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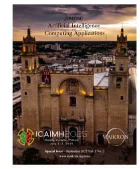

Expanded abstract

Automated detection of academic anxiety levels: proposal of a machine learning-based expert system for educational and clinical settings

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ABSTRACT

Public speaking anxiety is a significant barrier to academic performance and social integration among university students. Despite its prevalence, research on targeted technological solutions remains limited. This study presents the development of an expert system designed to automatically classify academic anxiety levels related to oral expression using a supervised machine learning approach. A sample of 159 undergraduate students completed a 30-item psychometric questionnaire assessing cognitive dimensions associated with public speaking anxiety. Participants' scores were standardized into Z-scores and categorized into three anxiety levels: Low, Normal, and High. The Naive Bayes algorithm was employed due to its simplicity, efficiency, and interpretability. Model parameters were estimated using Python 3.11 and the scikit-learn library, with performance assessed via stratified 10-fold cross-validation, achieving an overall accuracy of 95.6% and an AUC above 0.99 across all categories. The system was implemented in an interactive Streamlit application, linked to Airtable for automatic data storage. Results indicate that the expert system reliably detects characteristic response patterns associated with each anxiety level, offering immediate, personalized clinical interpretations to users. This study demonstrates the potential of integrating classical psychometric methods with machine learning to develop accessible, explainable, and ethically responsible digital tools for mental health assessment and early intervention in educational settings.

Keywords: expert systems, social anxiety, machine learning

1. Introduction

Public speaking anxiety is a significant issue that impacts the teaching-learning process. It is among the most common fears in the general population and a prominent manifestation in individuals with social anxiety. According to Blöte et al. [1], public speaking anxiety can be classified as a specific and clinically relevant subtype of social anxiety, which is defined as intense fear or anxiety in situations where one may be subject to social evaluation [2]. Among university students, 20–30% report considerable difficulties speaking in public [3], and over 75% have avoided such situations at some point in their academic lives [4], with oral presentations being among the most stressful academic experiences [5]. Numerous studies have linked this form of anxiety to factors such as poor academic performance [6], explicit social evaluation, and high levels of self-demand [7]. At the cognitive level, individuals with social anxiety often overestimate social demands and underestimate their ability to cope with them [8]. They

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also tend to excessively focus their attention on their performance and process information in a biased way that confirms their fears [9]. These difficulties can lead to reduced classroom participation [10] and, in some cases, academic dropout [11], negatively affecting students' emotional well-being, academic identity, and social integration [12, 13]. Despite its relevance, research specifically addressing this type of anxiety in university settings remains limited [14].

From an applied perspective, various psychotherapeutic approaches have proven effective in addressing this problem, including graduated exposure, cognitive restructuring, and social skills training [15, 16]. However, the integration of emerging technologies such as artificial intelligence (AI) opens new possibilities for the diagnosis, monitoring, and early intervention in mental health [17]. In light of this need, it becomes pertinent to explore innovative approaches to assess and classify this form of anxiety, including AI-based technological solutions. In particular, machine learning techniques have proven useful for predicting psychological conditions using structured data [18, 17]. Supervised machine learning is a branch of AI in which an algorithm learns to predict a category or value from a previously labeled dataset. This involves training the model on examples with known outcomes (classes or labels), so it can later classify new instances based on the learned patterns [19]. This methodology has shown considerable promise in clinical and educational psychology, particularly for identifying complex patterns within large datasets derived from questionnaires, scales, or records [20].

One of the most widely used supervised algorithms for classification tasks due to its simplicity, efficiency, and performance is Naive Bayes. This model is based on Bayes' theorem and assumes conditional independence among the predictor variables—meaning each variable contributes independently to the probability of a given class [21]. While this assumption is a simplification, Naive Bayes has proven effective in practice even when predictors are moderately correlated. Its probabilistic interpretation supports the development of transparent and interpretable expert systems suitable for educational and clinical applications.

The present study aims to present the development and implementation of an expert system for the automatic classification of academic anxiety related to oral expression, based on a Naive Bayes model trained on response patterns to 30 valid and reliable items assessing cognitive variables associated with public speaking anxiety. Through the recognition of psychological data patterns, the system classifies users into anxiety categories (low, normal, or high) based on their responses to specific items in a digital questionnaire. The system interface was programmed in Python 3, implemented using the Streamlit framework, and connected to an Airtable database for automatic result storage.

