

RESEARCH ARTICLE

Machine learning-driven prediction of decisional uncertainty among medical students post-Kahramanmaraş earthquake

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Abstract

Background: Predicting psychiatric outcomes in individuals indirectly affected by natural disasters remains a significant challenge. While direct victims receive immediate attention, indirect victims—including family and friends of those affected—can also experience considerable psychological distress.

Objective: This study explores the tendency to report decisional uncertainty (selecting “not sure” responses) regarding emotional and academic states, which may be associated with depressive symptoms. We operationalized this tendency using a pragmatic proxy: the sum of “not sure” responses across four self-report domains, rather than a validated decisional uncertainty scale.

Methods: Medical students ($n = 129$), both indirectly affected and unaffected by the Kahramanmaraş earthquake through family exposure, were recruited. The proxy measure for decisional uncertainty was calculated from responses concerning hobbies, nutrition, occupational satisfaction, and academic success. Associations with depression, anxiety, and earthquake exposure were analyzed using correlation analyses. Exploratory machine learning (ML) models—including random forest (RF), gradient boosting machines, and support vector machines—were employed to explore the feasibility of classifying this decisional uncertainty proxy.

Results: A weak positive correlation was found between the decisional uncertainty proxy and depression scores ($r = 0.247$, $p = 0.005$). However, a multivariable model identified academic and nutritional status as stronger independent predictors of the proxy than depression or anxiety scores. In exploratory ML analysis, models such as RF demonstrated the feasibility of classifying decisional uncertainty, achieving above-chance accuracy.

Conclusion: Preliminary findings suggest a weak association between a simple proxy for decisional uncertainty and depressive symptoms. Exploratory ML approaches show initial promise in identifying this proxy status. These results highlight a novel methodological pathway; however, they are preliminary and underscore the necessity for future validation and calibration against a dedicated, clinically validated decisional uncertainty instrument before any substantive clinical or predictive claims can be made.

Keywords: Depression; Anxiety; Earthquake; Prediction; Machine learning; Kahramanmaraş earthquake; Medical students; Decisional uncertainty

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1. Introduction

Turkey is highly susceptible to earthquakes due to its active fault lines.¹ The magnitude-7.7 and magnitude-7.5 earthquakes that struck Kahramanmaras in February 2023 resulted in unprecedented destruction. The earthquake-affected region extended across an area of approximately 500 km wide.² These powerful quakes not only caused widespread destruction in the immediate region but also had a profound emotional and psychological impact across the entire country. Friends and family members of those affected felt the shock deeply, and the tragedy resonated nationwide, uniting Turkey in collective grief and solidarity.³ Researchers have examined factors (e.g., gender, proximity to the earthquake center, hobbies, diet, and certain psychological factors) that contribute to earthquake risk and its associated impacts. A range of scales was used to assess the participants' psychological states. It is worth noting, though, that participants sometimes struggled to determine how to answer the questions.

A growing body of literature has documented the psychological and mental health impacts of earthquakes on affected populations. The effects of the earthquake can extend to individuals who were not directly exposed to it. There is limited literature on indirect exposure to earthquakes in Turkey. Earthquakes can have a devastating impact on public well-being and social capital and are linked to heightened state anxiety.⁴ Particularly when earthquakes affect large regions, they can have cumulative effects on individuals, whether directly or indirectly. Such consequences may unfold through a cascade of interconnected factors—for instance, disrupting livelihoods, straining infrastructure, or triggering secondary psychosocial stressors—thereby amplifying the long-term impact beyond the immediate seismic event.

Miami-based Haitian Americans had a wide range of indirect exposures to the 2010 Haitian earthquake. Especially significant was the fact that they had multiple indirect exposures through the on-the-scene experiences of numerous family members in Haiti.⁵ Highlighting research such as Shultz *et al.*⁵ is critical to advancing a comprehensive understanding of the multifaceted impacts of disasters, particularly in diaspora communities. It enables the development of informed, culturally sensitive interventions that address both the overt and latent psychological effects experienced by indirectly affected populations. Also, it is important to determine risk factors such as gender, hobbies, diet, and certain psychological factors (e.g., anxiety and depression).

A previous study found that females were at greater risk of developing post-traumatic stress disorder (PTSD) and anxiety. One notable outcome is that female survivors tend

to experience higher levels of trauma compared to their male counterparts.⁶ Additionally, being unmarried was linked to a higher likelihood of experiencing depression and anxiety.⁷ Thus, the university student population could be a significant research domain for individuals affected by earthquakes.

