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MACHINE LEARNING-BASED CLIMATE ANXIETY RISK PROFILING FOR UNIVERSITY STUDENTS: BASIS FOR CAMPUS ENVIRONMENTAL SUSTAINABILITY PLANNING

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Abstract

Climate anxiety has emerged as an increasingly significant psychological concern among university students due to the growing awareness of climate change and its associated impacts. However, conventional assessments primarily rely on descriptive analyses and often lack predictive and intervention-oriented capabilities. This study developed and evaluated an Intelligent Climate Anxiety Risk Profiling Framework for university students using educational analytics, supervised machine learning, and explainable artificial intelligence. A quantitative predictive analytics research design was employed using climate anxiety data collected from 315 undergraduate students from Isabela State University–San Mariano Campus during the First Semester of Academic Year 2025–2026. The Climate Change Anxiety Scale was utilized to measure four dimensions of climate anxiety: Cognitive–Emotional Impairment, Functional Impairment, Personal Experience, and Behavioral Engagement. A Climate Anxiety Index (CAI) was computed and transformed into low-, moderate-, and high-risk categories. Three classification algorithms, namely Logistic Regression, Random Forest, and XGBoost, were developed and compared using an 80:20 stratified train-test split and five-fold cross-validation. The results revealed that the respondents exhibited a moderate overall level of climate anxiety ($M = 3.254$, $SD = 0.685$), with Behavioral Engagement obtaining the highest mean score ($M = 3.969$). Most students were classified as moderate risk (47.0%), followed by high risk (37.5%) and low risk (15.6%). Among the evaluated models, Logistic Regression achieved the highest predictive performance, obtaining an accuracy of 88.9%, precision of 89.1%, recall of 89.3%, and F1-score of 89.2%. SHAP analysis identified Functional Impairment, Cognitive–Emotional Impairment, and Personal Experience as the strongest predictors of climate anxiety risk. An operational example further demonstrated how raw survey responses were transformed into interpretable risk profiles and evidence-based intervention recommendations. The findings suggest that the proposed framework can serve as an effective decision-support tool for the early identification of climate anxiety and the implementation of targeted mental health interventions within higher education institutions.

Introduction

Climate change has emerged as one of the most pressing global challenges of the twenty-first century, affecting not only ecological systems and economic stability but also human psychological well-being. Increasing exposure to environmental degradation, extreme weather events, and uncertainty regarding future climate conditions has contributed to emotional responses characterized by persistent worry, fear, helplessness, and distress. This phenomenon, commonly referred to as climate anxiety or eco-anxiety, has gained recognition as an important area of mental health research because of its potential influence on daily functioning and quality of life [1], [2]. Moreover, climate anxiety has been conceptualized as a distinct psychological construct that extends beyond general environmental concern and reflects individuals' emotional reactions to perceived climate threats [3], [4].

Young adults and university students are considered particularly vulnerable to climate-related psychological distress. This developmental period involves academic pressures, identity formation, and future career planning, which may heighten concerns regarding the long-term implications of climate change. A recent systematic review reported that climate-related distress among young people is

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associated with reduced well-being and increased psychological burden [5]. Similarly, a global survey involving adolescents and young adults revealed widespread worry about climate change and dissatisfaction with societal responses to the environmental crisis [6]. These findings suggest that university students constitute an important population for understanding the psychological consequences of climate change.

The expansion of digital communication platforms has also increased exposure to climate-related information. Continuous encounters with alarming environmental news and discussions through social media and online channels may intensify perceptions of threat even in the absence of direct disaster experiences. Jarrett et al. observed that indirect exposure to climate change narratives contributes substantially to eco-anxiety and emotional distress among younger populations [7]. Consequently, climate anxiety is increasingly understood as a multidimensional experience shaped by both lived experiences and mediated environmental awareness.

Several studies have examined the psychometric properties and dimensions of climate anxiety. Cross-cultural validation studies demonstrated that climate anxiety encompasses cognitive-emotional responses, functional impairment, and behavioral manifestations [8], [9]. Among university students, greater awareness and knowledge regarding climate change have been associated with elevated levels of eco-anxiety, indicating that increased understanding of environmental problems may simultaneously promote environmental responsibility and psychological vulnerability [10], [11].

Although climate anxiety is frequently associated with adverse mental health outcomes, its effects are not exclusively maladaptive. Moderate levels of climate concern may encourage individuals to engage in environmentally responsible behaviors and participate in climate action initiatives. Ogunbode et al. reported that climate anxiety may facilitate pro-environmental engagement when accompanied by adaptive coping strategies [12]. Conversely, excessive fear may result in avoidance, helplessness, and diminished behavioral participation, thereby limiting constructive responses to environmental challenges [13].

The Philippine context provides a particularly relevant setting for investigating climate anxiety because of the country's high vulnerability to climate-related hazards. Frequent exposure to typhoons, flooding, and other environmental disasters has intensified concerns regarding the psychological consequences of climate change. Alibudbud emphasized that climate change has become an emerging mental health concern within the Philippines, requiring greater attention from researchers and policymakers [1]. Likewise, Reyes et al. found significant associations between climate anxiety and psychological distress among Filipino Generation Z populations, highlighting the need for targeted interventions within educational settings [14].

