

Pre-service Teachers and Public Speaking Anxiety. Insights and possible interventions through AI and IoT

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Abstract. Public speaking is an essential skill for pre-service teachers as it plays a critical role in both professional success and the teaching-learning process. Despite its importance, many individuals, particularly students, experience public speaking anxiety, which can affect their performance. This paper explores the intersection of self-assessed public speaking anxiety levels and biometric data collected through stress tracker devices and AI-based emotion detection tools, aiming to investigate students' awareness of their anxiety during public speaking. Data were collected from 257 students enrolled in a first-year course at the University of Macerata (2023/24). Students were asked to complete a survey and give an oral presentation in groups. A subset of 25 student responses were compared with biometric data, including heart rate measurements and data obtained by an AI emotion recognition system. Cross-referencing self-reported anxiety levels with heart rate data showed varying degrees of convergence, suggesting that students often misperceived their emotional state. In some cases, their self-assessments did not align with the biometric indicators of stress, suggesting a lack of self-awareness regarding their anxiety levels. These findings highlight the potential for AI and IoT technologies to provide useful data that can help teachers identify and support students who are not aware of their emotional state and who also have anxiety management issues. By incorporating these tools, university teachers can develop optimized and tailored interventions aimed at improving students' public speaking skills and emotional regulation. Further research should explore the effectiveness of these tools across different courses and sample sizes.

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Keywords: Public Speaking Anxiety, Pre-service Teachers, AI, IoT.

1 Introduction

Public Speaking (PS) is the ability to speak effectively in front of an audience [1]. PS falls under the broader category of oracy [2], which represents the essential set of oral communication skills, including coherent speaking, active listening, and effective participation in discussions. It is a crucial skill for both professionals and university students. Parvis [3] emphasizes that PS is a key skill for professional success, as it allows individuals to present their ideas and persuade the audience, thereby facilitating the achievement of shared goals. Specifically, the ability to speak in public is an essential skill for pre-service teachers who must master it to avoid compromising effectiveness and to enhance the teaching-learning process [4]. To improve one's PS skills, it is important for the speaker to use intonation, rhythm, cadence, and volume effectively [5]. Non-verbal language also plays a central role during PS, as eye contact and facial and body movements can establish a connection with the audience and help maintain attention levels [6]. This is also crucial for teachers who, through verbal and non-verbal language, can capture and sustain their students' attention [7].

One of the main challenges people face when approaching PS is related to anxiety. Anxiety can be seen as a feeling of unease and heightened arousal that a person encounters in response to a situation perceived as broadly threatening. Karakaya [8] characterizes it as an excessive and irrational condition marked by intense fear and excitement, accompanied by a reaction to the perceived threat. More specifically, Public Speaking Anxiety (PSA) is defined as “a specific social anxiety occurring during or in anticipation of an oral presentation” [9], representing a common experience for most people, with affected individuals exceeding half of the population [10][11]. Indeed, pre-service teachers often mention anxiety as a concern related to teaching experiences [12].

Obtaining data regarding PSA is not simple and remains an area of ongoing exploration in the literature. One of the main limitations is that it is not an easy phenomenon to capture, as some of the most commonly used tools, such as interviews and self-assessments, do not always present objective data and are often closely tied to the individual's perception of themselves and the anxiety-inducing situation. Some opportunities to explore PSA in a more systematic and less subjective way involve measuring cardiovascular responses, such as blood pressure and Heart Rate (HR), as well as electrodermal activity measurements [13]. Specifically, a high HR variability during PS is correlated with lower stress levels and a greater ability to regulate emotions [14]. Although not yet widely present in the literature, research combining HR data collected during PS with self-assessment data on PSA could provide an interesting framework to initiate a discussion on PSA prevalence, its effects on affected individuals, and possible improvement interventions. Given that PS is currently one of the key skills for nearly all professions, it is crucial that frequency monitoring, reflection, and possible interventions are considered starting from school, with particular attention in the university setting.