A recent study focusing on the Kahramanmaras earthquake suggested that future research should explore psychological resilience across various types of events involving diverse participant groups.⁸ Future research should aim to include diverse populations—such as different age groups, cultural backgrounds, and socioeconomic statuses—to identify universal and context-specific factors (e.g., decision-making factors) that contribute to resilience. Earthquakes profoundly affect women's well-being and can also have far-reaching consequences for the entire family.⁹ A prior study reported that 29.0% of participants met criteria for PTSD, and 38.8% exhibited symptoms of depression. Identified risk factors for PTSD included unemployment, bereavement, and the use of alcohol or tobacco.¹⁰ PTSD may be further related to depressive symptoms.¹¹ The identified risk factors (e.g., unemployment, substance use) indicate that socioeconomic status and coping behaviors play a role in mental health outcomes. The link between PTSD and depressive symptoms also suggests a need for integrated interventions addressing both conditions in post-disaster mental health support.

Moreover, anxiety-related depression may influence the decision-making processes of individuals impacted by the earthquake. Difficulty in making decisions stands as a central symptom of depression.¹² Another study suggests that the anticipation of negative consequences arising from decision-making choices plays a more significant role in anxiety and depression than a tendency toward decisional delay or avoidance. The results offer evidence that aversive indecisiveness is situated within a nomological network of risk factors for anxiety and depression.¹³ Furthermore, current evidence indicates that developing effective treatment strategies to improve cognitive functioning is essential for individuals with psychiatric disorders.¹⁴ Within the framework of our study, anxiety-related depression following an earthquake may hinder survivors' decision-making abilities, largely due to an overwhelming fear of negative outcomes associated with potential choices. Fear elicits a range of autonomic responses when individuals perceive a threat,¹⁵ and these effects are especially pronounced in uncertain environments that commonly arise after disasters. This tendency represents a significant vulnerability in individuals experiencing mental health symptoms. Targeting this cognitive-affective process—

referred to as “aversive indecisiveness”—is therefore essential for improving psychiatric interventions and supporting recovery in earthquake-affected communities.

Despite growing awareness of the mental health consequences of earthquakes, current assessment methods largely rely on self-reported data and post-event surveys, which can be time-consuming, subjective, and often fail to identify those at risk in real-time. It is also important to recognize that self-report scales require individuals to choose from predefined options, even when they may feel uncertain about how to respond. There is an urgent need for objective, scalable, and predictive tools that can help institutions identify affected individuals more efficiently and accurately.

Machine learning (ML) offers a powerful approach for analyzing complex data patterns and predicting outcomes from multifactorial inputs. By applying ML algorithms to data on medical students’ demographics, academic performance, and self-reported symptoms, we can develop a predictive model to identify those at high risk of adverse effects from the earthquake. Such a model could support proactive and personalized intervention strategies, ultimately helping to mitigate long-term psychological and academic consequences. Therefore, this study is essential for narrowing the divide between psychological assessment and computational tools. It presents an innovative method for disaster response in academic institutions, using a sample of individuals indirectly affected by an earthquake through their families.

2. Methods

2.1. Participants

This study recruited 129 Turkish medical students via social media platforms and official university communication channels. Participants were stratified by academic year, corresponding to Turkey’s six-year medical education system. Data collection commenced in May 2023, three months following the Kahramanmaraş earthquake. The sample consisted of 87 females (67.4%) and 42 males (32.6%), with third-year students representing the largest subgroup (24.8%). All participants were Turkish nationals aged over 18, and written informed consent was obtained voluntarily without compensation.

Ethical approval was granted by the university ethics committee (approval no: 26.04.2023/07). The study adhered to transparent reporting of a multivariable prediction model for individual prognosis or diagnosis—artificial intelligence guidelines to ensure methodological transparency. All participants confirmed their immediate family members survived the earthquake, minimizing

bereavement-related confounding effects. The final sample represented 24.7% of the total medical student population ($n = 522$) at Kars Kafkas University.

Regarding the impact of the earthquake, 27.13% reported that family members were affected. Health behaviors included 39.5% maintaining a healthy diet, 34.2% smoking, and varied alcohol consumption patterns. Socioeconomically, 53.49% identified as middle class and 33.4% as high socioeconomic status. Leisure activities revealed 27.13% had adequate hobby time, 58.91% lacked sufficient time, and 13.95% were uncertain. All instruments were administered in Turkish, and participants were categorized using standardized measures, including a five-tier socioeconomic scale.

2.2. Statistical analysis

Jupyter Notebook version 7.0.8 was used to conduct statistical analysis. Furthermore, we have utilized the Statistical Package for the Social Sciences for correlation analysis. No missing values were identified. Random forest (RF) and support vector machine (SVM) analyses were conducted using the Scikit-learn package of Python.¹⁶ Hyperparameter optimization was conducted using GridSearchCV, which applied 5-fold cross-validation within the training set to evaluate candidate parameter combinations.