Despite the growing body of literature, most climate anxiety studies remain limited to descriptive analyses, psychometric evaluations, and group comparisons. Existing investigations primarily estimate prevalence and identify demographic differences without generating individualized profiles capable of supporting preventive interventions. Recent evidence suggests that differences in coping styles and functional impairment contribute to variations in climate anxiety experiences across populations [15], [16]. However, traditional statistical approaches may be insufficient for capturing the complex interactions underlying these multidimensional outcomes.

Advances in educational analytics and artificial intelligence offer opportunities to overcome these limitations through predictive modeling techniques. Machine learning approaches have increasingly been utilized to identify vulnerable individuals and detect mental health conditions using large and complex datasets. Multi-task learning methods, for example, have demonstrated effectiveness in recognizing psychological conditions through digital behavioral patterns [17]. Similarly, natural language processing approaches have successfully identified vulnerable online communities experiencing elevated anxiety and psychological distress [18].

The integration of artificial intelligence into mental health research has shifted analytical approaches from descriptive assessments toward predictive and preventive applications. Systematic reviews have highlighted the potential of natural language processing and machine learning techniques to support scalable mental health interventions and improve early identification strategies [19]. Predictive frameworks have likewise been employed to enhance the assessment of psychological disorders using clinical records and other multidimensional data sources [20], [21].

As machine learning applications expand, concerns regarding transparency and accountability have become increasingly important. Predictive accuracy alone may not be sufficient in educational and mental health settings where algorithmic outputs inform intervention decisions. Ribeiro et al. argued that users must understand why predictive systems generate specific classifications before such systems can be trusted and adopted in practice [22]. Addressing this concern, Lundberg and Lee introduced SHapley Additive exPlanations (SHAP), an explainable artificial intelligence approach capable of quantifying the contribution of individual predictors while preserving consistency and interpretability [23]. These developments provide opportunities to combine predictive performance with transparent decision support within educational analytics.

Although explainable machine learning has been widely applied to depression, anxiety, and other mental health conditions, its application to climate anxiety among university students remains limited. Existing studies rarely extend beyond conventional inferential analyses to identify students at elevated risk and generate evidence-based recommendations for institutional intervention. Consequently, higher education institutions often lack intelligent tools capable of proactively identifying vulnerable students and supporting climate-related mental health initiatives.

In response to these gaps, this study proposes an Intelligent Climate Anxiety Risk Profiling Framework for University Students Using Educational Analytics. The proposed framework integrates multidimensional indicators of climate anxiety with demographic characteristics to generate predictive risk profiles using machine learning techniques. By incorporating explainable artificial intelligence methods to identify the factors most strongly associated with elevated climate anxiety, the framework seeks to provide evidence-based insights that may assist university administrators, guidance counselors, and policymakers in designing targeted interventions aimed at strengthening psychological resilience, promoting adaptive climate engagement, and enhancing student well-being within higher education institutions.

Methodology

A. *Research Design*

This study employed a quantitative predictive analytics research design utilizing educational analytics and explainable machine learning techniques to develop an intelligent climate anxiety risk profiling framework for university students. The study integrated descriptive analytics, predictive modeling, and explainable artificial intelligence (XAI) to identify students at varying levels of climate anxiety risk.

The framework was developed using survey-based climate anxiety data obtained from university students and transformed into predictive inputs suitable for machine learning analysis. The proposed methodology extended beyond conventional descriptive approaches by generating individualized climate anxiety risk profiles and identifying the factors contributing to elevated climate anxiety. The methodological framework consisted of six major phases:

- Data acquisition and preparation
- Climate Anxiety Index construction
- Data preprocessing and feature engineering
- Predictive model development
- Explainable machine learning analysis
- Development of the intelligent risk profiling framework.

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Figure 1 presents the overall methodological framework adopted in the study.