The use of machine learning algorithms in psychology goes beyond classical approaches based on normative scores or z-transformations, offering more dynamic, tailored, and explanatory alternatives. Such models not only enhance diagnostic accuracy but also support the design of interactive, user-adapted evaluation and intervention systems [18]. In this context, the present study contributes to the growing field of machine learning applications in mental health data analysis, emphasizing the utility of expert systems as support tools in clinical, educational, and psychological research settings.

2. Methodology

This study is based on a sample of 159 university students from various undergraduate programs of the National Autonomous University of Mexico, obtained through non-probabilistic convenience sampling. Participation was voluntary and anonymous, carried out through online forms. Participants completed a 30-item psychometric questionnaire assessing academic anxiety related to oral expression. The instrument demonstrated strong psychometric properties (CVI = .97, $\alpha =$ .90; [22]). Each item was rated on a Likert scale ranging from 0 (never) to 5 (always), allowing for significant variability in responses.

Subsequently, each participant's raw scores were transformed into Z-scores. Based on these standardized values, normative thresholds were established to classify participants into three levels of anxiety: Low ($z < -1$), Normal (z between -1 and 1), and High ($z > +1$). These categories served as supervised labels for training the machine learning model. This procedure provided a psychometric criterion for defining the classes used by the expert system.

2.1 Applied AI model

For the development of the expert system, the Naive Bayes algorithm was selected—a classical supervised machine learning technique that offers advantages such as fast training, interpretability, robustness with small samples, and performance comparable to that of more complex models [21, 19]. This algorithm is based on Bayes' theorem and assumes conditional independence among predictor variables, thereby simplifying the calculation of class membership probabilities.

The model parameters (mean and standard deviation per class for each item) were estimated using Python 3.11 with the scikit-learn library, employing the Gaussian Naive Bayes function and stratified 10-fold cross-validation. These parameters were subsequently exported and integrated into an interactive application developed in Python 3.11, using Streamlit as the visual interface and Airtable for data and results storage.

The system calculates, for each user, the log-likelihood of membership in each class (High, Normal, Low) and assigns the classification according to the class with the highest logarithmic value. This classification is presented alongside an automated and personalized clinical interpretation, displayed within the user interface.

2.2 Experimental setup and evaluation metrics

A training set of 159 labeled instances was constructed, with Z-score-based norms serving as the target classes. The model's performance was assessed using stratified 10-fold cross-validation, yielding an overall accuracy of 95.6%, a Kappa coefficient of 0.934, and F-measure values exceeding 0.94 for all categories. These results suggest a high level of effectiveness in distinguishing between different levels of academic anxiety.

In addition, individual metrics for each class were reported:

- High Anxiety: Precision = 0.981, Recall = 1.00, F-Measure = 0.991
- Normal Anxiety: Precision = 0.979, Recall = 0.887, F-Measure = 0.931
- Low Anxiety: Precision = 0.912, Recall = 0.981, F-Measure = 0.945

These findings indicate that the expert system is particularly effective in detecting cases of high and low anxiety, while maintaining sufficient precision for normal levels. Furthermore, the practical implementation in Streamlit allowed for testing the application with real users and verifying its functionality as a digital diagnostic tool.

3. Results and discussion

The developed expert system demonstrated a high level of accuracy in the automatic classification of academic anxiety related to oral expression. Through the implementation of the Naive Bayes algorithm, users were successfully classified into three distinct levels—High, Normal, and Low—based on their responses to 30 psychometric items.

The 10-fold cross-validation performed during the modeling phase yielded an overall accuracy of 95.6%. The model exhibited areas under the ROC curve (AUC) close to 0.99 across all categories, indicating outstanding predictive performance.

3.1 Classification rules

The Naive Bayes algorithm used infers the most probable class for each user by calculating the joint probability of their responses in specific items under the estimated normal distributions for each class. Broadly speaking:

- Users with high response averages (between 3 and 5) on items related to fear of public speaking and oral expression tend to be classified as "High."
- Users with moderate response averages (around 2) tend to be classified as "Normal."
- Users with very low response averages (between 0 and 1) are classified as "Low."

Table 1 presents a summary of the central tendency (means) and dispersion (standard deviations) for each class, based on a representative subset of psychometric items.

These systematic differences enable the expert system to reliably detect characteristic patterns associated with each level of anxiety. For the complete list of items and their descriptive statistics, see Table A1.

3.2 Clinical interpretation presented to the user

After classification, the system provides an automated interpretation based on the user's profile:

- High: "Your profile suggests a high level of academic anxiety associated with oral expression. It is likely that you frequently experience fear of being judged by others, even when you are well-prepared, and that you tend to avoid participating or presenting due to fear of ridicule or disapproval."
- Normal: "Your profile indicates a moderate or normal level of academic anxiety. You may experience occasional doubts or insecurities in oral academic contexts, but they do not significantly interfere with your performance."
- Low: "Your profile reflects a low level of academic anxiety in oral expression contexts. You are likely to feel comfortable participating, presenting, or engaging in class discussions."