To complement regression and assess predictive utility, we employed an ML framework. Four algorithms were evaluated: logistic regression (LR), RF, SVM, and gradient boosting model (GBM). Development and evaluation used a rigorous nested cross-validation procedure (five folds in each of the outer and inner loops) to ensure unbiased performance estimates and mitigate overfitting. Model performance was assessed using accuracy, balanced accuracy, F1 Score, area under the receiver operating characteristic curve (ROC-AUC), area under the precision-recall curve, and the Brier score.

All statistical analyses, conceptual interpretations, and conclusions were developed and verified by the authors. A chi-square test was conducted to compare categorical variables (e.g., decisional uncertainty and gender). Spearman’s rank correlation was used to analyze the relationship between decisional uncertainty scores and other relevant factors. Overall, the moderate Kuder-Richardson-20 and mixed item-total correlations indicate that while a subset of items forms a reliable construct (particularly anxiety and depression-related items), other items may require revision to improve internal consistency.

2.2.1. Machine learning models

(a) Random forest

Random forest consists of multiple tree-based predictors. In an RF, each individual tree relies on the values of a random vector. This random vector is sampled independently, and all the trees in the forest have it sampled from the same probability distribution.¹⁷ It is successfully used in various relevant fields such as psychiatry and psychology.¹⁸

(b) Support vector machine

Support vector machines are a classic ML approach that remains effective for classification tasks in big data scenarios.¹⁹ In psychology, the use of SVM reflects a growing trend toward leveraging computational tools to analyze complex behavioral, cognitive, or neurological data. In our study, two kernel functions were evaluated: a linear kernel for linearly separable data and a radial basis function kernel for capturing potential non-linear relationships.

(c) Gradient boosting machine

Gradient boosting machines are a powerful ensemble learning method used for both classification and regression tasks in ML. GBM is used in psychology.²⁰ GBM offers potential applications for the analysis and interpretation of psychological data.

2.3. Feature importance assessment

Feature importance was evaluated according to the modeling approach. For RF and GBM, importance was measured as the mean decrease in node impurity (Gini index), with values summed across all trees and normalized; the highest-scoring feature was considered most predictive. For LR and SVM, importance was based on the absolute values of model coefficients, with larger magnitudes indicating stronger influence on decisional uncertainty.

2.4. Hobby status

Hobby status was categorized into three categories (having a hobby, no hobby, undecided).

2.5. Nutrition

Nutrition status was categorized into three variables (healthy, unhealthy, undecided).

2.6. Depression score

The Turkish version of the Beck depression scale was utilized to measure levels of depression.²¹ This choice of measurement tool allows researchers to quantify depressive symptoms in a standardized manner within the study's Turkish-speaking sample.

2.7. Anxiety score

The Turkish version of the Beck anxiety scale was applied to measure anxiety levels.²² It consists of 21 items that evaluate the severity of anxiety symptoms experienced over the past week, offering a reliable measure of somatic and cognitive aspects of anxiety.

2.8. Decisional uncertainty proxy: definition and operationalization

The primary outcome of this study was a pragmatic proxy for decisional uncertainty. This was operationalized as the sum of “not sure” responses across four self-assessment domains: hobby engagement, nutritional status, occupational satisfaction, and academic success. Each domain was measured using a single-item, three-option question, with the third option being “undecided” or “not sure.” The total score could thus range from 0 to 4.

To enable binary classification in LR and ML analyses, a score ≥ 2 was used to define “high decisional uncertainty.” This threshold was selected as it represented a meaningful departure from minimal uncertainty (score of 0 or 1) while maintaining a sufficient sample size in the positive class for analysis. The distribution of scores is presented in [Table 1](#).

Table 1. Frequency of decisional uncertainty responses

Value	Frequency
0	46
1	47
2	29
3	5
4	2

2.9. Statistical analysis plan

Analyses proceeded in two sequential phases: a primary inferential analysis and an exploratory predictive analysis.

2.9.1. Primary inferential analysis

To identify independent factors associated with high decisional uncertainty (score ≥ 2), we conducted a prespecified multivariable LR. The model included the following covariates, selected based on conceptual relevance: gender, academic year, family earthquake exposure (yes/no), standardized scores for depression

and anxiety, and binary indicators for academic success (yes versus no/undecided), healthy nutrition (yes versus no/undecided), and hobby engagement (yes versus no/undecided). To address potential model separation and instability due to sample size, we employed Firth's penalized-likelihood estimation and validated the odds ratios using 1,000 bootstrap samples. Model performance was assessed using the Nagelkerke R^2 and area under the ROC curve (AUC). Secondary analyses included Spearman correlations between the continuous decisional uncertainty score and depression/anxiety scores, and chi-square tests for categorical associations.