This contribution presents data from an experiment conducted with 25 students enrolled in the first year 'Foundations of Teaching and Learning' course of the Master's Degree in Primary Education at the University of Macerata in the 2023/24 academic year. Nevertheless, it is useful to report the data from the PSA survey administered to all 257 students in the course.

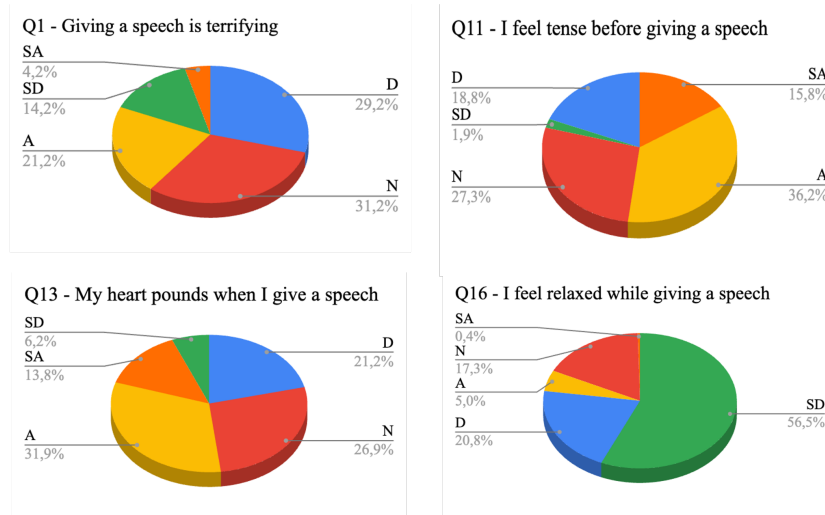


Fig. 1. Some PSAS answers returned by the 257 students before the PS activity.

The data (Fig.1) indeed show that the majority of students closely associate the idea of PS with feelings of anxiety. As shown in the pie charts, over 50% of the students find "giving a speech terrifying," while more than 60% of the total report feeling tense before speaking in public. These data highlight the need to further investigate the issue of PS-related anxiety and, at the same time, suggest the necessity of directly working on this skill, especially for pre-service teachers who will have to engage in PS daily.

It should be noted, however, that most of the stress and anxiety we encounter daily are psychological in nature and particularly related to our interpretation of events [15]. For this reason, self-assessing one's level of anxiety, especially if done prior to an event, cannot serve as an effective measure in itself. Therefore, it is important to pair qualitative investigation methods with quantitative methods that can both provide feedback to the initial self-assessment and offer objective data on the stress felt by those facing PS.

The proliferation of AI solutions has led several researchers to develop new models in education aimed at helping students improve their knowledge and skills and helping teachers develop strategies to improve the quality of teaching. AI solutions have not only been adopted to assist students during the learning journey but can also be used to detect the emotions felt during learning activities [16], facilitating the instructor's identification of potential issues in students that can negatively impact performance. Another aspect that can affect student performance is the level of stress perceived, which

can influence memory and prevent from achieving learning outcomes [17]. Several researchers have identified the increase in HR during classroom activities as a sign of stress [18]. The collection of this data through stress tracker devices could be particularly beneficial to teachers during the feedback process [19].

From these premises, two research questions were formulated:

1. Are pre-service teachers aware of their anxiety levels related to PS?
2. Is there a convergence between the self-assessment data of students regarding their PSA levels and the quantitative data obtained through an IoT device designed to capture biometric stress data and an AI software?

This paper investigates students' awareness of their emotional states during PS, offering insights to help university educators develop impactful training programs and empower students to navigate their emotions effectively.

2 Methods

2.1 The context

The research was carried out in the academic year 2023/24 and involved students enrolled in the first-year course 'Foundations of Teaching and Learning' of the Master's Degree in Primary Education at the University of Macerata.

The course aimed to provide the theoretical foundations of didactics focusing on the learning and teaching processes, and on the knowledge, skills and competences that underpin teaching professionalism. It consisted of 48 hours of lectures (with free attendance) and 20 hours of workshops (with compulsory attendance), which took place during the second semester.