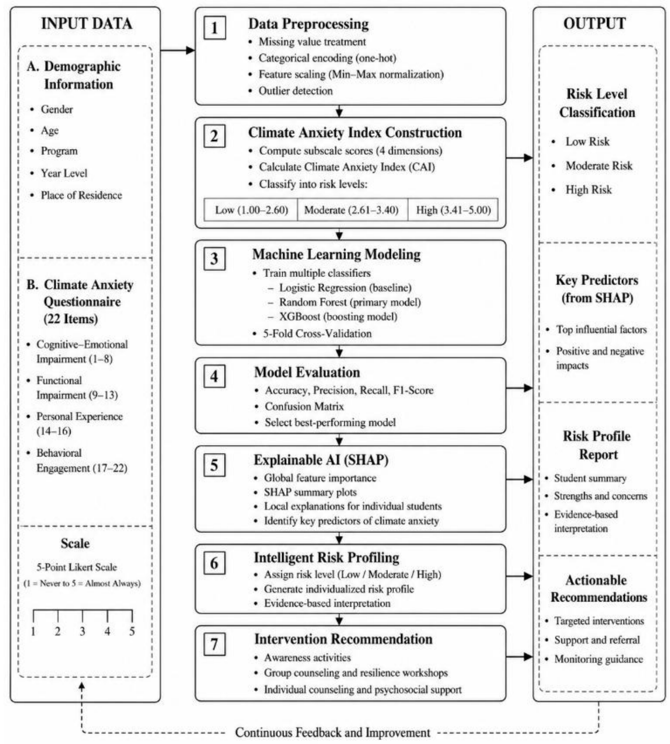

Fig. 1. Methodological Framework of the Study

B. Participants and Data Source

The study utilized the climate anxiety dataset collected from undergraduate students enrolled at Isabela State University–San Mariano Campus during the First Semester of Academic Year 2025–2026. A total of 315 respondents participated in the study through stratified random sampling to ensure adequate representation across academic programs and year levels. The demographic variables included:

- Gender
- Age
- Academic Program
- Year Level
- Place of Residence

The climate anxiety instrument consisted of twenty-two (22) items adapted from the Climate Change Anxiety Scale developed by Clayton and Karazsia [4]. Table 1 shows the four dimensions of the instrument.

TABLE I. DIMENSIONS OF THE INSTRUMENT

Dimension	Item Numbers	Description
Cognitive-Emotional Impairment	1–8	Emotional and cognitive reactions toward climate change
Functional Impairment	9–13	Interference with daily functioning
Personal Experience	14–16	Perceived direct exposure to climate impacts
Behavioral Engagement	17–22	Pro-environmental actions and efficacy beliefs

Responses were measured using a five-point Likert scale to determine the frequency of the respondents' experiences and perceptions. The scale ranged from 1 to 5, where 1 corresponded to Never, 2 to Rarely, 3 to Sometimes, 4 to Often, and 5 to Almost Always.

C. *Climate Anxiety Index Construction*

To facilitate predictive analysis, an overall Climate Anxiety Index (CAI) was computed for each respondent. The index was derived by calculating the mean score across the four dimensions of climate anxiety, namely Cognitive–Emotional Impairment, Functional Impairment, Personal Experience, and Behavioral Engagement. The Climate Anxiety Index for respondent (i) was computed as:

$$CAI_i = \frac{CE_i+FI_i+PE_i+BE_i}{4} \quad (1)$$

where CAI_i denotes the Climate Anxiety Index of respondent i; CE_i represents the Cognitive–Emotional Impairment score; FI_i represents the Functional Impairment score; PEi represents the Personal Experience score; and BE_i represents the Behavioral Engagement score.

The computed CAI values were subsequently transformed into categorical risk levels to facilitate machine learning classification. Respondents with CAI scores ranging from 1.00 to 2.60 were classified as Low Risk, those with scores from 2.61 to 3.40 were categorized as Moderate Risk, and those with scores from 3.41 to 5.00 were identified as High Risk. These risk categories served as the target classes in the development and evaluation of the predictive models.

D. *Data Preprocessing*

Prior to model development, the dataset underwent preprocessing to improve analytical quality and predictive performance.

1) Missing Value Assessment. The dataset was examined for incomplete observations. Missing values, if present, were imputed using median substitution for numerical variables and mode substitution for categorical variables.

2) Categorical Encoding. Demographic variables were transformed into machine-readable representations through one-hot encoding. Variables encoded included are gender, program, year level and residence classification.

3) Feature Scaling. Numerical predictors were normalized using Min–Max normalization:

$$x' = \frac{x-x_{min}}{x_{max}-x_{min}} \quad (2)$$

where x denotes the original value; x_{min} represents the minimum observed value; and x_{max} represents the maximum observed value.

4) *Feature Set Construction.* The final predictor set consisted of demographic characteristics, individual questionnaire items, subscale scores and climate anxiety index.

E. *Machine Learning Model Development*

The intelligent profiling framework employed supervised machine learning techniques to classify students according to their climate anxiety risk levels. To ensure that the distribution of risk categories was maintained across subsets, the dataset was partitioned using stratified sampling, with 80% of the data allocated for model training and 20% reserved for testing. During the training phase, five-fold cross-validation was conducted to assess model stability, reduce sampling bias, and enhance the generalizability of the predictive models.

Three classification algorithms were implemented and compared. Logistic Regression served as the baseline classifier due to its interpretability, computational efficiency, and demonstrated effectiveness in multiclass educational datasets. The model estimates the probability that an observation belongs to a particular climate anxiety risk category based on the weighted contribution of predictor variables.

Random Forest was utilized as the primary predictive model because of its robustness, resistance to overfitting, and ability to capture complex and nonlinear relationships among variables. The algorithm constructs multiple decision trees using bootstrap aggregation (bagging), where each tree independently generates a prediction. The final class assignment is determined through majority voting and is expressed as:

$$\hat{y} = \mathrm{mode}(T_1, T_2, \dots, T_n) \quad (3)$$

where $\hat{y}$ denotes the predicted climate anxiety risk category and T_n represents the class prediction produced by the n decision tree in the ensemble.