2.9.2. Exploratory predictive machine learning (ml) analysis

To complement the inferential model and explore the feasibility of classifying the decisional uncertainty proxy, we conducted an exploratory ML analysis. Using a nested cross-validation framework (five outer and five inner folds) to prevent overfitting, we evaluated three algorithms: RF, SVM, and GBM. Given the class imbalance (~28% positive cases), we emphasize balanced accuracy and the F1-score over raw accuracy. Feature importance was derived for each algorithm to identify salient predictors, corroborating findings from the LR. The robustness of performance metrics (accuracy, balanced accuracy, F1, ROC-AUC) was evaluated via 10,000 bootstrap samples to generate 95% confidence intervals.

3. Results

Table 1 shows the distribution of indecisiveness scores, with most participants reporting either no indecisive responses ($n = 46$) or only one ($n = 47$), while higher scores were relatively rare. **Table 2** presents the demographic and psychosocial characteristics of earthquake-affected ($n = 35$) and non-affected ($n = 94$) participants.

3.1. Predicting decisional uncertainty

Figure 1 displays how individuals with decisional uncertainty are distributed across different categories. **Table 1** presents the frequency of decisional uncertainty responses, detailing the number of individuals in each category, while **Table 2** provides demographic comparisons between individuals indirectly affected by the earthquake through family members and those not.

Lastly, **Table 3** displays predictive metrics, including the F1 score, accuracy, cross-validation score, and precision. **Table 4** presents the bootstrap-derived 95% confidence intervals for model performance metrics. Furthermore, the association between decisional uncertainty and anxiety/depression groups is presented in **Table 5**. The results of

the multivariable logistic regression analysis are presented in **Table 6**, and the corresponding bootstrap-derived confidence intervals for the key predictors are shown in **Table 7**.

3.1.1. Most predictive factors for decisional uncertainty status

(a) Logistic regression

The LR model identified the following top five predictive factors:

- (i) Nutritional status
- (ii) Academic status
- (iii) Hobby/leisure activity status
- (iv) Depression score
- (v) Anxiety score

(b) Random forest

The RF model identified the top five predictive factors as:

- (i) Nutritional status
- (ii) Anxiety score
- (iii) Depression score
- (iv) Academic status
- (v) Education year

(c) Support vector machine

The SVM model identified the most predictive factors based on coefficient magnitude as:

- (i) Nutritional status
- (ii) Academic status
- (iii) Depression score
- (iv) Anxiety score
- (v) Hobby/leisure activity status

(d) Gradient boosting machines

The GBM identified the key predictive factors as:

- (i) Nutritional status
- (ii) Academic status
- (iii) Anxiety score
- (iv) Education year
- (v) Hobby/leisure activity status

3.2. Frequency of undecided responses

The frequency of undecided responses is shown as follows:

- Hobby: 18 participants reported being undecided about their hobbies.
- Nutrition status: 42 participants were undecided about their nutrition status.
- Occupational satisfaction: 28 participants expressed decisional uncertainty regarding occupational satisfaction.

Table 2. Demographic information of those affected and those not affected by the earthquake

Demographic	Affected (<i>n</i> =35)	Non-affected (<i>n</i> = 94)	<i>df</i>	χ^2	<i>p</i>
Gender			1	0.028	0.522
Male	11 (31.4%)	31 (32.9%)	–	–	–
Female	24 (68.5%)	63 (67.02%)	–	–	–
Academics			2	3.925	0.141
Successful	20 (57.14%)	54 (57.45%)	–	–	–
Non-successful	7 (20.0%)	8 (8.51%)	–	–	–
Undecided	8 (22.85%)	32 (34.04%)	–	–	–
Academic pressure			3	3.012	0.111
Always	2 (5.71%)	5 (5.31%)	–	–	–
Sometimes	22 (62.85%)	44 (46.80%)	–	–	–
Undecided	8 (22.85%)	42(44.68%)	–	–	–
No pressure	3 (8.57%)	3 (3.19%)	–	–	–
Peer pressure			3	5.743	0.125
Frequently	1 (2.85%)	4 (4.25%)	–	–	–
Sometimes	12 (34.2%)	21 (22.34%)	–	–	–
No pressure at all	17 (48.57%)	64 (68.08%)	–	–	–
Undecided	5 (14.28%)	5 (5.31%)	–	–	–
Healthy diet status					0.867
Healthy	10 (28.57%)	41 (43.61%)	–	–	–
Unhealthy	14 (40.0%)	22 (23.40%)	–	–	–
Undecided	11 (31.4%)	31 (32.9%)	–	–	–
Smoking			1	2.314	0.169
Smoker	12 (34.2%)	20 (21.2%)	–	–	–
Non-smoker	23 (65.7%)	74 (78.73%)	–	–	–
Alcohol drinking status			2	1.356	0.508
Frequently drink alcohol	2 (5.74%)	8 (8.53%)	–	–	–
Rarely drink alcohol	12 (34.2%)	23 (24.4%)	–	–	–
Do not drink alcohol	21 (60.0%)	63 (67.02%)	–	–	–
Exercise status			1	0.004	0.95
Exercise (+)	11 (31.4%)	29 (30.8%)	–	–	–
Exercise (–)	24 (68.5%)	65 (69.1%)	–	–	–

(cont'd...)

