Skin Response; HRV = Heart Rate Variability; ECG = Electrocardiography

**Table 9** Systems based on biological signals, biomarkers and psychological tools for academic stress and anxiety detection

Author, year	Sample size	Signal/parameter	Sensor	Stressor label	Data analysis	Contribution
(Rodríguez et al., 2020)	21	SpO2, Br, ST, GSR, HR, STAI	e-Health V2 shield	S4	KNN stress, SVM anxiety	Best accuracy achieved for one GSR sensor and three features. A method for the anxiety detection using biosignals is outlined
(Desai et al., 2021)	80	HR, PSM-9	Omron Series 10	S9	ANOVA	Participants in the mindfulness-meditation group reported greater stress reduction after intervention than participants in the video game group
(Morales-Fajardo et al., 2022)	56	rPPG, IDARE	webcam	S2	RF, J48, KNN, SVM	The results show that the rPPG signals combined with students' demographic data and psychological scales provide 96% accuracy by using K-NN, J48, and RF

For questionnaire acronyms, see Table 3. For stressor labels, see Table 10. GSR = Galvanic Skin Response; HR = Heart Rate; ST = Skin temperature; SpO2 = Oximetry; Br = Breathing rate; rPPG = remote photoplethysmography; SVM = Support Vector Machine; KNN = K-Nearest Neighbor; RF = Random forest; J48 = Decision trees

### 3.2 Application of detection system

In the articles reviewed, data acquisition and analysis, experiments, measurements, surveys, interviews, questionnaire, and sampling were carried out. The most general aspects of data acquisition and analysis methods are presented below. This information can be used for further studies related to the identification of academic stress and anxiety.

### 3.3 Sample characteristics

In the systems based on biological signals and markers, the minimum population was 6 students, and the maximum was 110; the mean sample size was 48 subjects. In the systems based on psychological tools, the minimum number of participants was 19 students, and the maximum was 1,400; the mean sample size was 353 subjects. Likewise, in the systems with a combination of biological signals and markers with psychological tools, the minimum population was 12, and the maximum was 80, with 46 subjects on average.

University degrees in which the studies were conducted are as follows: Medical Sciences in 22 articles (50.00%), Engineering in 11 studies (25.00%), Education in 3 (7.00%), and Psychology in 1 (2.00%). In 7 papers (16.00%), the area of professional training to which the students belonged was not reported. All subjects in the reviewed studies were students except in one case (Hoskin et al., 2013), in which academic staff also participated.

### 3.4 Stressors

Situations, people, or objects that stimulate physiological and psychological stress responses are called stressors. Various academic activities, such as school workload, examination and evaluation periods, interaction with teachers, and even work periods in hospitals were used as stressors. Non-academic factors such as students' physical and mental health, demographic and social situation, logical and, cognitive activities, and physically uncomfortable (stressful) situations such as classroom temperature or putting a hand in a bucket of ice were used as stressors. Additionally, playful and competitive activities such as singing, playing video games, watching pictures and eating were also used as stressors. The purpose of applying stressors was to promote changes in the measured signals or to obtain responses in situations that could be differentiated from each other, before and after an evaluation. These changes were used as indicators of a response to stress and/or anxiety.

Although the stressors used correspond mostly to real-life situations and, given that biological signals were measured and questionnaires were answered in controlled conditions, it is considered that anxiety and stress conditions were also controlled. In all but three papers (Ramírez-Adrados, Fernández-Martínez, et al., 2020; Ramírez-Adrados, Beltrán-Velasco, et al., 2020; Morales-Fajardo et al., 2022), measurements were taken during the students' university exams. Then, post-experiment analysis of the signals obtained was carried out. Table 10 shows a summary

**Table 10** Tasks and situations considered as stressor in reviewed articles

Stressor	Label	<i>N</i>
Academic work during the semester	S1	13
Evaluation period	S2	10
Real-life situations, demographic, social, psychological, and health	S3	5
Mathematical tasks	S4	4
Video gaming	S9	3
Medical license test	S5	2
Academic examination	S6	2
Logic and memory tasks	S7	2
Oral exam or presentation	S8	2
Autopsy	S10	2
Admission to boarding school and professional practices	S11	2
Conversation with professors	S12	2
Unpleasant images	S13	1
Hyperventilation	S14	1
Psychological evaluation	S15	1
Place a hand inside an ice bucket, sing, Stroop Test, doing homework, eating, and e-mail management	S16	1
Controlled temperature inside the classroom	S17	1
Language of the oral presentation native or non native in academic examination	S18	1
Attending to patients	S19	1
History of abuse	S20	1

*N*: number of articles in which the stressor was used

of the stressors used in the reviewed papers. *N* indicates the number of times each stressor was used, either individually or in combination with others.

