AI and wearable sensors in Higher Education to investigate Public Speaking Skills

IA y sensores portátiles en la educación superior para investigar las habilidades de hablar en público

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Abstract
In most professional fields, being able to effectively communicate to an audience is considered an essential skill for professional advancement. However, the literature shows that anxiety disorders are among the most common mental disorders encountered by public speakers and that public speaking anxiety can negatively impact on the learning experience of undergraduate students. The present study involves university students from two different contexts and countries and examines their public speaking anxiety by cross-referencing data on cognitive self-perceptions, physiological reactions (heart rate), and behavioural aspects (facial expressions and body movements). It also explores the potential of wearable devices and artificial intelligence in data collection and analysis to identify different student profiles according to their levels of stress and public speaking anxiety. Despite various limitations, the cross-analysis showed good consistency and revealed interesting differences between the two samples, including stress-related clusters and emotional states. The data obtained encourage further research into the variables associated with public speaking and oratory skills. In addition, future developments of this study aim to further explore the potential contribution of these tools in assisting teachers in designing effective personalised training, as well as sharing and discussing data with students to promote awareness of their weaknesses and strengths.
Key words: undergraduate students, public speaking anxiety, artificial intelligence, wearable devices, heart rate, emotion recognition.

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Resumen
La capacidad de comunicarse eficazmente con el público se considera una habilidad esencial para el avance profesional. Sin embargo, la literatura científica muestra que los trastornos de ansiedad se encuentran entre los trastornos mentales más comunes que padecen los oradores públicos. El presente estudio involucra a estudiantes universitarios de dos contextos y países diferentes y examina su ansiedad al hablar en público mediante el cruce de datos sobre autopercepciones cognitivas, reacciones fisiológicas (frecuencia cardíaca) y aspectos conductuales (expresiones faciales y movimientos corporales). También explora el potencial de los dispositivos portátiles y la inteligencia artificial en la recopilación y el análisis de datos para identificar diferentes perfiles de estudiantes según sus niveles de estrés y ansiedad al hablar en público. El análisis cruzado mostró una buena consistencia y reveló diferencias interesantes entre las dos muestras, incluyendo grupos relacionados con el estrés y estados emocionales. Los datos obtenidos animan a seguir investigando las variables asociadas con la oratoria y las habilidades oratorias. Los desarrollos futuros podrían explorar la contribución potencial de estas herramientas para ayudar a los profesores a diseñar una formación personalizada eficaz y discutir los resultados con los estudiantes para promover la conciencia de sus debilidades y fortalezas.
Palabras clave: Estudiantes universitarios, ansiedad al hablar en público, inteligencia artificial, dispositivos portátiles, frecuencia cardíaca, reconocimiento de emociones.