Table 2. Continued

Demographic	Affected (<i>n</i> = 35)	Non-affected (<i>n</i> = 94)	<i>df</i>	χ^2	<i>p</i>
Hobbies status			2	2.530	0.282
Hobbies	6 (17.14%)	29 (30.85%)	–	–	–
No hobbies	24 (68.5%)	52 (55.31%)	–	–	–
Uncertain	5 (14.28%)	13 (13.89%)	–	–	–
Anxiety levels			3	10.459	0.015
Minimal anxiety	4 (11.42%)	28 (29.78%)	–	–	–
Mild anxiety	11 (31.42%)	32 (34.04%)	–	–	–
Moderate anxiety	7 (20.0%)	21 (22.34%)	–	–	–
Severe anxiety	13 (37.14%)	13 (13.89%)	–	–	–
Depression levels			3	9.607	0.022
Minimal depression	5 (14.28%)	34 (36.17%)	–	–	–
Mild depression	10 (28.57%)	32 (34.04%)	–	–	–
Moderate depression	16 (45.71%)	21 (22.34%)	–	–	–
Severe depression	4 (11.42%)	7 (7.44%)	–	–	–

Note: Categorical data are shown in percentages.

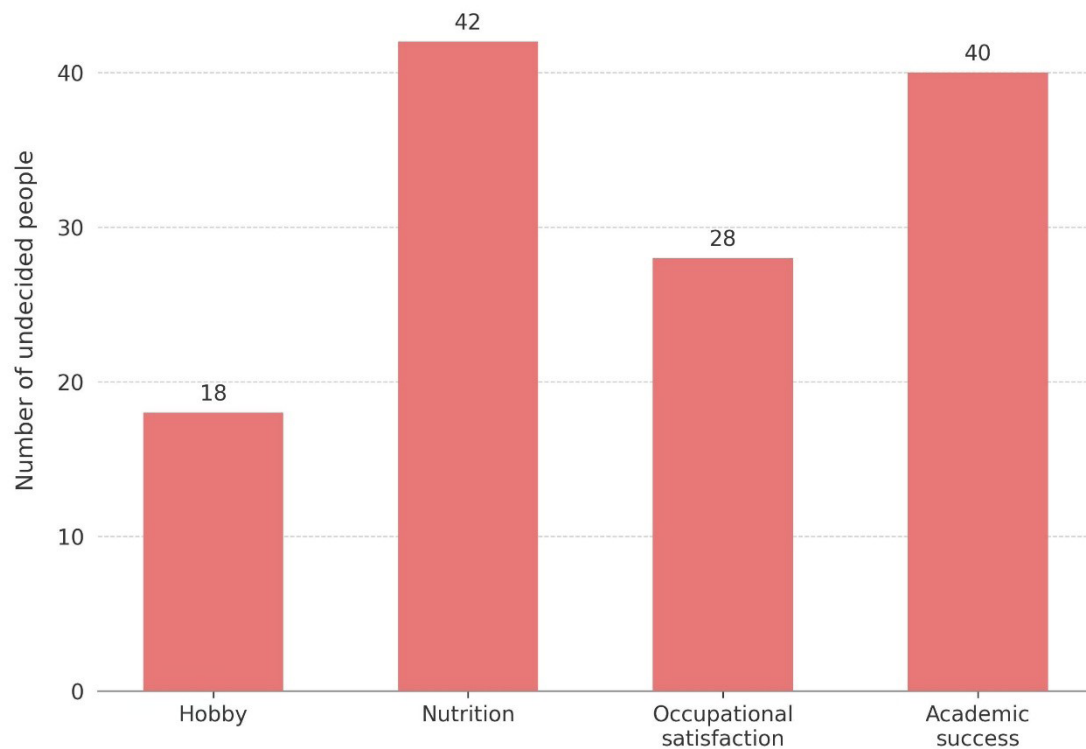


Figure 1. Frequency of decisional uncertainty by category.

Note: The bar chart shows the frequency of participants selecting “not sure” for each of the four domains comprising the decisional uncertainty proxy score.