### 3.5 Data analysis for stress and anxiety recognition

Once the signals, markers, and questionnaire responses had been acquired, data were processed and analyzed to identify stress and anxiety states. The reviewed works use two main analysis methods: statistical analysis and pattern recognition.

The calculation of statistical parameters was used in 32 (73.00%) of the articles reviewed. Measures of central and non-central tendency, dispersion, measures of shape, statistical moments, analysis of variance (ANOVA), and two-dimensional measures such as a correlation between variables were reported to analyze the behavior of the data obtained.

On the other hand, pattern recognition classifies objects into several categories or classes. Depending on the application, these objects may be signals resulting from measurements and classified into patterns (Theodoridis & Koutroumbas, 2003). The algorithms for pattern recognition used in the academic environment, according to the documentation reviewed, are the following: logistic regressions, linear



regressions, multiple regressions, and multivariate regressions (Stijnen & Mulder, 1999).; These algorithms were used in five articles (11.50%) as part of the statistical analysis. The K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) (Wu et al., 2007) algorithms were used in four papers (9.00%). Linear Discriminant Analysis (LDA) (Fisher, 1936) and Decision Tree (DT) (Rokach & Maimon, 2007) algorithms were used in three papers (7.00%). Random Forest (RF) (Ho, 1995) algorithms were used in two papers (4.50%). Whether individually or in combination with other tools, the following algorithms were used for data analysis in one article: Genetic Algorithm (Whitley, 1994); Gaussian Processes (Rasmussen, 2004), and Fuzzy Logic (Mockor et al., 1999). One of the most commonly used measures of the performance of a pattern-recognition algorithm is accuracy. The maximum accuracy achieved for classifying the presence of anxiety states was 100.00%, and the minimum accuracy reported was 77.18% (see Table 11).

### 3.6 Detected phenomenon

The objectives of the articles analyzed can be separated into five groups according to the variables of interest related to academic stress and anxiety.

- Four articles set out to analyze stressors or stressful tasks to determine whether students perceived them and which ones were most representative.
- Eight papers focused on assessing the consequences of stress and anxiety, such as physical and psychological health problems, poor academic performance, and/or social adjustment problems.
- Nine papers were about anxiety recognition in university students using daily activities as stressors, such as health, social and work-related issues.
- Twelve articles identified stress using academic activities similar to those in an academic setting as stressors.
- Twelve papers were centered on detecting stress related to activities in the non-academic lives of university students.

The variety of phenomena detected indicates that both academic stress and anxiety and their manifestations, sources, and consequences are of interest to researchers.

## 4 Discussion

This review provides a current perspective on identifying academic stress and anxiety in students to outline the advances and challenges facing the scientific community.

Forty-four papers were reviewed; 41.00% were written in the Americas and 29.50% in Europe. These studies focus mainly on analyzing the detection of stress and anxiety to improve students' academic performance to reduce absenteeism, failure, and dropout rates (the studies were primarily conducted in public institutions). On the other hand, 25.00% of the studies were conducted in Asia to reduce the

**Table 11** Pattern recognition algorithms used for data analysis in the reviewed articles

Author, year	Algorithm	Signal/parameter	Feature	Precision
(Santos et al., 2011)	Fuzzy Logic	HR, GSR	NR	99.50%
(Melillo et al., 2011)	LDA	HRV	Non-linear	90.00%
(Melillo et al., 2013)	DT	HRV	Time and frequency domain	87.00%
(Castaldo et al., 2016)	DT	HRV	Non-linear (Sam-pEn, RPlmean, ShamEn)	80.00%
(García et al., 2016)	Genetic Algorithm	GSR	Statistical (avg, std deviation, max and min)	77.18%
(Egilmmez et al., 2017)	RF	HR, GSR	Statistical (mean, min, symmetry), Kurtosis, IRQ	78.80%
(Castaldo et al., 2019)	KNN	HRV	Time and frequency domain	94.00%
(Desai et al., 2020)	Gaussian Process	Pro- EEG	Statistical	94.00%
(Rodríguez et al., 2020)	KNN, SVM	HR, SpO <sub>2</sub>	Statistical (mean, 91.85-ST, GSR, Br normalizations, RMS, differences)	95.56%
(Durán Acevedo et al., 2021a)	LDA, SVM	GSR, ECG, EMG	NR	88.00%-100.00%
(Durán-Acevedo et al., 2021b)	LDA, KNN, SVM	GSR, e-nose	NR	96.00%-100.00%
(Morales-Fajardo et al., 2022)	RF, SVM, DT	KNN, rPPG	HR values and demographic data	96.00%