The compulsory workshop was designed to deepen the core concepts covered in the lectures through a series of group activities led by a tutor. During the final session, we asked the students to give an oral presentation in groups (two or three students per group). Specifically, each group had to rethink and revise the metaphor, related to the teacher's role, which they had formulated in the first workshop session and then present its evolution orally to their colleagues.

In this study we discuss the results of the presentations held by 9 groups of students for a total of 25 students who were selected on a voluntary basis.

2.2 Data collection and design process

Before the presentation, each student was asked to complete the PSA survey [20]. The survey was designed to measure students' perceptions of anxiety, focusing in particular on how they perceive their own anxiety when they have to give a public oral presentation. It consisted of 17 items with a 5-point Likert response scale: 1- Strongly Disagree (SD); 2- Disagree (D); 3- Neutral (N); 4- Agree (A); 5- Strongly Agree (SA).

Group presentations were not graded but were monitored by video recording for up to 3-5 minutes (approximately 1 minute for each speaker) and each student was required

to wear a portable stress tracker device in order to extract the HR data needed to predict students' stress perceptions.

A Polar OH1+, an optical HR monitor connected to the online application 'Polar Flow' was used as it allows the accurate collection of 60 HR records per minute and the download of a csv file [21].

The data was then collected and pre-processed into a dataset containing the following features: ID device, heartbeat min, heartbeat max, heartbeat avg and heartbeat standard deviation.

A clustering technique was then applied to this dataset in order to find similarities between the student and grouping together in homogeneous clusters [22] to identify different stress levels during the PS. Specifically three algorithms (K-means [23], Mean Shift [24] and Gaussian Mixture Model [25]) have been implemented and compared the performance using the Silhouette Analysis [26] in order to identify the most effective. Using this approach, each cluster could be represented by a silhouette index based on the comparison of its cohesion and separation. The Silhouette Coefficient is measured using the formula:

$$S(i) = \frac{b(i) - a(i)}{\max \{a, b(i)\}}$$

In this formula, $a(i)$ is the average distance of the point i from all other points in the same cluster, while $b(i)$ is the smallest average distance of the point i from all points in the nearest cluster. Specifically, the range of the silhouette score $s(i)$ is $[-1, 1]$. If the silhouette index is close to 1, the sample is well-clustered and assigned to an appropriate cluster. Based on this method $s(i)$ needs to be closer to 1 to have good clusters [27].

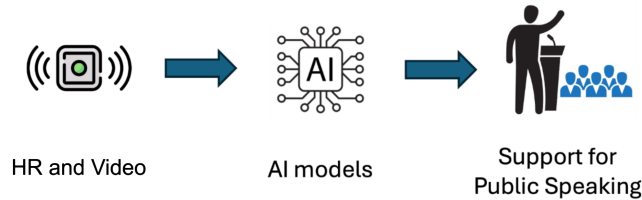


Fig. 2. The flow diagram of the data collection and data analysis involved in the research.

The subsequent study analyzed the video presentation of the students' public speaking in order to extract the main emotions felt during the activity. An AI detection model previously developed and tested during a group presentation activity, was adopted for this scope [28]. This model consists of a combination of deep learning and convolutional neural networks, which can extract emotions from facial expressions thanks to the use of the OpenCV framework. Emotion analysis was achieved based on symmetric filter characterization. Face key attributes were digitized and combined to facial landmarks. Based on the initial classification, emotions were mapped as landmark combinations that can classify emotions further down the line. A custom implementation of Python Keras and Tensorflow [29] was used to detect emotions. Detected landmarks

were filtered to maximize model efficiency and classification since some emotions were hard to classify e.g. Anger vs Fear. A similar technique, focusing on recognizing facial landmarks over frames was used to monitor changes in predominant facial landmark positions. This technique was scored across several frames achieving change monitoring. This technique was able to calculate face movement via optical flow. These movements were determined across several videos and resulted in being able to understand head nodding, turn, and angle of view across multi participants across video feeds. All the above filters were combined to be able to annotate videos by ingesting face recognition labels, emotion labels and head movement indicators. A final post-processing component was developed to be able to persist changes across frames and generate an annotated version of the original video.