1. Introduction and literature review

Public Speaking (PS) and oratory skills have played a key role in our culture since ancient times. Even more so today, in most professional fields, being able to generate and effectively communicate a message to an audience is considered an essential skill for professional advancement; therefore, educators at all levels should work to develop this skill in their students (Parvis et al., 2001; Haunts et al., 2022; Cherner et al., 2023). PS is characterised as the most common way of creating and exchanging meanings and to be effective requires mastery of verbal (intonation, rhythm, cadence, volume) and nonverbal (visual contact, face and body movements, gestures) communication (Mehrabian et al., 2017; Elia et al., 2024). Engagement in oral communication depends not only on learners' speaking and active listening abilities, but also on their affective and emotional state (El Shazly, 2020). The affective state is activated by psychological variables such as motivation, attitude, self-confidence, risk-taking, and anxiety (Krashen et al., 1982). According to El Shazly (El Shazly, 2020), situation-specific anxiety is a constant negative feeling that is mainly stimulated by a particular situation, such as a test, public speaking event, or class participation. Specifically, in Bodie's literature review (Bodie, 2010), Public Speaking Anxiety (PSA) is defined as «a situation specific social anxiety that arises from the real or anticipated enactment of an oral presentation». The author also reported two broad distinctions drawn in the extant literature: that between trait and state PSA and that between three components of PSA (physiology, cognitive, and behavioural). The Trait-State Distinction (Spielberg, 1966) differentiates anxiety experienced in a particular setting at a particular time (state) and a general tendency to experience anxiety across situations and time (trait), while the Three Systems model, originally proposed by Lang (Lang, 1968) , proposes that humans respond to stressful situations like PS in three systems: physiological, cognitive, and behavioural. The physiological system includes the central nervous, autonomic, and somatic systems, as well as the cellular and humoral systems, which regulate the human body and its response to stress (Andreassi, 2007). The most widely used are autonomic nervous system observations, particularly measures of cardiovascular response such as blood pressure and heart rate (HR) and measures of electrodermal activity such as palmar sweat. Then, the cognitive system refers to information obtained by the speaker through various instruments, such as interviews, self-reports, self-monitoring on PSA. Finally, the behavioural system refers to «the degree of assumed speaker anxiety perceived by observers on the basis of manifest speaker behaviour» (Mulac et al., 1975). Although several standard scales exist to measure behavioural speech anxiety, its observations remain little used in research since it is often confused with speech quality and it involves a decision on who evaluates this anxiety (the speaker, the audience, or an expert coder) (Bodie, 2010). Kirkwood and Melton (Kirkwood et al., 2002) state that anxiety disorders are among the most common mental disorders encountered by public speakers, while Lucas (Lucas, 2011) reported that «many people who converse easily in all kinds of everyday situations become frightened at the idea of standing up before a group to make a speech». However, the current socio-cultural and work environment increasingly demands the need to be effective public speakers, since to excel in many careers, individuals are expected to present at meetings or seminars conferences (physically or virtually) and express their opinions about a topic. Thus, it would be important for students to start working on PSA before they transit from academic to professional life. PS and oral assessments are common assessment types in higher education, which serve to measure a student's capacity to create and deliver an engaging, informed, and persuasive argument (Nash et al., 2016) and they are also examples of generic or personal transferable skills that may enhance employability. A survey of students from two UK universities, found that 80% of students consider oral presentations to be a source of social anxiety impacting on learning and well-being (Russel et al., 2012), while a more recent study of undergraduate students in the US found that 64% reported fear of PS (Ferreira et al., 2017). Raja's study (Raja, 2017) investigated the PSA of 50 undergraduate students of a reputable private sector business school in Pakistan to prove that this fear is very common among undergraduate students (75% of participants admitted it) and to highlight the need to integrate this skill into the curriculum from school to university (95% of participants agreed that this fear can be overcome if proper counselling, guidance, and coaching is provided). More recently, a qualitative survey conducted by Grieve et al. (Grieve et al., 2021) with 46 undergraduate and postgraduate students from a UK university clearly showed that PS tasks have an overall negative impact on the learning and experience of students with fear of PS or oral presentations. Specifically, the findings indicated that many students' main fears were related to being judged, uncertainty about the topic, and physical symptoms. Therefore, according to the authors, further evidence is also required on how fear of PS and oral presentations affects students' university experience to help educators plan oral presentations, gain a deeper understanding of students' fears, and support their needs. Recent research also explored the possible contribution of Artificial Intelligence (AI) to predict stress levels (Nalli et al., 2025) and to support learning and reduce anxiety (Elia et al., 2024; Wang, 2025). Literature shows also how the increase in HR during an in-class assessment activity is an indicator of a state of stress and anxiety in the students involved (Elwess et al., 2005). Specifically, several authors have demonstrated that a high HR fluctuation is associated with emotion regulation (Appelhans et al., 2006) and that this characteristic correlates with lower PSA (Egloff et al., 2006) . The recent integration of technological devices in educational settings has led researchers to develop new tools able to recognise anxiety states in students during PS. An example consists in the implementation and adoption of IoT wearable devices during classroom activities (Elbertsen et al., 2025), capable of collecting analog values (between 0 and 1023) of GSR

and HR to identify changes in terms of stress and anxiety during student interactions (Nalli et al., 2023). AI models have also been used to predict student anxiety, which consists of detecting the different emotions felt by students thanks to the analysis of facial biometric data through facial expression recognition using CNN (Alturki et al., 2025) and SVM algorithms (Rezaiguia et al., 2025). The present study involves university students from two different contexts and countries and investigates the three PSA-related systems reported by Bodie (Bodie et al., 2010), cognitive, physiological, and behavioural, to cross-reference data on speakers' cognitive self-perceptions, physiological reactions (HR), and behavioural aspects (biometric data such as facial expressions and body movements). Moreover, it explores the possible contribution of wearable devices and AI in collecting and analysing students' data in order to support teachers in defining specific intervention pathways. We thus formulated the following research questions:
RQ1: Is it possible to identify different levels of student stress and PSA to create distinct clusters? How do they differ in the two university contexts?
RQ2: Is there a consistency between the data obtained from students' sensors and the students' perception?