LDA = Linear Discriminant Analysis; DT = Decision trees; RF = Random forest; KNN = K-Nearest Neighbor; SVM = Support Vector Machine; HR = Heart Rate; GSR = Galvanic Skin Response; HRV = Heart rate variability; EEG = Electroencephalography; SpO<sub>2</sub> = Oximetry; ST = Skin temperature; ECG = Electrocardiography; EMG = Electromyography; Br = Breathing rate; rPPG = remote photoplethysmography; NR: not reported

prevalence of depression in students subjected to strict academic systems and reduce suicide rates. Finally, 4.50% of the studies were conducted in Africa, which shows interest in improving students' coping strategies when experiencing stress and anxiety as a result of academic activities. In general, the studies focused on the implementation or evaluation of a platform aimed at providing non-invasive, inexpensive, portable, and/or reliable stress detection systems. In all cases, such platforms were viewed as support tools for the experts.

On the other hand, the assessment of stress and anxiety from questionnaires depends on students' self-perception. In many cases, the internal consistency of questionnaire items is not representative of the stress or anxiety of the subject (Eack et al., 2006). Furthermore, although questionnaires can be answered by many students simultaneously, they cannot be answered while conducting academic tasks. The evaluation of responses takes time, so the information on stress and anxiety extracted from questionnaires may not be immediate. To overcome the disadvantage of using some psychological instruments with university students, some authors propose using electronic measurement platforms which rely on biosignals to reduce the subjectivity of self-reports or questionnaires.

There is no conclusive data on which sensors/biomarkers are more suitable for academic environments. In the literature review, the most employed sensors are ECG sensors used to detect HRV signals. Such sensors can be placed on the arms, but they perform best when the electrodes are placed on the chest (Sioni & Chittaro, 2015). Although not reported, the placement site could generate a recognition results bias of stress and anxiety states. Studies in other contexts have shown that stress levels in subjects are increased due to the presence and placement of the sensors before starting the experimental tests. For example, most women find having the sensors placed on the chest area uncomfortable, invasive, and stress-inducing (MacLean et al., 2013).

On the other hand, there are no conclusive results on the used of other biological signals whose sensor placement is considered less invasive in an academic setting. For example, the photoplethysmography signal in which the sensor can be placed on the wrist or fingertip under specific conditions is considered appropriate for detecting HRV signals (Selvaraj et al., 2008). Then, the objectives ought to be the creation of stress identification platforms that use non-invasive methods to reduce the stress induced by the placement and presence of sensors, and the identification of the most suitable biosignals and/or biomarkers for identifying anxiety and stress states in an academic environment in real-time.

Regarding the characteristics of the sample used in the reviewed papers, it was identified that the systems involving biological measurements have the smallest sample size, with a minimum of 6 students (Desai et al., 2020). Although it is difficult to define a minimum sample size to protect against skewness, some authors recommend a sample size equal to 30 (Fay & Gerow, 2013). Moreover, when using large sample sizes (>30), the distribution of the data can be ignored (Ghasemi & Zahediasl, 2012). In contrast, small sample sizes could render any experiment much less powerful. In general, 25% of the reviewed papers used a sample size of fewer than 30 subjects. Studies in which the sample size is smaller than 30 subjects limit the generalization and comparison of results. However, sample size was not an

exclusion criterion for the reviewed papers. Thus, it is suggested that future studies consider sample size as a main character in the experimental protocol in order that the results are statistically significant.

Regarding the identification of the psychological instruments, technological tools (data acquisition systems and sensors), and data processing techniques most commonly employed to identify stress and anxiety in academic settings, the results indicate that there is still no conclusive evidence. Various stress induction protocols, psychological tools (either alone or in combination with data acquisition systems, in the case of biosignals), and various data analysis techniques have been used to identify stress and anxiety in the academic environment. The results do not allow for the identification of any consensus among the scientific community on the use of protocols, psychological tools, sensors for data acquisition, and data analysis techniques. The most commonly used tool is psychological questionnaires used alone or in combination with biosignals. This was the case in 29 (66.00%) of the 44 studies reviewed.