To further evaluate ensemble learning approaches, Extreme Gradient Boosting (XGBoost) was implemented and compared with the bagging-based Random Forest model. XGBoost sequentially builds decision trees by correcting the errors of preceding trees and optimizing classification performance through gradient-based minimization of the objective function. Its regularization mechanisms and efficient tree-pruning strategies enhance predictive accuracy while mitigating overfitting. The comparative evaluation of these algorithms enabled the identification of the most suitable model for intelligent climate anxiety risk profiling among students.

F. *Model Evaluation*

The predictive performance of the machine learning models was assessed using the testing dataset. Model effectiveness was evaluated through commonly used classification metrics, including accuracy, precision, recall, and F1-score. These measures provided a comprehensive assessment of the classifiers' ability to correctly identify students' climate anxiety risk levels.

Accuracy was computed to determine the proportion of correctly classified instances relative to the total number of observations and is expressed as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

where (TP) denotes true positives, (TN) represents true negatives, (FP) corresponds to false positives, and (FN) refers to false negatives.

Precision measured the proportion of correctly predicted positive instances among all instances classified as positive and was calculated as:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

Recall, also known as sensitivity, quantified the ability of the model to correctly identify actual positive instances and was computed using:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

The F1-score was used to provide a balanced measure of precision and recall, particularly when class distributions were unequal. It was calculated as:

$$F_1 = \frac{2TP}{2TP+FP+FN} \quad (7)$$

where (TP) represents true positives, (TN) denotes true negatives, (FP) refers to false positives, and (FN) corresponds to false negatives. In addition to these quantitative measures, a confusion matrix was generated to visualize the classification outcomes across the low-, moderate-, and high-risk climate anxiety categories. The confusion matrix enabled the identification of correctly classified instances and the examination of misclassification patterns among risk groups. The classifier demonstrating the highest overall predictive performance across the evaluation metrics was selected as the final model for the intelligent climate anxiety profiling framework.

G. *Explainable Artificial Intelligence Using SHAP*

To enhance the transparency and interpretability of the intelligent profiling framework, SHapley Additive exPlanations (SHAP) were employed to explain the predictions generated by the best-performing classifier. SHAP is an Explainable Artificial Intelligence (XAI) technique grounded in cooperative game theory that quantifies the contribution of each predictor variable to the model's output. By assigning an importance value to every feature involved in a prediction, SHAP provides insight into how individual variables influence the classification of students into climate anxiety risk categories. SHAP analysis facilitated the identification of the variables that most strongly influenced climate anxiety risk classification and provided both global and local interpretability of the predictive model. Specifically, the analysis generated global feature importance rankings to determine the overall influence of predictors across the dataset, SHAP summary plots to visualize the direction and magnitude of feature effects on model predictions, and local explanations for individual student profiles to illustrate how specific factors contributed to a student's assigned climate anxiety risk category. These outputs enhanced the explainability of the intelligent profiling framework and supported evidence-based interpretation of machine learning results within the educational context.

H. *Development of the Intelligent Climate Anxiety Risk Profiling Framework*

The final phase of the study focused on the development of the Intelligent Climate Anxiety Risk Profiling Framework. Findings derived from the machine learning classification models and SHAP-based feature interpretation were synthesized to transform predictive outcomes into evidence-based intervention strategies. The framework translated the predicted climate anxiety risk levels into practical recommendations that can assist university stakeholders in the early identification and management of students experiencing climate-related psychological distress.

Based on the model outputs, students were classified into three distinct climate anxiety risk categories. Each category was associated with intervention strategies proportional to the severity of the identified risk. The proposed profiling framework is intended to guide guidance counselors, student affairs personnel, mental health practitioners, and university administrators in implementing timely and targeted support mechanisms that promote student well-being and resilience. Table II presents the recommended intervention according to climate anxiety risk level.

TABLE II. RECOMMENDED INTERVENTIONS ACCORDING TO CLIMATE ANXIETY RISK LEVEL

Risk Level	**Characteristics**	**Recommended Intervention**
Low Risk	Minimal manifestations of climate anxiety with limited interference in daily functioning	Participation in climate awareness campaigns, environmental education activities, and preventive psychoeducational programs
Moderate Risk	Emerging psychological concerns, occasional distress, and increasing vulnerability associated with climate-related issues	Group counseling sessions, resilience-building workshops, stress management programs, and peer support initiatives
High Risk	Elevated emotional distress and functional impairment that may adversely affect academic, social, or personal functioning	Individual counseling, comprehensive psychosocial assessment, targeted mental health interventions, and referral to appropriate support services when necessary

The framework operationalizes predictive analytics by linking risk classification results with corresponding intervention pathways. SHAP explanations were further utilized to identify the factors contributing most strongly to an individual's predicted risk level, thereby enhancing the transparency and interpretability of the intelligent profiling process. Such explanations enable practitioners to understand why a student was assigned to a particular risk category and to tailor interventions according to the student's specific needs.