This feedback was designed to be accessible and useful, enabling immediate understanding by the user without requiring technical knowledge of psychometrics or clinical psychology.

The results obtained in the present study indicate that the supervised machine learning approach is effective in detecting latent patterns within psychological data. Despite its simplicity, the Naive Bayes algorithm can achieve performance comparable to, and in some cases surpassing, that of more complex methods reported in prior research on psychological classification [18, 17]. Among the main advantages observed, the system's high interpretability stands out, as the probabilistic structure of the model facilitates a detailed explanation of each classification decision, which is particularly valuable in clinical and educational settings. Furthermore, the system exhibited scalability, as it can be readily applied to larger datasets while maintaining its accuracy and efficiency. In terms of clinical applicability, the system provides immediate user profiles that can serve as complementary tools for psychological diagnosis or educational intervention.

However, some inherent limitations of the model were also identified. One of the primary limitations is that the assumption of conditional independence among items—an intrinsic feature of the Naive Bayes algorithm—is not always strictly met in real psychological responses, which may introduce certain distortions in

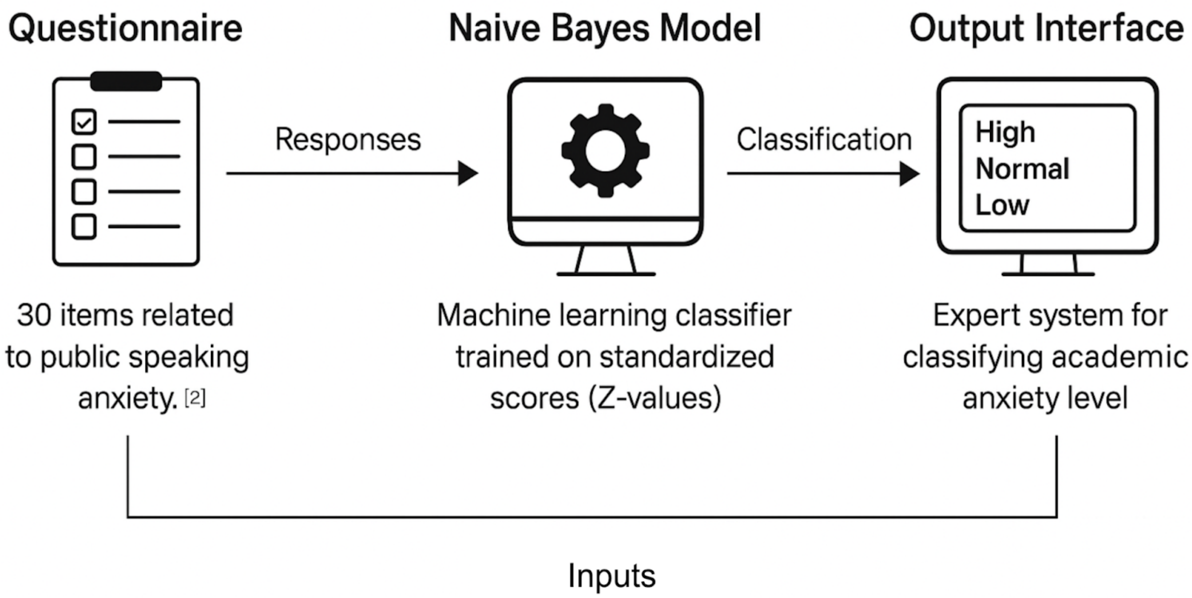

Figure 1. System architecture diagram. The diagram illustrates the operational flow of the system: users complete a digital questionnaire, whose values (inputs) feed into a Naive Bayes classification model previously trained on standardized psychological data. The model calculates the probability of belonging to each category (High, Normal, or Low) and generates an immediate interpretative output, including a diagnostic label and a descriptive profile. The data are automatically stored in an Airtable database for further analysis. This modular design allows for flexible integration in clinical or educational contexts.