Table 3. Machine learning model performance for decisional uncertainty (proxy) (nested cross-validation)

Model	ROC-AUC	PR-AUC	Accuracy	Balanced accuracy	F1 score	Brier score
Random forest	0.897	0.814	0.821	0.741	0.630	0.122
SVM	0.894	0.798	0.728	0.749	0.619	0.159
GBM	0.877	0.771	0.798	0.656	0.422	0.135
Baseline (majority)	0.500	0.279	0.721	0.500	0.000	0.201

Abbreviations: GBM: Gradient boosting machine; PR-AUC: Precision-recall area under the curve; ROC-AUC: Receiver operating characteristic-area under the curve; SVM: Support vector machine.

Table 4. Bootstrap 95% CI for model performance (decisional uncertainty proxy)

Model	Accuracy (95% CI)	ROC-AUC (95% CI)	Brier score (95% CI)
Random forest	0.822 (0.752–0.884)	0.883 (0.822– 0.936)	0.121 (0.093– 0.152)
SVM	0.736 (0.659–0.806)	0.865 (0.788– 0.929)	0.126 (0.096– 0.157)
Gradient boosting	0.806 (0.736–0.876)	0.843 (0.757– 0.917)	0.152 (0.104– 0.206)

Abbreviations: CI: Confidence interval; ROC-AUC: Receiver operating characteristic-area under the curve; SVM: Support vector machine.

Table 5. Chi-square analysis of decisional uncertainty (proxy) with anxiety and depression groups

Variable	Chi square	<i>p</i> -value	Significance	Cramer's <i>V</i>
Anxiety group	7.54	0.05655	<i>p</i> > 0.05	0.242
Depression group	5.79	0.12228	<i>p</i> > 0.05	0.212

Table 6. Multivariable logistic regression for decisional uncertainty (proxy)

Predictor	aOR	95% CI	<i>p</i> -value
Demographic factors			
Gender (male versus female)	0.58	0.23–1.46	0.250
Academic year	0.85	0.66–1.08	0.181
Earthquake exposure			
Family affected by the earthquake	0.84	0.21–3.27	0.798
Psychological factors			
Depression score (per SD)	1.06	0.99–1.15	0.172
Anxiety score (per SD)	0.95	0.93–1.01	0.149
Daily functioning markers			
Academic success (yes versus no/undecided)	0.18	0.08–0.40	<0.001
Healthy nutrition (yes versus no/undecided)	0.22	0.09–0.52	0.001
Has hobby (yes versus no/undecided)	0.45	0.18–1.12	0.085

Notes: This table presents the primary prespecified multivariable logistic regression model for inferential analysis. Model performance metrics (Nagelkerke $R^2 = 0.241$, ROC-AUC = 0.801) differ from cross-validated predictive performance in [Tables 3](#) and [4](#) due to methodological differences: this model is for effect estimation, while the [Tables 3](#) and [4](#) models are for predictive accuracy assessment. Model statistics: Nagelkerke $R^2 = 0.241$; Hosmer-Lemeshow test: $\chi^2(8) = 6.32$, $p = 0.612$; Area under ROC curve = 0.801 (95% CI: 0.712–0.890); Brier score = 0.136.

Abbreviations: CI: Confidence interval; ROC-AUC: Receiver operating characteristic-area under the curve; SD: Standard deviation

Table 7. Bootstrap confidence intervals for key predictors (1,000 iterations)

Predictor	Median aOR	95% bootstrap confidence interval
Academic success	0.18	0.07–0.42
Healthy nutrition	0.22	0.08–0.55
Has hobby	0.45	0.17–1.15
Depression (per standard deviation)	1.06	0.98–1.16
Anxiety (per standard deviation)	0.95	0.92–1.02

- Academic success: 40 participants reported being undecided about their academic success.

3.3. Correlations and associations with decisional uncertainty

The correlations and associations with decisional uncertainty are shown as follows:

- A weak positive correlation was observed between the total decisional uncertainty score and total depression score ($r = 0.247, p = 0.005$).
- No significant correlation was found between the total decisional uncertainty score and anxiety ($r = 0.096, p > 0.05$).
- Controlling for gender or grade separately did not yield significant correlations between decisional uncertainty score and depression score (gender: $r = 0.161, p > 0.05$; grade: $r = 0.145, p > 0.05$).
- No significant association was found between grade and gender ($p > 0.05$).