Consequently, the proposed framework serves not only as a predictive decision-support mechanism but also as an actionable tool for developing proactive and evidence-informed mental health initiatives within higher education institutions. By facilitating early detection and timely intervention, the framework contributes to strengthening institutional capacity to address the growing psychological impacts of climate change among university students.

I. *Algorithm of the Proposed Intelligent Climate Anxiety Risk Profiling Framework*

Algorithm 1 describes the sequence of procedures employed in the proposed framework. The process begins with loading and preprocessing the climate anxiety dataset, followed by the computation of climate anxiety indices and the generation of risk categories.

Algorithm 1. Intelligent Climate Anxiety Risk Profiling Framework

Input: Climate anxiety dataset D

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```
Output: Risk profile and intervention recommendations
Initialize parameters and data structures;
Load dataset D;
Preprocess data;
   Handle missing values;
   Encode categorical variables;
   Normalize numerical variables;
Compute subscale scores for each respondent;
Construct Climate Anxiety Index (CAI);
Classify respondents into risk levels;
Split dataset into training set (80%) and testing set (20%);
for each model in {Logistic Regression, Random Forest, XGBoost} do
   Train model using the training set;
   Perform 5-fold cross-validation;
   Evaluate model using Accuracy, Precision, Recall, and F1-Score;
end for
Select the best-performing model;
Train the best model on the entire training set;
Test the best model using the testing set;
Compute final performance metrics;
Perform SHAP analysis on the best model;
   Generate global feature importance;
   Generate SHAP summary plots;
   Generate local explanations for individual students;
Generate individualized risk profiles;
Map risk levels to intervention recommendations;
if risk level = Low then
   Assign climate awareness activities;
else if risk level = Moderate then
   Assign group counseling and resilience workshops;
else if risk level = High then
   Assign individual counseling and targeted psychosocial support;
end if
Output risk profiles and recommended interventions;
End.
```

Multiple machine learning classifiers are then trained and evaluated using five-fold cross-validation. The best-performing model is selected and interpreted through SHAP analysis to determine the predictors that most strongly influence climate anxiety risk. Finally, individualized student risk profiles are generated and linked with appropriate intervention strategies, resulting in an intelligent decision-support framework capable of facilitating proactive and evidence-based mental health interventions within university settings.

J. *Ethical Consideration*

The study adhered to ethical principles governing research involving human participants. Institutional approval and informed consent were obtained prior to data collection. Participation was voluntary, anonymity was maintained, and all responses were treated confidentially. The resulting predictive framework was intended solely to support preventive mental health initiatives and educational interventions and not to replace professional clinical judgment.

RESULTS AND DISCUSSIONS

K. *Descriptive Statistics of Climate Anxiety Responses*

Table III summarizes the descriptive statistics of the climate anxiety dimensions. The mean scores indicate the extent to which students experienced the various manifestations of climate anxiety.

TABLE III. DESCRIPTIVE STATISTICS OF CLIMATE ANXIETY RESPONSES

Dimension	Mean	SD	Interpretation
Cognitive–Emotional Impairment	2.769	0.871	Moderate
Functional Impairment	2.817	1.022	Moderate
Personal Experience	3.46	0.936	High
Behavioral Engagement	3.969	0.65	High
Climate Anxiety Index	3.254	0.685	Moderate

Behavioral Engagement obtained the highest mean score (M = 3.969, SD = 0.650), indicating that respondents frequently engaged in pro-environmental behaviors and demonstrated heightened awareness of climate-related issues. Personal Experience also yielded a relatively high mean score (M = 3.460, SD = 0.936), suggesting that many students perceived themselves as directly affected by climate-related events. Conversely, Cognitive–Emotional Impairment (M = 2.769, SD = 0.871) and Functional Impairment (M = 2.817, SD = 1.022) were interpreted as moderate. These findings imply that while students exhibited concern regarding climate change, such concerns did not consistently result in severe emotional dysfunction or substantial interference with daily functioning. The Climate Anxiety Index yielded a mean score of 3.254 (SD = 0.685), corresponding to a moderate level of climate anxiety among university students.

L. *Climate Anxiety Risk Classification of University Students*

A total of 315 undergraduate students participated in the study. Prior to analysis, the dataset underwent preprocessing to ensure analytical quality. Missing values were treated using median substitution for numerical variables, while categorical inconsistencies were addressed through data validation procedures. One out-of-range response detected in Item 20 was corrected using median imputation. The cleaned dataset was subsequently transformed into machine-learning-ready inputs through normalization and feature construction. Table IV presents the recommended intervention according to climate anxiety risk level.

TABLE IV. RECOMMENDED INTERVENTIONS ACCORDING TO CLIMATE ANXIETY RISK LEVEL

Risk Level	Frequency	Percentage
Low Risk	49	15.6
Moderate Risk	148	47.0
High Risk	118	37.5
Total	315	100