The model thus returns 5 main emotions and a list of body movements made by the students during the presentation.

Thanks to these data, it was possible to check potential changes in the emotional states of the students by monitoring the increase in HR during the video or the HR variability, which can be influenced by the stress condition [30]. Collected data were then processed and cross-referenced for analysis.

3 Results

3.1 Cluster analysis

The identification of the different students' emotional changes during the PS required the application of clustering techniques aimed to discover the different levels of stress.

Once the necessary data had been collected during the student presentations using the stress tracker device and merged into a unique dataset, various clustering algorithms were applied.

Specifically, the following algorithms have been implemented to this scope: Gaussian Mixture Model, Mean Shift and K-means.

The clustering models have been developed in Python using the Scikit learn libraries using a pre-processed and normalized dataset. The results returned by the different models were then compared using silhouette analysis to identify the most powerful models able to produce the most consistent clusters.

Table 1. Comparison of the performance of the different models.

Clustering algorithms	Silhouette score
K-means	0.5519710282079947
Mean Shift	0.5291762884532173
Gaussian Mixture Model	0.5315497925996401

Table 1 shows the silhouette index obtained for each model and shows that K-means is the best-performing model. K-means returned 3 different clusters, each one identifying different levels of stress perceived by the students during the PS. The levels were identified taking into account previous research in this area, which identified a normal resting HR for adults as a range between 60 and 90 beats per minute (bpm) [31].

Specifically, Cluster 1 consists of 8 students, all female, with an average HR of 101.2 and a standard deviation of 3.5, Cluster 2 consists of 11 students, 9 female and 2 male, with an average HR of 124.5 and a standard deviation of 5.1 and Cluster 3 consists of 6 students, 5 female and 1 male, with values of average HR of 149.8 and standard deviation 6.6. Each cluster shows a small value of standard deviation, which indicates that the data points are close to the mean [32], so the value of the average HR was crucial in identifying stress levels. Cluster 1 was identified as “Stress”, Cluster 2 as “High stress” and Cluster 3 as “Very high stress”.

Table 2. Features values associated with distinct clusters.

Clusters	N.	Sex	MIN	MAX	AVG	ST. DEV
1. Stress	8	0% M 100% F	94.5	107.5	101.2	3.5
2. High Stress	11	18% M 82% F	115.3	131.3	124.5	5.1
3. Very High Stress	6	17% M 83% F	137.8	158.33	149.8	6.6

3.2 AI emotion recognition

The AI emotion recognition using the video analysis, instead, was performed on a 32GB Intel X2 Intel E5-2660v4 3.2GHz, and the workflow was deemed successful over more than 1400 processing turns, achieving an overall efficiency of 92.37%, and at the same time with an achieved rate of 96.74% face recognition.

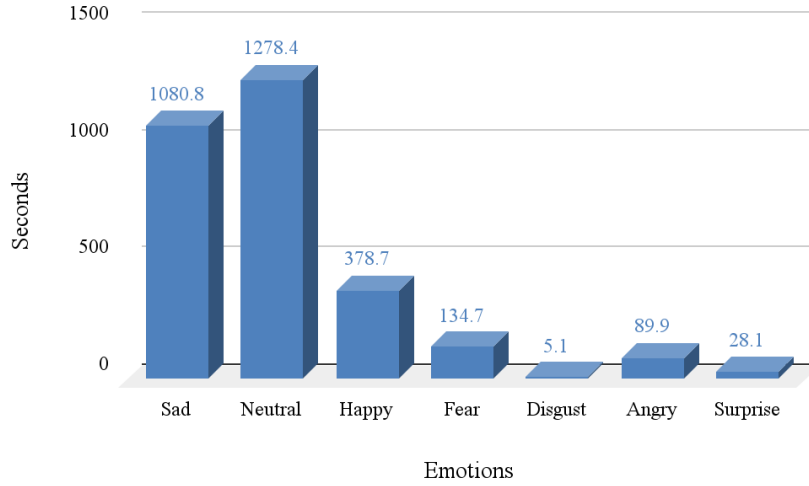


Fig. 3. Emotions felt by the 257 students during the PS activity.