2. Research methodology

2.1 Context and participants

The study, carried out in the academic year 2023/24, analysed undergraduate students' PSA in two different university contexts. Specifically, it involved 23 students attending the "Foundations of Teaching and Learning" course in the first year of the Master's degree course of Primary Education at the Department of Education, Cultural Heritage and Tourism at the University of Macerata (Italy) (Unimc sample) and 32 students enrolled in the "Strategic Information Systems Management" module in the third year of the "Information Technology and Business Information Systems" undergraduate programme at the Department of Computer Science at Middlesex University London (UK) (Middlesex sample). In addition to the field of study, the two samples were also heterogeneous in terms of age, gender, and race. The first sample consisted of 22 females and 3 males aged 19-20, all of Italian nationality, who are studying to become future primary or pre-school teachers. The second sample consisted of local (UK) and international (Nigeria, India, and China) students, 10 females and 22 males, aged between 22 and 33 years. The students took part in the study on a voluntary basis and signed a data treatment consent form.

2.2 Data Collection

To answer our research questions, we scheduled short oral presentations (3-5 minutes) in both contexts, to be carried out in small groups of 2 or 3 students, and we chose three instruments to collect data for cross-analysis. Before giving the group presentation, we asked each student to fill in the Public Speaking Anxiety Survey (PSAS), administered via Google form. The PSAS was developed by Bartholomay and Houlihan (Bartholomay et al., 2016) to create «a psychometrically sound instrument that can provide good data for both diagnostic and tracking purposes». This brief survey consists of 17 questions that can be rated on a 5-point Likert scale - '1'= strongly disagree (SD), '2'= disagree (D), '3'= neutral (N), '4'= agree (A), '5' = strongly agree (SA) - to indicate to what extent participants consider the statement to be characteristic or true for them. It thus allowed to collect participants' perceptions of their own anxiety levels during PS experiences. Then, the students presented their work standing in front of other students and speaking one at a time for about 1 minute. During the presentation, we asked students to wear a portable device in order to extract the HR data. Specifically, we used a Polar OH1+, an optical HR monitor connected to the online application 'Polar Flow', as it allows the accurate collection of 60 HR records per minute and the download of a csv file (Mandal et al., 2023). Each student was also video-recorded to track facial expressions using a machine-learning emotion detector model, previously developed and tested during a group presentation activity (Fekry et al., 2019). This model consists of a combination of deep learning and a convolutional neural network, which is able to extract emotions from facial expressions thanks to the use of the OpenCV Python library. The model required a process called segmentation, which is able to split the video according to the analysis of each student's face. Once it has captured all the facial expressions provided by the students, it returns the main emotions for each student among those detected by the emotion detection model (e.g. happy, neutral, fear, sad, angry, surprise) and the corresponding percentage of expressions that allow each emotion to be identified.

2.3 Data analysis

The HR data allows to identify changes in students' emotional states by monitoring the increase in HR or the HR fluctuation, which can be influenced by the stress condition (Shubert et al., 2009) . However interpreting students' HR data is not an easy task, and a pre-processing step was required to define a dataset for the data analysis. Firstly, all the csv files related to each students' presentations were downloaded from Polar Flow and then processed using Microsoft Excel, returning the average, minimum, maximum and the fluctuation using standard deviation (Bruggerman et al., 1991). The extracted data were then collected in two datasets (one for each sample) containing the following features for each student: Id, HR St.dev., HR min, HR max, and HR avg. The data analysis consisted in the application of the unsupervised machine learning models, by developing clustering algorithms in Python, aimed at grouping students with similar HR conditions during the PS. Indeed, clustering aims to identify similarities between the data in the dataset and group them together in the same cluster to create different groups of homogeneous elements (Brezočnik et al., 2023).

Three clustering algorithms have been developed in order to select the most powerful:

- K-means (Saxena et al., 2017)
- Mean Shift (Comaniciu et al., 2002)
- Gaussian Mixture Model (Alshabandar et al., 2018)

These were compared using the Silhouette Analysis method (De Amotim et al., 2015) and the algorithm with the best score was selected for the final development. The machine learning model returned different clusters identifying the different levels of stress felt by students with at least the AVG value of HR above the range between 60 and 90 beats per minute (bpm), which is considered the normal resting HR for adults (Mason et al., 2007). These were then matched to the emotions extracted from the videos and compared with the results of the PSAS surveys.