The Climate Anxiety Index (CAI) was computed by averaging the scores obtained from the four climate anxiety dimensions: Cognitive–Emotional Impairment, Functional Impairment, Personal Experience, and Behavioral Engagement. The resulting CAI scores were then categorized into low-, moderate-, and high-risk groups according to the thresholds established in the methodology. The results revealed that the largest proportion of respondents belonged to the moderate-risk category. Specifically, 148 students (47.0%) were classified as moderate risk, followed by 118 students (37.5%)

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classified as high risk, while only 49 students (15.6%) were categorized as low risk.

M. Item-Level Analysis of Climate Anxiety

To further understand the manifestations of climate anxiety, descriptive statistics were generated for each questionnaire item.

The highest-rated items included Item 19 (M = 4.42), Item 22 (M = 3.98), Item 18 (M = 3.96), Item 17 (M = 3.89), and Item 20 (M = 3.84). These statements primarily reflected behavioral engagement and climate-related responsibility, indicating that students were willing to adopt actions that contribute to environmental sustainability. In contrast, the lowest mean scores were observed for Item 3 (M = 2.27), Item 13 (M = 2.37), and Item 4 (M = 2.38), suggesting that severe emotional disruption and significant impairment in daily activities were less frequently experienced. The pattern of responses suggests that climate anxiety among students is characterized more by heightened awareness and adaptive engagement than by debilitating psychological distress.

N. Predictive Performance of Machine Learning Models

Three supervised machine learning classifiers were developed and evaluated using an 80:20 stratified train-test split. Logistic Regression served as the baseline classifier, whereas Random Forest and XGBoost represented ensemble learning approaches. The comparative performance of the models is presented in Table V.

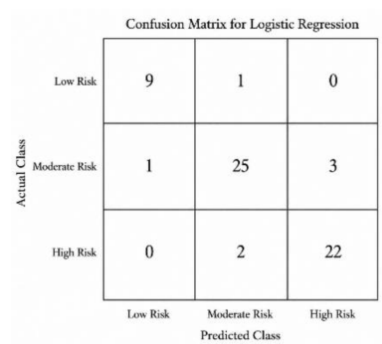
TABLE V. SIX QR CODE CARD MODULE SET AND CURRICULUM ALIGNMENT

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.889	0.891	0.893	0.892
Random Forest	0.857	0.87	0.843	0.855
XGBoost	0.857	0.898	0.86	0.874

Among the evaluated classifiers, Logistic Regression demonstrated the highest overall predictive performance, achieving an accuracy of 88.9% and an F1-score of 89.2%. These findings indicate that the relationships between the climate anxiety indicators and the resulting risk categories were sufficiently distinguishable using a linear probabilistic model. Although Random Forest and XGBoost are capable of capturing nonlinear interactions, their performance did not surpass Logistic Regression. This outcome suggests that the constructed Climate Anxiety Index and related predictors possess strong discriminatory characteristics that can be effectively modeled using interpretable classification techniques. The superior performance of Logistic Regression is advantageous in educational contexts because it combines predictive effectiveness with transparency, thereby facilitating institutional acceptance and practical implementation.

O. Confusion Matrix Analysis

Figure 2 presents the confusion matrix generated



by the Logistic Regression classifier.

Fig. 2. Confusion Matrix of the Logistic Regression Model

The figure illustrates the classification performance of the Logistic Regression classifier in identifying students' climate anxiety risk levels. Most observations were correctly classified, with only a few misclassifications occurring between the moderate- and high-risk categories. The light color

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gradient enhances visual clarity while preserving the interpretability of the classification outcomes. These findings further support the utility of the proposed framework as an early detection mechanism for identifying vulnerable students.

P. *Explainable Artificial Intelligence Through SHAP*

To improve transparency and interpretability, SHAP analysis was employed to identify the predictors contributing most strongly to climate anxiety classification. Table VI shows the top predictors of climate anxiety risk.

TABLE VI. TOP PREDICTORS OF CLIMATE ANXIETY RISK

Predictor	Importance
Functional Impairment	0.1214
Cognitive–Emotional Impairment	0.1145
Personal Experience	0.1066
Item 11	0.0574
Item 12	0.0524
Behavioral Engagement	0.0522

The findings indicate that Functional Impairment emerged as the strongest contributor to risk classification, followed closely by Cognitive–Emotional Impairment and Personal Experience. These results imply that the degree to which climate-related concerns disrupt daily activities and emotional functioning substantially influences whether a student is categorized as low, moderate, or high risk. While behavioral engagement remained important, it was less influential than indicators reflecting psychological burden. The use of SHAP explanations transformed the framework from a “black-box” predictor into an interpretable decision-support system. Guidance counselors and university personnel can therefore understand the rationale behind model predictions and formulate interventions that address the underlying sources of distress.

Q. *Operationalization of the Intelligent Climate Anxiety Risk Profiling Framework*