The STAI is the most widely used psychological instrument in the academic setting. It was used in 10 (28.00%) studies of the reviewed papers. Stressful situations commonly elicit feelings of anxiety in subjects (Jamieson et al., 2013). Moreover, anxiety is considered as an emotional response to a subject's perception of a stressful activity or experience (Koelsch et al., 2011; Hook et al., 2013). A correlation between STAI score and cortisol level has been determined;  $r = 0.509$  (Kurokawa et al., 2011) and  $r = 0.375$  (Honda et al., 2013). Typically, higher cortisol levels correlate with higher STAI scores. The advantages of the STAI assessment are the easy interpretation of results and the short time required to answer all the questions on the form. The disadvantage of cortisol level analysis is that the process requires specialized and expensive equipment. The test requires blood or saliva samples (for the latter, the sampling and analysis process takes at least 15 minutes; otherwise, the results are not valid). Thus, using the STAI questionnaire seems a viable option for stress and anxiety identification.

Regarding the use of biosignals and biomarkers during the stress screening procedure, ECG, GSR, EEG signals, and cortisol tests in saliva and blood were reported in 19 (79.00%) of the 24 studies. The most commonly used feature is HRV, reported in 8 (33.50%) studies. The use of this signal reached an accuracy of more than 90.00% (Castaldo et al., 2019; Melillo et al., 2011) in the classification and identification of stress in the academic setting. However, there is evidence that the GSR signal could be used in conjunction with pattern recognition models for the identification of academic stress with an accuracy more than 95.00% (Durán Acevedo et al., 2021a; Rodríguez et al., 2020). New emerging methods, such as rPPG in combination with demographic data or e-nose, achieved an accuracy over 96.00% (Durán-Acevedo et al., 2021b; Morales-Fajardo et al., 2022).

Data analysis for identifying anxiety and stress states is mainly performed using statistical analysis techniques. However, in recent years, pattern recognition algorithms have been increasingly used in academic settings. In most cases, although data acquisition can be carried out on-site and in a short time, data

analysis is still not done immediately, i.e., in most studies, data is first acquired, and further analysis is then performed.

Detecting stress and anxiety in college students leads to the possibility of correlating these conditions with predictable or treatable physical and mental illnesses based on knowledge of their stress status. Academic performance can also be improved by teaching coping strategies to students whose stress level has been detected as a detrimental factor. Some authors recognize stressors and triggers of anxiety related to the academic environment. However, without conclusive results and in some cases due to the sample size, these cannot be generalized. The best accuracy (100%) reported was achieved by the SVM algorithm with a GSR signal, but the characteristics used for the algorithm are not reported. The most used signal is ECG; and the one with the second best performance (99.50%) was reported in those studies in which this signal was used in combination with Fuzzy Logic.

Relevant studies highlight the potential benefits of physiological data and psychological scales in developing tools that provide learners with immediate support as they learn. For example, a previous study combined single-item self-report questionnaires with electrodermal activity data to examine how subjects' perceptions and physiological responses interact during collaborative learning and how they affect academic performance (Dindar et al., 2020). That study found that physiological synchrony, measured by electrodermal activity, was significantly positively associated with cognitive change in high school students in self-regulated learning. Hence, opportune detection of academic stress or anxiety by physiological or psychological-based systems could support the development of psycho-pedagogical interventions to improve student learning.

Finally, the limitations can be summarized as follows. These limitations should be considered in future research:

- Small sample sizes for systems based on biosignal measurement.
- Lack of conclusive results on the use of biosignals in academic contexts and the use of non-invasive sensors to obtain physiological signals.
- Not all studied performed the tests in academic spaces or real situations. It is preferable to avoid controlled environments or laboratory tests (stressors).
- Instrumentation of students is time-consuming and leads to bias in measurements due to the possible stress induced by the placement of sensors or participation in the experiment. Consequently, alternatives for signal acquisition and measurement should be proposed, or pre-test and post-test conditions should be considered in the experimental protocols.
- Bias in results due to students' self-perception in filling-out self-reports and inventories.
- Need to develop and validate specific psychological tools for student populations in academic settings.
- The results of academic stress and anxiety detection are not immediate, limiting the possibility of providing feedback to students on specific academic activities.