Table 1. Representative Psychometric Items by Anxiety Level

Summarized Item	**High** ($\mu \pm \sigma$)	**Normal** ($\mu \pm \sigma$)	**Low** ($\mu \pm \sigma$)
Fear of being ridiculed during a presentation	3.28 ± 0.73	1.39 ± 0.91	0.09 ± 0.35
Fear of answering questions	3.79 ± 0.45	1.52 ± 0.96	0.37 ± 0.65
Thinking that one's question is foolish	3.35 ± 0.70	1.21 ± 1.01	0.11 ± 0.31
Belief in one's inability to present	3.35 ± 0.70	1.43 ± 1.00	0.24 ± 0.43
Arguing within a group	3.58 ± 0.52	1.88 ± 0.92	0.69 ± 1.20

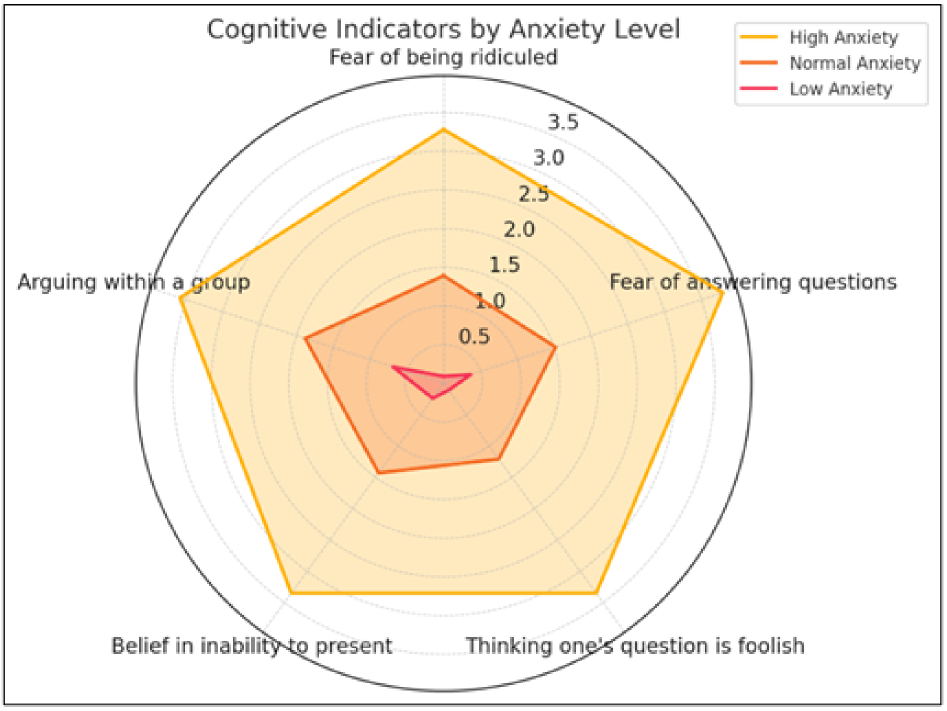

Figure 2. Radar chart displaying the average scores of five key cognitive indicators associated with academic social anxiety, differentiated by anxiety level (High, Normal, and Low). A clear pattern of higher intensity in dysfunctional thoughts is observed in the High Anxiety group.

specific cases. Additionally, although the sample used was suitable for developing a functional prototype, it would be necessary to expand and diversify the sample in future studies to achieve more robust and generalizable validations across different population contexts.

4. Conclusion

The expert system developed in this study represents a successful convergence of classical psychometric principles and contemporary machine learning methodologies, illustrating that data-driven models can be effectively adapted to create accessible, interpretable, and ethically responsible solutions within the domains of mental health and higher education. Leveraging the Naive Bayes algorithm, the system enabled the automatic, transparent, and real-time classification of academic anxiety levels related to oral expression, delivering immediate, evidence-based feedback grounded in validated psychological constructs.

The principal contributions of this work include: the design of a novel hybrid evaluation model that seamlessly integrates classical psychometric frameworks, grounded in Z-score norms, with the predictive capabilities of supervised machine learning techniques, enabling pattern recognition within psychological datasets; and the development of an accessible and open-source platform (utilizing Streamlit and Airtable) that promotes its applicability in both clinical and educational contexts. In addition, the system's ability to generate user-friendly, personalized interpretations enhances its potential as a complementary tool for early diagnosis, psychoeducational intervention, and longitudinal monitoring of academic anxiety.

Nevertheless, several challenges and avenues for future research remain. To enhance the external validity and generalizability of the model, it is imperative to expand the dataset to encompass more diverse and representative university populations. Moreover, future studies could explore methodological alternatives that relax the conditional independence assumption inherent in Naive Bayes, employing more sophisticated algorithms such as Random Forests, neural networks, or deep learning architectures, while maintaining a critical balance between predictive accuracy and model interpretability. Incorporating capabilities for longitudinal tracking of anxiety profiles and adaptive feedback mechanisms would further strengthen the system's clinical and educational utility. Finally, the integration of automated intervention modules, offering personalized recommendations based on users' profiles, represents a promising direction for extending the system's impact.