To demonstrate the operational process of the proposed framework, Figure 3 presents an illustrative example showing how raw student responses are transformed into interpretable climate anxiety risk profiles and corresponding intervention recommendations. The framework begins with students' responses to the climate anxiety instrument. The responses are aggregated to compute the corresponding subscale scores representing cognitive–emotional impairment, functional impairment, personal experiences related to climate change, and behavioral engagement. These dimensions are subsequently integrated to derive the Climate Anxiety Index (CAI), which serves as the basis for assigning students to an appropriate climate anxiety risk category. In this example, the computed CAI value of 3.75 resulted in a High-Risk classification. The machine learning component further validated this categorization, with the Logistic Regression model producing a consistent prediction. To ensure transparency and interpretability, SHAP analysis was applied to explain the model output. The explanation revealed that cognitive–emotional impairment, functional impairment, and personal experience exerted the greatest influence on the high-risk prediction.

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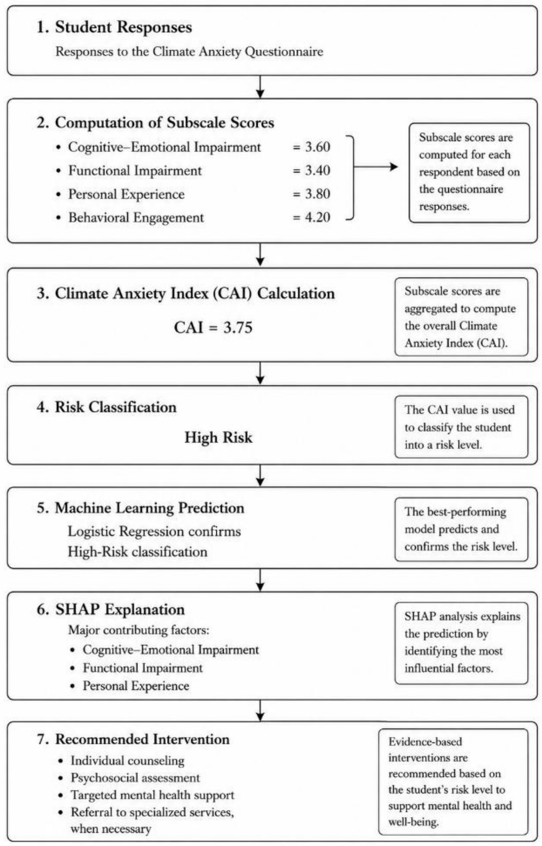

Fig. 3. Transformation of Student Responses into Evidence-Based Intervention Recommendations

The identified risk profile was then translated into actionable recommendations tailored to the student's level of need. Students classified as high risk were advised to undergo individual counseling, psychosocial assessment, and targeted mental health support, with referral to specialized services when warranted. This example demonstrates how the proposed Intelligent Climate Anxiety Risk Profiling Framework integrates educational analytics, machine learning, and explainable artificial intelligence to convert survey data into meaningful, transparent, and evidence-based intervention pathways. By enabling the early identification of vulnerable students and supporting informed decision-making among university stakeholders, the framework contributes to the development of proactive and student-centered mental health initiatives within higher education institutions.

R. Discussions

The descriptive statistics indicate that the study involved a diverse group of university students representing different demographic backgrounds. The inclusion of respondents across various genders, age groups, academic programs, year levels, and places of residence enhanced the representativeness of the dataset and strengthened the applicability of the proposed framework within the university context. Such diversity suggests that the resulting predictive model captured a broad range of student experiences and perceptions related to climate anxiety.

The analysis revealed that Behavioral Engagement obtained the highest mean score, followed by Personal Experience, whereas Cognitive–Emotional Impairment and Functional Impairment registered moderate levels. These findings suggest that students are generally aware of climate-related issues and actively engage in environmentally responsible behaviors. Although respondents expressed concerns regarding climate change, these concerns did not consistently translate into severe emotional distress or substantial interference with everyday functioning. The moderate overall Climate Anxiety Index further

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indicates that climate anxiety among students is present but remains manageable for most respondents.

The majority of respondents were classified under the moderate-risk category, followed by the high-risk group. Only a relatively small proportion of students belonged to the low-risk category. This distribution implies that climate anxiety has become a significant concern among university students, with approximately four-fifths of the participants exhibiting moderate to elevated levels of anxiety. The findings underscore the importance of early detection initiatives and preventive mental health programs aimed at addressing emerging climate-related psychological concerns.

Among the evaluated classifiers, Logistic Regression achieved the highest accuracy, precision, recall, and F1-score. The superior performance of this model indicates that the relationships among demographic characteristics, climate anxiety indicators, and risk classifications were sufficiently distinguishable using an interpretable linear classifier. The results demonstrate that accurate climate anxiety profiling can be achieved without relying exclusively on more computationally complex ensemble methods, thereby supporting the feasibility of deploying transparent predictive models within educational settings.

The confusion matrix demonstrated that the Logistic Regression model correctly classified the majority of students across the three risk categories. Misclassifications occurred primarily between moderate- and high-risk groups, which may be attributed to overlapping characteristics among adjacent risk levels. Notably, the absence of major classification errors between low-risk and high-risk students suggests that the framework effectively distinguished individuals requiring intensive intervention from those exhibiting minimal symptoms. This capability is particularly valuable for prioritizing limited mental health resources.

SHAP analysis identified Functional Impairment, Cognitive–Emotional Impairment, and Personal Experience as the most influential predictors of climate anxiety risk. These findings indicate that disruptions in daily functioning and emotional responses to climate-related events substantially influence students' risk classifications. The incorporation of SHAP enhanced the interpretability of the framework by providing clear explanations of how specific variables contributed to predictions, thereby increasing stakeholder confidence in the model outputs and facilitating evidence-based decision-making.