The results obtained by the AI emotion recognition confirmed the stress perceived by students returning mainly negative and neutral emotions. In particular, Cluster 1 returned as main emotions 50% sad, 37% neutral and 13% happy, Cluster 2 82% neutral and 18% sad and Cluster 3 33% sad, 33% neutral and 33% happy (see Table 3).

The distribution of emotions in the three clusters does not seem particularly significant, but we believe that these results are influenced by some contextual conditions that may have negatively affected the analysis. During the presentation, the students tended to frequently consult the notes on their devices (mobile phone and tablet). As a result, their gaze was directed downwards towards the screen, which may have made the task of detecting movement and facial expressions more difficult. We also believe that the AI emotion recognition system may have identified 'happy' expressions that were not actually happy, such as a pulled smile, an expression of nervousness.

Table 3. Features values and main emotions associated with distinct clusters.

Clusters	N.	Sex	AVG	ST. DEV	Main emotions
1. Stress	8	0% M 100% F	101.2	3.5	50% Sad 37% Neutral 13% Happy
2. High Stress	11	18% 82% F	124.5	5.1	82% Neutral 18% Sad
3. Very High Stress	6	17% M 83% F	149.8	6.6	33.3% Sad 33.3% Neutral 33.3% Happy

3.3 PSA survey

We examined the students' perceptions within the sample and whether their perceptions matched their actual state, as measured by the stress tracker device, to determine the level of self-awareness of their emotional state. We report the questions that matched the stress levels measured by the stress tracker device and the questions that didn't match.

As can be seen from Table 4, the response to Q4, which indicates the difficulty of refocusing on the speech after making a mistake, shows a 37% neutral and 12% agreement rate in Cluster 1 - stress, which rises to 40% in Cluster 3 - very high stress.

Similarly, Q6, where students are asked whether they concentrate on what they are saying during the speech, shows a percentage of around 50% agreement (A+SA) in Cluster 1, a percentage that reaches 90% in Cluster 2 and even 100% in Cluster 3. This can be explained by the assumption that those who are more confident in PS can control the reactions of the audience and the context, whereas those who are very anxious tend to focus exclusively on the content of the speech and what they have to say. Also, with regard to Q11 and 12, the percentages of A and SA with regard to feeling tense and trembling are significantly higher in Clusters 2 and 3 than in Cluster 1.

Table 4. PSAS results (Q4, Q6, Q11 and Q12) based on the clusters.

Clusters	Q4 - If I make a mistake in my speech, I am unable to re-focus	Q6 - I am focused on what I am saying during my speech	Q11 - I feel tense before giving a speech	Q12 - I fidget before speaking
1. Stress	25% SD	0% SD	12% SD	12% SD
	25% D	0% D	25% D	25% D
	37% N	50% N	25% N	37% N
	12% A	37% A	37% A	25% A
	0% SA	12% SA	0% SA	0% SA
2. High Stress	30% SD	0% SD	0% SD	0% SD
	10% D	10% D	50% D	60% D
	50% N	0% N	10% N	10% N
	10% A	90% A	30% A	20% A
	0% SA	0% SA	10% SA	10% SA
3. Very High Stress	20% SD	0% SD	20% SD	20% SD
	20% D	0% D	0% D	0% D
	20% N	0% N	0% N	20% N
	40% A	60% A	40% A	40% A
	0% SA	40% SA	40% SA	20% SA

On the other hand, it should be noted that other questions (see Table 5) produce data that do not match the clustering, showing that personal perceptions are not always fully in line with what is perceived by sensors attached to the body. The most obvious example of this divergence is Q13, where only 40 percent of the 3-Very High Stress group admit that their heart beats fast when they have to give a speech, while the percentages of agreement with Q1 and Q10, which should have been predictably high, are actually 0 for the SA score and around 20 per cent for the A score.