3. Results and Discussion

3.1 RQ1

The first step required the creation of the datasets (one for each University), needed to allow the clustering algorithm to process the data. Once collected all the data and merged together in two csv files, a preprocessing step was required, by using the MinMaxScaler Python method from sklearn preprocessing library in order to normalise the data in a single scale and facilitate the analysis. The development process required the implementation of 3 different clustering algorithms (K-means, Mean Shift, and Gaussian Mixture Models), implemented with the standard parameters of the scikit learn library. The performances obtained by running each algorithm on the generated datasets were then evaluated using the silhouette analysis (method to interpret and validate the consistency within the clusters) and then compared to select the most performant one to be used for the final machine learning model. The range of the silhouette value S(i) is [-1, 1] and according to the method, the coefficients need to be as big as possible and close to "1" in order to have good clusters.

Figure 1.
Silhouette scores of the clustering algorithms for Middlesex

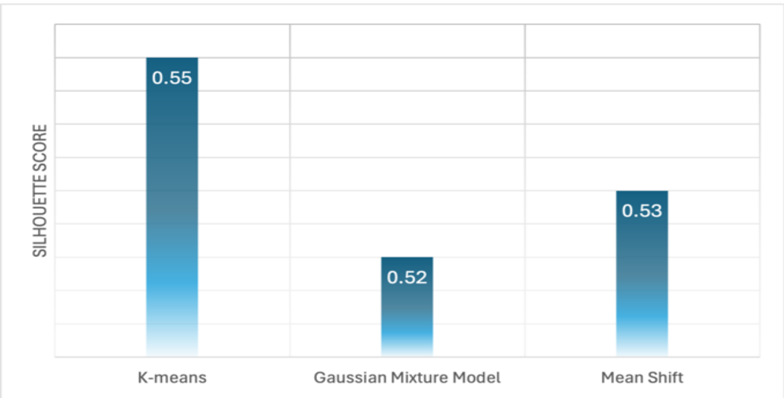

Figure 2.
Silhouette scores of the clustering algorithms for Unimc

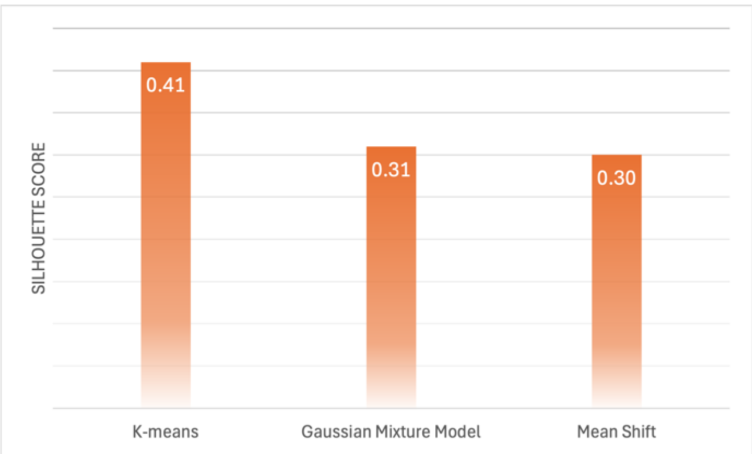

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Figure 3.
Elbow method processed for Middlesex

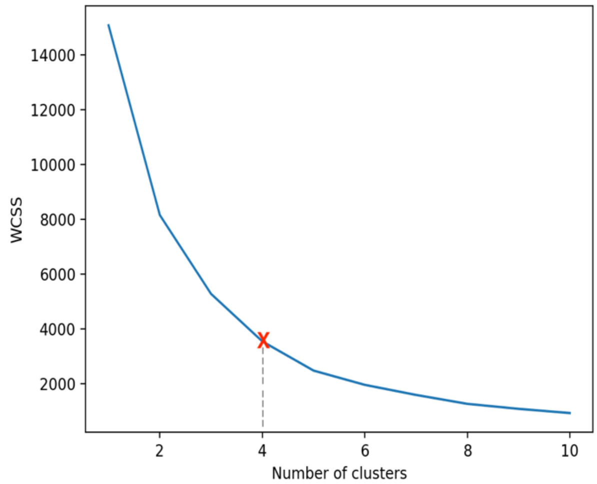
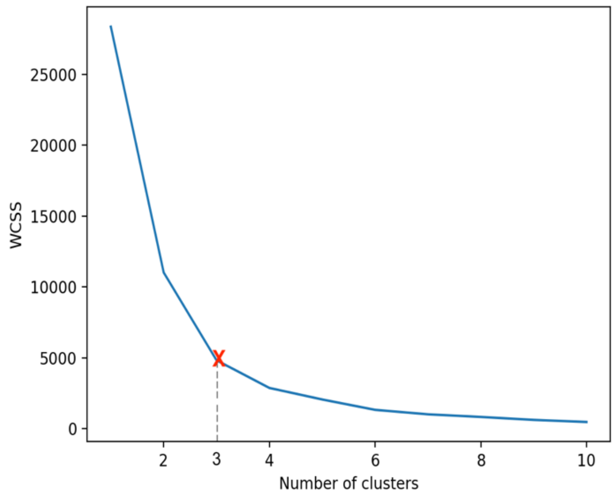