The illustrative example demonstrated how the framework transforms raw student responses into actionable recommendations. Beginning with questionnaire responses, the system computed subscale scores and generated a Climate Anxiety Index, which was subsequently classified using the Logistic Regression model. SHAP explanations then identified the factors most responsible for the assigned risk category, enabling the generation of individualized intervention strategies. This process highlights the practical value of the framework as a decision-support tool that integrates predictive analytics with transparent interpretation and targeted mental health interventions.

S. Implication of the Proposed Framework

The findings demonstrate that educational analytics and explainable machine learning can effectively support the early identification of climate anxiety among university students. The integration of predictive modeling, SHAP-based interpretation, and intervention mapping enables universities to move beyond descriptive assessments toward proactive mental health management. By linking climate anxiety risk profiles with corresponding support mechanisms, the proposed Intelligent Climate Anxiety Risk Profiling Framework provides a practical tool for guidance counselors, student affairs offices, mental health practitioners, and university administrators. The framework enhances institutional capacity to recognize emerging psychological concerns, prioritize interventions, and implement timely responses that promote resilience and student well-being in the context of increasing climate uncertainty.

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II. Conclusion and Recommendations

A. Conclusion

This study successfully developed and evaluated an Intelligent Climate Anxiety Risk Profiling Framework capable of transforming climate anxiety survey responses into interpretable student risk profiles and evidence-based intervention recommendations. The findings revealed that university students generally exhibited a moderate level of climate anxiety, characterized by strong behavioral engagement and personal experiences related to climate change while demonstrating only moderate levels of emotional and functional impairment. Nevertheless, the distribution of climate anxiety risk indicated that a substantial proportion of students belonged to the moderate- and high-risk categories, highlighting the growing need for institutional initiatives that address climate-related psychological concerns.

The predictive modeling results demonstrated that Logistic Regression outperformed Random Forest and XGBoost in classifying students according to climate anxiety risk levels. Its high accuracy and balanced predictive performance indicate that climate anxiety indicators possess strong discriminatory power and can be effectively modeled using interpretable techniques. Furthermore, the incorporation of SHAP enhanced transparency by identifying Functional Impairment, Cognitive–Emotional Impairment, and Personal Experience as the most influential predictors of climate anxiety risk. These explanations transformed the predictive framework into a transparent decision-support mechanism capable of supporting evidence-based decision-making.

The operationalization of the framework illustrated its practical value by converting raw student responses into individualized risk classifications and corresponding intervention pathways. By integrating educational analytics, machine learning, and explainable artificial intelligence, the proposed framework extends traditional descriptive assessments toward proactive, personalized, and actionable mental health support. Consequently, the framework provides universities with a viable approach for strengthening institutional capacity to identify vulnerable students, prioritize interventions, and promote resilience in the face of increasing climate uncertainty.

B. Recommendations

Based on the findings and conclusions of the study, it is recommended that higher education institutions integrate climate anxiety screening into routine student wellness and psychosocial assessment programs to facilitate the early identification of students who may be vulnerable to climate-related psychological distress. Universities may also adopt a tiered intervention approach in which low-risk students participate in climate awareness and preventive psychoeducational activities, moderate-risk students receive resilience-building programs and group counseling, and high-risk students are provided with individualized counseling, psychosocial assessment, and referral to specialized mental health services when necessary.

Guidance and counseling offices are likewise encouraged to utilize predictive analytics and risk profiling outputs to prioritize students requiring immediate support and to optimize the allocation of limited mental health resources. The incorporation of explainable artificial intelligence techniques, such as SHAP, is further recommended to enhance transparency, improve stakeholder confidence in predictive systems, and facilitate evidence-based intervention planning.

Moreover, universities may establish longitudinal monitoring mechanisms to periodically reassess students' climate anxiety levels and evaluate the effectiveness of implemented interventions over time. Future studies may validate the proposed framework using larger and more diverse populations across multiple higher education institutions to strengthen its generalizability and external validity. Researchers are also encouraged to investigate additional predictors of climate anxiety, including coping strategies, social support, psychological resilience, environmental exposure, and academic stress, to further improve the predictive capability and practical applicability of intelligent climate anxiety risk profiling systems.

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