In sum, this study opens new pathways for the ethical, efficient, and scientifically grounded application of artificial intelligence in psychological assessment, contributing meaningfully to the development of innovative, user-centered tools for promoting mental health and academic well-being in educational environments. Overall, this research highlights the value of explainable

AI in digital mental health tools and lays the groundwork for scalable interventions that support emotional resilience in academic population.

Ethics Statement

This study used anonymized data collected via an online survey. No personally identifiable information was collected. Ethical approval was deemed unnecessary according to the guidelines of UNAM.

CRediT authorship contribution statement

José Manuel Sánchez Sordo: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing.

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

The authors utilized ChatGPT to refine sentence structure and enhance readability. No content was generated by AI; all scientific insights and original ideas are the authors' own.

Declaration of competing interest

The authors declare no competing interests.

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Table A1. Complete List of Psychometric Items by Anxiety Level

Summarized Item	**High** ($\mu \pm \sigma$)	**Normal** ($\mu \pm \sigma$)	**Low** ($\mu \pm \sigma$)
Fear of being ridiculed during a conference	3.28 ± 0.73	1.39 ± 0.91	0.09 ± 0.35
Fear of answering questions	3.79 ± 0.45	1.52 ± 0.96	0.37 ± 0.65
Thinking that one's question is foolish	3.35 ± 0.70	1.21 ± 1.01	0.11 ± 0.31
Belief in one's inability to present	3.35 ± 0.70	1.43 ± 1.00	0.24 ± 0.43
Arguing within a group	3.58 ± 0.52	1.88 ± 0.92	0.69 ± 1.20
Being ridiculed during social interactions	3.00 ± 1.22	1.09 ± 0.95	0.00 ± 0.17
Fear of ridicule during a presentation	3.18 ± 0.82	1.26 ± 0.89	0.26 ± 0.64
Fear of not being understood in debates	3.37 ± 0.62	1.77 ± 0.76	0.67 ± 0.86
Thinking that others mock when participating	3.08 ± 0.74	1.62 ± 0.91	0.35 ± 0.55
Fear of not understanding during an oral exam	3.17 ± 0.98	2.09 ± 0.83	0.52 ± 0.96
Avoiding giving opinions in a team	3.26 ± 0.89	1.38 ± 1.20	0.07 ± 0.26
Making incorrect comments in class	3.21 ± 0.65	1.69 ± 0.81	0.67 ± 0.63
Lack of knowledge within a team	2.96 ± 1.06	1.18 ± 0.84	0.26 ± 0.44
Not being accepted by a team	2.85 ± 1.20	0.96 ± 1.00	0.00 ± 0.17
Fear that the professor gets angry when participating	2.91 ± 1.05	1.01 ± 0.85	0.17 ± 0.37
Failing to capture attention during a presentation	3.15 ± 1.05	1.20 ± 0.93	0.30 ± 0.66
Fear of doubts arising during a conference	3.33 ± 0.77	1.79 ± 1.01	0.45 ± 0.81
Fear of raising one's hand	3.30 ± 0.79	1.84 ± 1.10	0.52 ± 0.63
Avoiding expressing ideas in a team	2.96 ± 1.00	0.86 ± 1.01	0.11 ± 0.31
Fear of not finding the right words during an exam	3.54 ± 0.76	2.13 ± 0.97	1.01 ± 0.94
Fear of appearing like a charlatan at a symposium	2.88 ± 1.25	0.75 ± 0.82	0.17 ± 0.50
Fear of responding in public	3.01 ± 1.10	1.47 ± 1.00	0.41 ± 0.76
Having uninteresting conversations	3.00 ± 1.24	1.37 ± 0.99	0.54 ± 0.90
Not being taken into account by the team	2.56 ± 1.28	0.96 ± 1.08	0.11 ± 0.31
Lowering one's voice out of nervousness	2.71 ± 1.15	1.66 ± 0.75	0.56 ± 0.87
Fear of participating in class	3.03 ± 0.93	1.88 ± 0.81	0.98 ± 0.78
Not feeling part of the group	3.24 ± 0.94	1.57 ± 1.26	0.66 ± 0.86
Negative evaluation from classmates	2.96 ± 1.08	1.50 ± 0.96	0.67 ± 0.84
Thinking that one does not know the answer during an oral exam	3.22 ± 1.03	1.84 ± 1.07	0.83 ± 0.84
Fear that others will not pay attention when speaking	2.86 ± 1.19	1.39 ± 1.18	0.32 ± 0.60