Table 5. PSAS results (Q1, Q7, Q10 and Q13) based on the clusters.

Clusters	Q1 - Giving a speech is terrifying	Q7 - I am confident when I give a speech	Q10 - I feel sick before speaking in front of a group	Q13 - My heart pounds when I give a speech
1. Stress	25% SD	12% SD	50% SD	12% SD
	37% D	25% D	37% D	25% D
	25% N	50% N	12% N	50% N
	12% A	12% A	0% A	12% A
	0% SA	0% SA	0% SA	0% SA
2. High Stress	40% SD	0% SD	20% SD	10% SD
	20% D	30% D	30% D	30% D
	10% N	50% N	40% N	20% N
	30% A	20% A	0% A	20% A
	0% SA	0% SA	10% SA	20% SA
3. Very High Stress	40% SD	20% SD	20% SD	0% SD
	0% D	0% D	0% D	40% D
	40% N	40% N	60% N	20% N
	20% A	40% A	20% A	0% A
	0% SA	0% SA	0% SA	40% SA

This allows us to affirm that the levels of concern and anxiety perceived by students do not always coincide with the values detected by the sensors and the expressions collected by the AI emotion recognition system, and that it is necessary to design pathways for anxiety and stress recognition literacy in the PS, but also, more generally, pathways for managing stress and emotions that are elements present in the daily lives of students and teachers.

At the same time, we believe we can state that a correct discrimination of the signals coming from our body and the ability to manage emotions and stress are important and significant skills for pre-service teachers, which should be pursued and built through

specific pathways designed and implemented with the aim of training a skill that is not only relevant to the teaching profession, but also necessary for active participation in social life [33][34].

4 Conclusions

The analysis of the 257 answers gathered from the PSA survey shows that most students report high levels of PSA, as already stated in the introduction.

To answer the research questions, we cross-referenced survey responses from the 25 selected students with HR data collected from the stress tracker device and AI-based emotion detection tools. In some cases, we found a convergence between PSA data and the HR values, while in other cases substantial differences emerged. Indeed, students' considerations on their PSA, excerpted from the survey, were not consistently reflected in the emotional state detected by stress tracker devices and AI tools. While it is important to consider some limitations inherent in our video-recording process, which affected the AI-based analysis, the discrepancy between students' self-assessments and the data gathered from the tools mentioned above could stem from a lack of self-awareness among students, as well as their generally negative perception of PS. These findings revealed that students were not always able to correctly self-assess their PSA, underestimating or overestimating it.

This data analysis shows that AI-based emotion recognition software and stress tracker tools can help teachers identify and support students who are not aware of their emotional state and who also have anxiety management issues as well as students with high levels of PSA. Research has identified a significant impact of teachers' emotional state on the learning and teaching process. Teachers' emotions are linked to various classroom aspects such as students' well-being [35], motivation [36], and academic outcomes [37]. Various researchers have shown that more positive emotions lead to more innovative ideas and strategies [38], while a prevalence of negative emotions decreases motivation [39]. Furthermore, teachers' emotions have an impact on their personal and professional lives [40], and negative emotions, depending on anxiety and stress, could affect teachers' effectiveness [41].

Finally, collecting students' perception of their emotional states and PSA and biometric data can assist university teachers in designing targeted training on PS and in enhancing personalized and inclusive learning paths.

Future developments should include some key issues. First, it would be beneficial to test these tools in a broader range of courses and with a larger sample size to gain more comprehensive insights. Additionally, refining the video detection conditions to enhance the quality of video recordings could lead to more accurate responses from the AI emotion recognition system. Finally, the results of this research could be leveraged to identify students who experience higher levels of PSA, allowing for the implementation of targeted training programs, potentially incorporating virtual reality (VR) strategies, to help these students improve their PS skills.

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