Figure 4.
Elbow method processed for Unimc



Once evaluated the models, the results plotted in Fig. 1 and Fig. 2 , showed that the best algorithm was K-Means, with the highest values among other algorithms in both models (Middlesex and Unimc) so that it was used to obtain for the clustering process. The implementation of K-means required the number of clusters to be generated as an input, so the elbow method was used to find the optimal number of clusters based on the datasets provided (Hackeling, 2017). The clusters obtained were then analysed to identify the different levels of stress perceived during the oral presentation, by highlighting the most influential features within the grouping.Fig. 3 and Fig. 4 show the elbow method used to find the number of clusters to create for each module. These returned the graph from which it was possible to extract the ideal number of clusters to generate, specifically 4 for Middlesex and 3 for Unimc, which was added as input to the related K-means algorithm. The algorithm created 4 clusters for Middlesex [characterised by 7 students (cluster 1), 11 students (cluster 2), 4 students (cluster 3) and 10 students (cluster 4)] and 3 clusters for Unimc [characterised by 11 students (cluster 1), 8 students (cluster 2), 6 students (cluster 3)], as shown in Fig. 5 and Fig. 6.

Figure 5.
Cluster plots for Middlesex

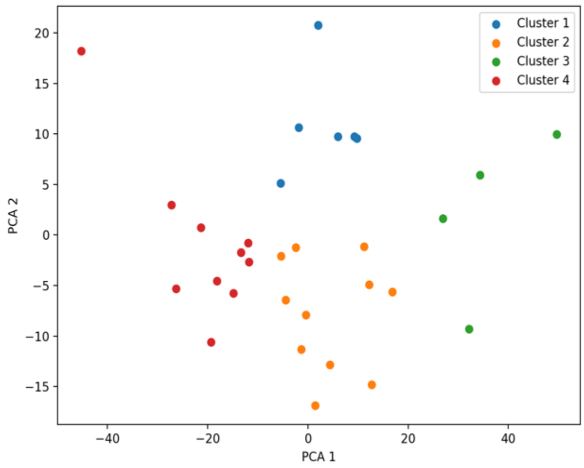


Figure 6.
Cluster plots for Unimc

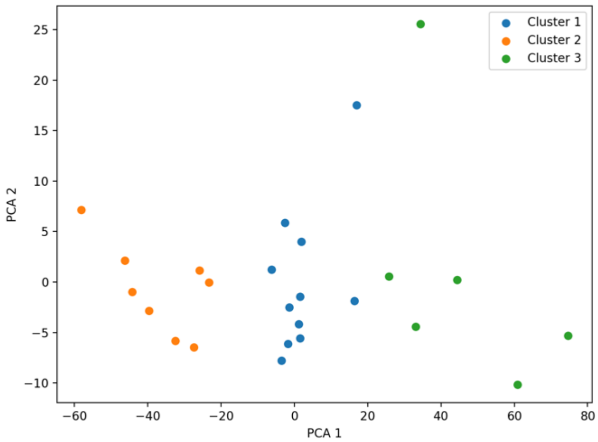


Table 1 shows the different levels of stress identified within each cluster at Middlesex. In particular, cluster 4 represents students who were relaxed during the speech with an HR average of 85, which is within the range of normal resting HR for adults (Mason et al., 2007) and with a lower standard deviation, which means a low HR fluctuation that keeps the HR state below the value of stress. The other clusters represent different levels of stress, starting with cluster 1 (low stress) with an HR average of 99, a little higher than the normal resting condition and a higher standard deviation that allow to be able to better manage their PSA compared to cluster 2 (stress) where the standard deviation is low, highlighting a longer stress condition without significant fluctuations in terms of HR. Cluster 3 (high stress), on the other hand, despite the higher value of the average HR, gave a higher value of the standard deviation that identifies the students’ ability to quickly return to a state of rest after the stressful condition. The students' emotions extracted from the video analysis using the AI emotion detector model also support these findings, with ‘neutral’ as the main emotion for students in cluster 4 (Relax) and the clusters with better stress management conditions (cluster 1 and cluster 3), while cluster 2, characterised by an opposite condition, returned ‘sad’ as the predominant emotion.