## 4.1 Implications

Some studies have shown that using psychological instruments in combination with the measurement of biological signals is an adequate strategy for identifying academic stress and anxiety. However, it is impossible to have conclusive results for which signals have greater feasibility in academic settings. In addition, there are no conclusive results on the impact that stress and anxiety states have on students' academic life. The authors suggest conducting research focused on identifying the correlation between psychological instruments and biosignals and markers in real academic environments to avoid bias in the results derived from students' perception when answering inventories or self-reports in controlled spaces.

Regarding the conditions for data acquisition, most of the stressors employed were laboratory activities that attempted to replicate academic work in the school term; assessment periods (exams), and students' daily life contexts. Some authors report stress and anxiety induction protocols that include non-academic tasks (Egilmez et al., 2017), or apply the punishment-reward phenomenon to the stress-detection task (Rodríguez et al., 2020). Stress is a multifactorial process; thus, its origin outside controlled environments is virtually unidentifiable. The detection of stress and anxiety during academic tasks in a specific place with immediate results has not been reported. In two studies, measurements were taken during oral presentations, but the data analysis was performed with recorded signals, leading to a lack of immediate results. Whether it is a specific academic task such as an oral presentation or a conversation with a professor, there is evidence that the stress response and anxiety are prevalent in advance of the occurrence of the event (Lin et al., 2019; Sánchez et al., 2019). In addition, it is necessary to identify academic activities that could represent the classification of stress and anxiety states within the classroom.

The strategies for data analysis were divided into two main groups: descriptive statistical analysis and pattern recognition. The most commonly-used analysis by the authors was statistical analysis, and the most-commonly analyzed parameters were the correlation between variables and mean value (Honda et al., 2013; Waqas et al., 2015). On the other hand, some authors employed pattern recognition methods. The review showed that the most used algorithms are regressions and machine learning algorithms such as KNN and SVM. Using these in combination was also reported (Rodríguez et al., 2020). The accuracy reached by the pattern recognition algorithms was 100.00% in the best case (Durán Acevedo et al., 2021a, b), and 77.18% in the worst case (García et al., 2016). It can be proposed that the accuracy of the pattern recognition algorithm on stress and anxiety detection lies between these values. It is worth mentioning that while more frequently used features are temporal, frequential, and nonlinear HRV signals in stress detection in academia; statistical measures, which are less complicated to compute, of the GSR signal yield better accuracies; above 95.00% (Durán Acevedo et al., 2021a; Rodríguez et al., 2020; Santos et al., 2011). In addition, GSR sensors are less invasive, given that they are placed on the fingers; all this could indicate the need to explore the potential of the GSR signal in stress and anxiety detection. However, this review shows that the resources of pattern recognition science are not widely exploited in academia; one reason for this could be the expertise needed for its implementation. Therefore, future work should

propose using pattern recognition techniques to develop and implement measurement platforms to identify anxiety and stress states in real time and provide feedback to students and teachers to improve the learning environment in the classroom.

The presence of chronic stress and anxiety in students increases the likelihood of developing illness (Mejía-Rubalcava et al., 2012), sleep problems (Waqas et al., 2015), depression problems (Dube et al., 2018; Lin et al., 2019; Mahroon et al., 2017; Romo-Nava et al., 2019), social and environmental maladjustment (Sánchez et al., 2019), anticipatory anxiety before stressful events (Ramírez-Adrados, Fernández-Martínez, et al., 2020; Ramírez-Adrados, Beltrán-Velasco, et al., 2020; Honda et al., 2013; Melillo et al., 2013), and neurosis (Chen et al., 2020). However, the presence of episodic stress reported by study participants served in some cases to improve academic performance (Barbic et al., 2020; Reyes-Carmona et al., 2017). This is in contrast to cases where the presence of anxiety diminished participants' cognitive performance, and caused episodic stress (Hoskin et al., 2013; Pozos-Radillo et al., 2014; Martínez-Otero, 2014; Nepal et al., 2018). On the other hand, some studies report that participants' ability to cope with the stress response had a positive impact on their performance and adaptation (Bati et al., 2013; Rivas-Acuná et al., 2014). While chronically experienced stress and anxiety are precursors of physical and mental illness, when they appear episodically, students' lack of coping skills negatively affects their cognitive performance. Then, the use of stress and anxiety detection systems in the academic environment and the evaluation of students' academic performance implies aiming to develop accompanying strategies to improve students' coping skills and the intervention of educational institutions in the process.