Chi-square analyses revealed:

- No significant relationship between occupational satisfaction and perceived economic status ($\chi^2 = 1.601, p = 0.809$).
- No significant association between earthquake exposure status and uncertainty about hobbies ($\chi^2 = 0.004, p = 0.947$).
- No significant relationship between earthquake exposure status and uncertainty about academic success ($\chi^2 = 1.492, p = 0.222$).
- No significant association between sex and academic success perception ($\chi^2 = 0.676, p = 0.411$).
- No significant relationship between sex and hobby status ($\chi^2 = 2.406, p = 0.121$).
- No significant association between anxiety and hobby status ($\chi^2 = 0.676, p = 0.977$).
- No significant relationships between anxiety and occupational satisfaction ($\chi^2 = 4.975, p = 0.174$),

nutrition status ($\chi^2 = 2.781, p = 0.427$), or academic satisfaction ($\chi^2 = 2.781, p = 0.427$).

4. Discussion

This study aimed to investigate a pragmatic proxy for decisional uncertainty among medical students following a major earthquake and to explore its associated factors using both traditional and ML methodologies. Our principal finding is that while a simple, four-item decisional uncertainty proxy demonstrated a weak but significant correlation with depressive symptoms, its primary predictive factors in a comprehensive model were not the psychological constructs of anxiety and depression, but rather markers of daily functioning and academic standing.

4.1. Interpretation of main findings

The most robust predictors identified across multiple ML algorithms were academic status and nutritional status. This pattern was remarkably consistent, with both features ranking as the top two predictors in three of the four models (LR, SVM, and GBM). This suggests that in our sample of medical students navigating post-disaster circumstances, uncertainty in self-assessment may be more closely tied to concrete domains of daily life and perceived competence (academics, self-care) than to the level of emotional distress per se. Furthermore, students uncertain about their academic standing or basic health habits may extend this uncertainty to broader emotional and existential questionnaires.

Our ML models demonstrated the feasibility of classifying the decisional uncertainty proxy with moderate accuracy (73–82%). The RF model performed best, consistent with its ability to capture complex interactions. The bootstrap 95% confidence intervals provide a more realistic range of expected performance in similar populations, with accuracy for the best model (RF) likely falling between 75.2% and 88.4%. However, it is crucial to

interpret these results with caution due to the significant class imbalance in our sample, where only approximately 28% of participants were categorized as having high decisional uncertainty (score ≥ 2). In such contexts, standard accuracy can be misleading.

Beyond discrimination metrics, we assessed model calibration using the Brier score to evaluate how well predicted probabilities matched observed outcomes. All models demonstrated reasonable calibration (Brier scores: 0.122–0.159), with RF showing the best calibration. While we did not generate visual calibration plots due to the exploratory nature of this analysis and sample size constraints, the Brier scores provide quantitative evidence that the models' probability estimates were generally well-calibrated to the observed outcomes.

4.2. Frequency of decisional uncertainty choices

Undecided frequency refers to the tendency to experience frequent indecision or difficulty making choices, while its relationship to psychology involves exploring how this tendency connects to cognitive, emotional, and behavioral patterns. Undecided frequency may be related to certain psychological problems, such as depression. There is scant literature on this subject in psychiatry. Moreover, certain psychological scales do not include an “unsure” option, which can be problematic because it forces individuals to select a definite choice.

There is a literature on indecisiveness and personality.²³ Furthermore, previous findings suggest that low self-esteem serves as a robust predictor of exploratory indecisiveness.²⁴ In the context of the study, we cannot reach a conclusion about low self-esteem; however, it is important to know that self-esteem is related to depression. The performance impairment observed in major depressive disorder arises from protracted decision-making processes, not slowed sensory processing or motor response execution.²⁵

One study explores the differences in career-related concerns between undecided and decided college students. Compared with their decided peers, undecided students showed lower levels of career decision-making self-efficacy, more frequent negative thoughts about career choices, and greater difficulty making career decisions. The findings indicate that undecided students are equally prepared to make career-related decisions as their decided peers, but they might lack clear career information or receive conflicting guidance.²⁶

Based on the literature, undecided choices may be related to depression. In our study, we found a significant weak positive correlation between the total decisional uncertainty score and the total depression score ($p = 0.005$, $r = 0.247$). However, we did not find a significant correlation

between total decisional uncertainty score and anxiety ($r = 0.096$, $p > 0.05$). It suggests that individuals with anxiety may not experience decision-making difficulties as they assert, claiming uncertainty about their choices.

4.3. Anxiety

Psychological challenges such as depression and anxiety experienced by nurses who were not present in the earthquake-affected area diminished their professional engagement and motivation, ultimately impairing the quality of patient care.²⁷ Additionally, anxiety has been associated with heightened participation in behaviors aimed at avoiding threats, while depression is connected to decreased involvement in behaviors focused on pursuing rewards. Notably, depression differs fundamentally from anxiety in both its underlying mechanisms and behavioral manifestations. Whereas anxiety typically manifests as hyperarousal and vigilance toward potential threats, depression is characterized by anhedonia, anergia, and persistent low mood.