Table 1.
Differences between the clusters of Middlesex and details of the features analysed.

Clusters	N. Students	Sex	MIN	MAX	AVG	ST. DEV	MAIN EMOTIONS
Relax (cluster 4)	10	80% Male 20% Female	68.1	102.2	85.4	8.2	60% Neutral 40% Sad
Low Stress (cluster 1)	7	43% Male 57% Female	64.5	124.28	99.8	15.4	57 % Neutral 29 % Sad 14 % Angry
Stress (cluster 2)	11	73% Male 27% Female	82.4	117.8	100.4	8.8	55% Sad 45% Neutral
High Stress (cluster 3)	4	50% Male 50% Female	85.7	145.5	116.4	17.2	100% Neutral

Table 2.
Differences between the clusters of Unimc and details of the features analysed.

Clusters	N. Students	Sex	MIN	MAX	AVG	ST. DEV	MAIN EMOTIONS
Stress (cluster 1)	8	0% Male 100% Female	94.5	107.5	101.2	3.5	50% Sad 37% Neutral 13% Happy
High Stress (cluster 2)	11	18% Male 82% Female	115.3	131.3	124.5	5.1	82% Neutral 18% Sad
Very High Stress (cluster 3)	6	17% Male 83% Female	137.8	158.33	149.8	6.6	33.3% Sad 33.3% Neutral 33.3% Happy

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Table 3.
The demographic differences between the students in the Middlesex and Unimc clusters.

Clusters	Institution	Europe	Africa	Middle East	Asia
Relax (cluster 4)	Middlesex	0%	40%	20%	40%
Low Stress (cluster 1)	Middlesex	14%	86%	0%	0%
Stress (cluster 2)	Middlesex	0%	73%	0%	27%
High Stress (cluster 3)	Middlesex	0%	75%	0%	25%
Stress (cluster 1)	Unimc	100%	0%	0%	0%
High Stress (cluster 2)	Unimc	100%	0%	0%	0%
Very High Stress (cluster 3)	Unimc	100%	0%	0%	0%

Table 2 instead shows the clusters returned by the analysis of the Unimc dataset, and several differences emerge. Firstly, there are no clusters identifying a state of relaxation, so all the clusters returned represent the different levels of stress. Specifically, cluster 1 identifies a state of stress with an HR average of 101, cluster 2 (high stress) returns an HR average of 124 and cluster 3 (very high stress) returns an HR average of 149.

In the Unimc sample, students display a wider spectrum of emotions, ranging from ‘neutral’, the predominant emotion for students in cluster 2 (high Stress), to ‘sad’ (50% in cluster 1 - stress) and ‘happy’ (present to a minimal extent in cluster 1 and at 33% in cluster 3).

This pattern may appear somewhat inconsistent with the ‘very high stress’ label assigned to cluster 3.

It is important to underscore that a facial expression classified by AI as ‘happiness’ may, in fact, correspond to ‘nervous smiling,’ that is, the tendency to smile in stressful or uncomfortable situations as a strategy for managing social tension.

Indeed, recognizing and measuring emotions in social contexts, and assigning appropriate relational meaning to facial expressions, remains extremely challenging and complex. Recent work has also highlighted the limitations and potential misclassifications of AI-based emotion recognition systems. (Barker et al., 2025; Khare et al., 2024)

Table 3 illustrates the demographic differences between the two institutions grouped by cluster to identify possible hidden patterns related to the country of origin.

Overall, it can be seen that there are not significant outcomes for Unimc, because all the students are European.

In contrast, looking at the Middlesex students, it can be seen that students coming from Africa tend to be more stressed than relaxed, those who come from the Middle East result more relaxed, while Asian learners are distributed between relax and stress clusters.

3.2 RQ2

The PSAS was then analysed. The survey was proposed to students before the oral presentation and was designed to capture students' perceptions of anxiety, focusing in particular on how they perceive their own anxiety when they have to give a public oral presentation.

The paper first examines students' perceptions and then whether their perceptions match their actual state, as measured by the wearable device, to determine the level of self-awareness of their emotional state.

The four questions that best matched the stress levels measured by the wearable device were selected (Table 4) from the PSAS surveys at the two universities and then compared.

Table 5 shows the perceptions of the Middlesex students grouped into clusters, and the responses seem to correspond to the stress conditions measured by the HR sensor.