## 4.2 Challenges ahead

The most widely used signal for stress detection in academia is HRV. Cortisol has been used in correlation with the STAI questionnaire. Commercial measurement systems, the cost of which is not affordable for many educational institutions, have also been reported. The stress that the placement of the sensors can induce has been commented on, making it challenging to identify physiological signals that can serve as indicators of stress and anxiety using less invasive sensors and developing systems which are more accessible to institutions. In addition to HRVs, the GSR signal appears to be an excellent candidate to address this challenge.

In the reviewed studies using psychological instruments, although most of them were performed under actual stress conditions, the questionnaires could not be answered at the same time as academic activities. On the other hand, in the biosignal-based measurement systems, only three experimental tests were developed during the performance of academic activities (doing an exam) (Ramírez-Adrados, Fernández-Martínez, et al., 2020; Ramírez-Adrados, Beltrán-Velasco, et al., 2020; Morales-Fajardo et al., 2022). The rest were performed under controlled stress conditions. Besides, in all the studies reviewed, data analysis was performed offline. For sensing systems to be helpful in an academic context, they need to be brought into students' daily activities, wearable measurement systems, optimization of recognition algorithms, mobile applications, and integration of sensing tasks could be helpful to address this. Although questionnaire response and data evaluation takes a long

time, almost all students have access to smart mobile devices. Then, an integrated project with a short stress and anxiety screening inventory targeted at students and an application for questionnaire response and data analysis may result in a portable, reliable, low-cost stress and anxiety screening system. These may reduce response time and may be suitable for the characteristics of the student population.

Encouragement of teachers' interest in detecting stress and anxiety among students to improve their quality of life and academic performance can reduce failure rates and dropout, while increasing the chance of success in the learning process. In addition, it would contribute to the reduction of stress-related health problems and it could increase the capacity for self-control and adaptation in social interaction. Shortening the time it takes to deliver the results of systems through online-data analysis and their incorporation in the classroom is one of the main challenges, along with the design and implementation of stress management and coping strategies.

### 4.3 Limitations of the study

Since only research published in indexed journals and conference proceedings was reviewed, other works that could enrich this analysis and these conclusions are likely outside this inclusion criterion. The characteristics analyzed aimed to answer two specific questions in the field of engineering. However, some other questions or characteristics may be analyzed for other areas of knowledge.

The limitations found in previous studies are summarized:

1. There are no conclusive results on the use of stress and anxiety detection systems in academia.
2. A lack of consensus regarding which anxiety and stress detection tools are most appropriate in the academic setting: psychological instruments or biological signals.
3. The necessary conditions and appropriate activities for academic stress and anxiety testing in the academic setting are unclear.
4. No unified guidelines on experimental protocols have been established in academia to acquire and measure biological signals.

## 5 Conclusions

A systematic search for information related to the detection of academic stress and anxiety was carried out, which resulted in the analysis of 44 scientific articles (published between 2011 and 2022). This analysis allowed us to identify the current limitations in this topic and identify the advances and challenges in the detection of students' stress and anxiety in academic environments.

Systems based on psychological instruments are the most widely used in anxiety and stress detection among university students. However, the use of psychological instruments suffers from a lack of reliability due to their dependence on the students' self-perception and the need for design and validation for a specific population.



The HRV is the most commonly used parameter in stress detection systems based on biosignal measurements. However, its effectiveness depends on experiments in controlled environments and sensor placement, as both factors are stress triggers, generating a bias in the results. Nevertheless, some results show that the use of other signals, such as PPG and GSR, could serve as biological signal patterns to be used in academic environments, but more studies are needed to obtain conclusive outcomes.

Data analysis in the academic environment is mainly performed using statistical tools; only nine papers use pattern recognition without statistical analysis. In general, these studies achieve an accuracy between 80.00% and 100.00% in academic stress and anxiety detection by using biosignals in combination with pattern recognition algorithms in controlled environments. Therefore, the authors suggest exploring the use of pattern recognition in academic environments for academic stress and anxiety identification.

Limitations have been presented, and lines of work have been suggested to address the issues in the reviewed papers. Bringing electronic platforms and wearable systems into the classroom in order to identifying stress and anxiety in the short term in real situations is still a challenge.

The interest of educators in the detection of stress and anxiety among students aims to improve students' quality of life, increase coping and self control abilities, and achieve greater adaptability to social interaction and context. Thus, using physiological data and psychological scales to identify critical moments that trigger stress or anxiety could aid in developing interventions that can provide learners with temporary support as they struggle with a challenge in terms of a specific problem. Shortening the response time of the detection systems and the strategies designed and implemented by educational institutions' staff can lead the way to overcoming it.

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## Declarations

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