Additionally, compared to students who did not lose relatives in the earthquake, those who did exhibited higher scores in every variable except somatization.²⁸ According to our analysis, we did not find any relationship between anxiety and hobby status. It may not be directly related to anxiety.

4.4. Depression

The Kahramanmaraş earthquake in 2023, which claimed over 50,700 lives and left millions homeless, has led to a significant increase in depression cases among survivors, as they struggle to come to terms with the loss of loved ones, the destruction of their homes, and the disruption of their daily lives. Indirectly affected individuals—such as those who witnessed the disaster through media, experienced financial losses due to disrupted supply chains, or felt heightened anxiety from the collective trauma—may also suffer emotional impacts, including stress, grief, or even symptoms of depression, as the ripple effects of such a catastrophic event extend beyond the immediate disaster zone.

The analysis results showed that with the increase in the intensity of exposure to disaster news, the stress, depression, and anxiety levels of the participants also rose. Compared with those who did not directly experience the earthquake but followed the news and those whose relatives experienced the earthquake, individuals who experienced the earthquake and participated in volunteer relief activities had higher depression and anxiety scores, and higher total scores on the Depression Anxiety Stress Scales-21 items scale.²⁹

We found a weak positive correlation between total decisional uncertainty score and total depression score ($p = 0.005$, $r = 0.247$). However, we did not find a significant correlation between total decisional uncertainty score and anxiety ($r = 0.096$, $p > 0.05$).

4.5. Gender

The primary factors influencing disaster preparedness were gender, age, education level, marital status, and experience of the February 6 earthquakes. Compared to those with indirect exposure, individuals directly affected by the dual earthquakes exhibited higher levels of depression symptoms, anxiety symptoms, and stress, along with lower disaster preparedness levels.³⁰ The results showed that compared with males and individuals without previous direct earthquake experience, former earthquake survivors and females had higher scores on the personal impact factor.³¹

In our study, we found a weak but significant correlation between the total decisional uncertainty score and depression ($r = 0.247$). However, we did not find a significant correlation between the decisional uncertainty score and the total depression score after controlling for gender ($r = 0.161$). Taken together, these results underscore the interconnectedness of demographic traits, direct disaster exposure, psychological distress, and decision-making tendencies, with gender emerging as a particularly relevant factor in shaping both personal impact and the relationship between decisional uncertainty and depression.

4.6. Limitations

Low sample size is one of the main limitations of our study. Furthermore, relying on scales may not provide a clear diagnosis of depression. Additionally, we commenced data collection three months after the earthquake. In addition, the study neglected other potentially relevant factors (e.g., access to healthcare) that may influence anxiety outcomes among participants. Moreover, the decisional uncertainty proxy is defined as the count of “not sure” responses across four items (hobbies, nutrition, occupational satisfaction, and academic success; range 0–4). Although pragmatic, this measure has not been validated as a psychological construct and may capture a mix of indecision, disengagement, or item ambiguity.

5. Conclusion and future directions

We found a weak association between the total decisional uncertainty score and the total depression score. Exploratory ML approaches demonstrated initial feasibility in classifying the proxy, although performance

was constrained by sample size and class imbalance. These results highlight a novel, exploratory methodological pathway for future research using validated instruments.

Existing prediction models can be used to detect people who are unaffected by the earthquake. Furthermore, longitudinal studies can be designed to foresee the course of depression and anxiety symptoms. Future studies should explore subtypes of decisional uncertainty (e.g., difficulty initiating decisions versus revisiting choices) to identify specific links with depression. Digital interventions aimed at enhancing social support networks among those indirectly affected by the earthquake may be critical to alleviating stressors triggered by such disasters. Furthermore, the present findings are exploratory. Future research would benefit from using a validated decisional uncertainty scale to yield more robust and generalizable conclusions.

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Conflict of interest

There is no conflict of interest to state.

Author contributions

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Ethics approval and consent to participate

The study was reviewed and approved by the Ethics Committee of Kars Kafkas University (Approval No: 26.04.2023/07). All participants provided written informed consent prior to participation after being informed about the study's purpose, procedures, and their right to withdraw at any time without penalty. Participant confidentiality and data privacy were strictly maintained by anonymizing all identifying information and securely storing data in password-protected files accessible only to the research team. The research procedures adhered to the

ethical standards outlined in the Declaration of Helsinki.

Consent for publication

All participants provided written informed consent for the publication of anonymized data collected during this study.

Availability data

Some data supporting the findings of this study are available from the corresponding author upon reasonable request. The available data include the encoded questionnaire data after redaction, which support the findings of this study.

Further disclosure

Chatbots (GPT-4o) were used to improve the language and figures of the manuscript. No generative AI tools were used to create or fabricate data, analyses, or scientific interpretations.

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