Relaxed students indeed don’t think giving a speech is terrifying (Q1: 20% A+SA), they are able to focus on what they have to say (Q6: 90% A+SA), they don't feel sick before public speaking (Q10: 10% A+SA) and not all of them feel their heart pounding during the performance (Q13: 40% A+SA).

Table 4.
PSAS survey with in bold the selected questions for the data analysis

Questions
1. Giving a speech is terrifying
2. I am afraid that I will be at a loss for words while speaking
3. I am nervous that I will embarrass myself in front of the audience
4. If I make a mistake in my speech, I am unable to re-focus
5. I am worried that my audience will think I am a bad speaker
6. I am focused on what I am saying during my speech
7. I am confident when I give a speech
8. I feel satisfied after giving a speech
9. My hands shake when I give a speech
10. I feel sick before speaking in front of a group
11. I feel tense before giving a speech
12. I fidget before speaking
13. My heart pounds when I give a speech
14. I sweat during my speech
15. My voice trembles when I give a speech
16. I feel relaxed while giving a speech
17. I do not have problems making eye contact with my audience

On the other hand, the stressed students reported the following perceptions:

The speech was terrifying (Q1). In detail the clusters low stress returned 43% of agreement (A+SA), while stress 36% (A+SA) and high stress 50% (A+SA)

Despite their stressful conditions, they are able to focus on what they have to say (Q6), in detail the cluster low stress with 42% (A+SA), the cluster stress with 72% (A+SA), and the cluster high stress with 100% (A+SA)

They are more prone to feel sick before public speaking (Q10) compared to the relaxed students, specifically low stress with 28% (A+SA), stress with 27% (A+SA) and high stress with 25% (A+SA)

They feel their heart pounding during the performance (Q13) and it increases with the stress conditions, matching properly with the HR values analysed. The low stress clusters returned 57% (A+SA), the stress cluster 63% (A+SA) and the high stress cluster 100% (A+SA).

Table 5.
PSAS results based on the Middlesex clusters

Clusters	Q1	Q6	Q10	Q13
Relax	10% SD	0% SD	40% SD	20% SD
	10% D	0% D	10% D	20% D
	60% N	10% N	40% N	20% N
	10% A	90% A	0% A	30% A
	10% SA	0% SA	10% SA	10% SA
Low Stress	14% SD	0% SD	14% SD	14% SD
	0% D	0% D	14% D	14% D
	43% N	57% N	43% N	14% N
	0% A	14% A	14% A	57% A
	43% SA	28% SA	14% SA	0% SA
Stress	0% SD	9% SD	18% SD	0% SD
	18% D	0% D	36% D	9% D
	45% N	18% N	18% N	27% N
	18% A	63% A	9% A	54% A
	18% SA	9% SA	18% SA	9% SA
High Stress	0% SD	0% SD	0% SD	0% SD
	25% D	0% D	75% D	0% D
	25% N	0% N	0% N	0% N
	50% A	100% A	25% A	100% A
	0% SA	0% SA	0% SA	0% SA

Table 6 shows the perceptions of the Unimc students grouped into clusters, and the responses seem to be more moderate compared to those of the Middlesex students. In fact, the students, although there are no clusters labelled as ‘relax’ and also presenting a very high stress conditions, are not terrified by giving a speech (Q1), with the clusters stress collecting only 12% agreement (A+SA), high stress 30% (A+SA), and very high stress 20% (A+SA). This also corresponds to Q6, where students seem to be concentrated on what they have to say with the cluster stress with 49% agreement (A+SA), high stress with 90% (A+SA), and very high stress with 100% (A+SA). This difference can be explained by the Italian university system which often requires students to perform oral exams, so they are more familiar with situations that require PS and communication skills.

Table 6.
PSAS results based on the Unimc clusters

Clusters	Q1	Q6	Q10	Q13
Stress	25% SD	0% SD	50% SD	12% SD
	37% D	0% D	37% D	25% D
	25% N	50% N	12% N	50% N
	12% A	37% A	0% A	12% A
	0% SA	12% SA	0% SA	0% SA
High Stress	40% SD	0% SD	20% SD	10% SD
	20% D	10% D	30% D	30% D
	10% N	0% N	40% N	20% N
	30% A	90% A	0% A	20% A
	0% SA	0% SA	10% SA	20% SA
Very High Stress	40% SD	0% SD	20% SD	0% SD
	0% D	0% D	0% D	40% D
	40% N	0% N	60% N	20% N
	20% A	60% A	20% A	0% A
	0% SA	40% SA	0% SA	40% SA

Additionally, students don’t feel sick before PS (Q10), returning a lower percentage than Middlesex students. In fact, the cluster stress doesn’t return any student agreement (0% of A+SA), high stress 10% agreement (A+SA) and very high stress 20% (A+SA). Finally, Q13 returned similar results compared to Middlesex matching with the sensor’s values. In detail, the cluster stress returned 12% (A+SA), high stress 40% (A+SA), very high stress 40% (A+SA).

4. Conclusion

PS and oral examinations are common forms of assessment in higher education, but they are also a major source of anxiety for students, often affecting their performance. In addition to the impact on their academic careers, this criticality can also be very limiting for future professional careers, where effective oral skills are increasingly in demand. Therefore, as emphasised in the literature, it is important that students start working on PSA early in their education and that teachers are attentive to this issue. The present research proposes a first pilot study on the topic to explore the possibility of identifying different student profiles according to their levels of stress and PSA in two different university settings, and to compare the two samples. The diverse tools used for data collection and analysis proved valuable for this purpose. In particular, the HR values detected by the sensors allowed us to identify clusters for each sample, which were then compared with the students' perceptions collected by the survey and the emotions detected by visual tracking, although the samples used for this study highlighted some demographic differences between the institutions. The Middlesex sample mainly consists of students coming from Africa, Asia and the Middle East, while the Unimc sample only includes European students. These aspects could undoubtedly have an effect on the level of stress experienced by the students, but the different enrolment policies of the universities make it challenging to provide two balanced groups of students to voluntarily involve in the project. Another relevant issue is that individualised resting baselines were not collected for the participants involved in the study. As a consequence, the comparison relied on the 'absolute' values recorded during the presentation. Despite various limitations, the cross-analysis of the three types of data, linked to the three systems reported by Bodie (2010), showed good consistency. In fact, students who showed greater HR fluctuation, which can be interpreted as an ability to maintain emotional balance, reported a good ability to cope with stress when responding to the PSAS. At the same time, students who showed a high HR value for the entire duration of the speech expressed opinions and behaviours associated with high levels of stress, both in the PSAS and in the video analysis. The data analysis also revealed interesting differences between the two university samples, including stress-related clusters and emotional states. In particular, the Unimc sample was distributed across stress levels from medium to very high, whereas the Middlesex students were more evenly distributed across stress levels from relaxed to high, without reaching a very high level. This difference could be related to the higher age and university experience of the Middlesex students compared to the Unimc students. Another difference seems to be related to the typology of emotions detected by the artificial agent, which in the Middlesex sample was mainly sad and neutral, while in the Unimc sample it varied between sad, neutral and happy. Surprisingly, the Italian students, despite showing very high levels of stress, gave moderate responses in some areas of the PSAS compared to the Middlesex students. Specifically, in Q1 and Q10, students collocated in the 'very high stress' cluster referred to not being terrified by giving a speech and not feeling sick before speaking in front of the public, thus demonstrating feelings in contrast to what they reported in the other responses. A possible interpretation of these data could be related to the students' tendency not to show their vulnerability or fragility, or to their habit of doing oral exams. The data obtained encourage further research into the variables associated with PS and oral communication skills. In addition, future developments of this study aim to further explore the potential contribution of wearable devices and AI in assisting teachers in identifying student profiles and designing effective training to help them become aware of and overcome their PSA. Finally, another area of research could involve sharing and discussing physical, cognitive, and behavioural data with students to promote individual awareness of their weaknesses and strengths.

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Author statement on the use of LLMs

The AI hasn't been adopted for the content development. A translator tool was used to refine some sentences in the paper.

Author statement on ethical considerations

The collection of biometric data in educational settings raises critical ethical concerns regarding privacy, autonomy, and awareness. In addition, the European Union's AI Act (2024) highlights the need for heightened safeguards when processing biometric or emotion-recognition data, particularly in educational contexts. Participants were fully informed about the purpose and scope of the study and provided their consent. Data minimization, secure storage, and de-identification procedures were implemented to reduce potential harm. Moreover, the ethics committees of Unimc and Middlesex University ensured that data collection practices respected students' rights and avoided any undue pressure associated with academic participation.

Declaration of authors' contributions

L.G., F.G., L.M.C., G.N. conceptualized the study, designed the methodology and writing of the manuscript. G.D., A.T., S.K. and G.N. contributed to the investigation and data curation.
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