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Explainable Machine Learning for Predicting Healthcare Workers' Emergency Preparedness Using Disaster-Readiness and Built-Environment Indicators

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Abstract: *Healthcare workers must be prepared to respond to disasters, disease outbreaks, infrastructure failures, and other emergencies. Common assessments often describe general readiness but may not show which staff groups need extra support or why. This paper presents a simple, explainable machine-learning approach for estimating healthcare workers' self-reported emergency preparedness using professional background, training experience, emergency exposure, organizational factors, and perceptions of the healthcare facility environment. The study described in the source paper used questionnaire responses from 360 healthcare workers across 12 facilities. Three models were compared, with the third adding perceived built-environment resilience to demographic, professional, training, and emergency-exposure information. The addition improved ROC-AUC from 0.795 to 0.834 and reduced the Brier score from 0.186 to 0.167. Previous disaster training, environmental resilience, profession, drill participation, and work area were among the strongest explanatory factors. The results suggest that explainable prediction may help institutions plan training and facility improvements. However, the model was internally validated only and requires external testing and recalibration before real-world use.*

Keywords: Explainable AI, machine learning, emergency preparedness, healthcare workers, disaster readiness, built environment, SHAP

I. INTRODUCTION

Emergency preparedness is important for hospitals and healthcare services because emergencies can happen suddenly and may affect patients, staff, equipment, and buildings. Healthcare workers need suitable knowledge, practical training, clear communication, emergency drills, and support from their organization. Their ability to respond can also be affected by the layout and condition of the workplace.

Traditional preparedness surveys are useful for finding general gaps, but they usually summarize the answers collected from a group. They may not provide a clear estimate of which staff groups are more likely to report lower preparedness or which factors contribute most to that estimate. Machine learning can help identify patterns across several types of information, while explainable AI can make the model's predictions easier to understand.

The paper considered here focuses on whether perceived built-environment resilience adds useful information beyond workforce, training, and emergency-exposure indicators. Environmental factors include evacuation access, wayfinding, circulation, visibility, crowd management, isolation support, safety, and staff-support spaces. These are staff perceptions and should not be treated as direct architectural measurements.

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II. RELATED WORK AND PROBLEM DEFINITION

Research on healthcare emergency preparedness commonly examines knowledge, attitudes, preparedness practices, willingness to respond, previous training, and organizational readiness. Such assessments help identify areas where staff education or institutional planning may be improved. However, descriptive results do not always produce individual or unit-level risk estimates, and they may offer limited explanation for prioritizing different interventions.

Machine learning is used in healthcare to support prediction and decision-making. A useful model should not be judged by accuracy alone. It should also be checked for information leakage, stability, calibration, performance on unseen groups, and practical value. Explainable AI methods such as SHAP can show which input features contribute most to a model's output. The source study used these ideas to build a prediction approach that remains interpretable.

The purpose of this study is to examine whether explainable machine learning can help estimate healthcare workers' self-reported emergency preparedness. It also checks whether staff perceptions of the healthcare facility environment add useful information beyond professional background, training, and previous emergency experience. The intended use is to support planning for training, drills, and facility improvements—not to replace professional judgment or make automatic decisions about staff.

Purpose of the Study

In many preparedness assessments, healthcare organizations collect survey responses about staff knowledge, confidence, training, and readiness. These assessments are useful for understanding general needs, but summary results may not clearly show how different factors work together or which factors contribute most to a prediction. The source study develops a machine-learning approach and compares models that gradually add training, emergency-exposure, and perceived built-environment information. Its explainability step helps show which variables are most influential.

Existing System

A. Problem Definition

Healthcare organizations need a practical way to identify possible preparedness gaps and select suitable actions. A survey may show the average readiness of staff, but it may not clearly indicate which combinations of training, experience, professional role, and workplace conditions are associated with lower self-reported preparedness. The problem is to develop an explainable prediction process that combines these factors without using outcome information improperly as an input.

B. Aim and Objectives

The main aim is to assess whether explainable machine learning can estimate self-reported emergency preparedness and whether built-environment perceptions improve prediction. The objectives are: (1) organize workforce, training, emergency-exposure, and environmental indicators; (2) compare models that add predictor groups step by step; (3) identify important factors through explainability; and (4) discuss how model outputs could support training and facility planning while recognizing the need for further validation.

III. METHODOLOGY

A. Study Data

The source study used a cross-sectional questionnaire dataset containing 360 valid responses from healthcare workers at 12 healthcare facilities. Data collection took place between 10 February and 12 April 2026. The paper reports institutional ethics approval and electronic informed consent. Because the dataset was questionnaire-based and moderate in size, the study emphasized a transparent workflow and careful internal validation.

B. Predictor Groups and Outcome

Predictors were organized into three nested groups. Model 1 included demographic and professional information such as age, education, profession, facility type, work area, work schedule, and experience. Model 2 added previous disaster

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training, participation in drills, COVID-19 work experience, and previous major emergency experience. Model 3 added a score describing perceived built-environment resilience.

The target outcome was high self-reported preparedness. The primary threshold was a preparedness score of at least 70%; 65% and 75% thresholds were also checked. The outcome was calculated from knowledge, attitudes, practices, willingness, and organization-related domains. Built-environment resilience was kept separate from the outcome and used only as an independent predictor. This separation helped reduce data leakage.

IV. PROPOSED MACHINE-LEARNING FRAMEWORK

The proposed process takes questionnaire information, checks and prepares the data, estimates preparedness, explains the prediction, and supports an appropriate institutional response. It is intended as a decision-support approach rather than a system that automatically judges or penalizes individual healthcare workers.

A. Data Preparation

Continuous variables were standardized and categorical variables were encoded within the training folds. This means the preparation steps were learned from training data and then applied to held-out data, reducing the risk of information from the test set influencing model training. The study did not use synthetic oversampling; class weighting was used for logistic regression to address the moderate difference between the outcome groups.

B. Model Development

Three nested models were evaluated so that the additional value of each predictor group could be measured. Logistic regression was selected as the main model because its structure is comparatively transparent and suitable for a moderate-sized dataset. Random forest, support vector machine, and gradient boosting were also tested as comparison methods.

C. Validation and Evaluation

The study used stratified 10-fold cross-validation to preserve the proportion of outcome groups across folds. It also used leave-one-facility-out validation, where data from one facility were held out while the model was trained on the remaining facilities. The evaluation included ROC-AUC, PR-AUC, F1-score, accuracy, precision, recall, specificity, and Brier score. Calibration and decision-curve analysis were included because useful predictions should be reasonably reliable and potentially helpful for decisions.

D. Explainability

SHAP-based explanations were used to identify which variables had the greatest influence on predictions. The study also examined whether the leading explanations stayed reasonably consistent across validation folds. This is important because a decision-support tool is more useful when its main reasons are understandable and do not change unpredictably between samples.

Framework flow (conceptual):

Questionnaire Data	**Data Cleaning & Encoding**	**ML Prediction (Model 1–3)**	**SHAP Explanation**	**Training / Facility Action**

Fig. 1. Conceptual workflow of the explainable preparedness prediction system.

V. RESULTS AND DISCUSSION

At the primary 70% preparedness threshold, adding perceived built-environment resilience improved the model's results. Model 2 achieved a ROC-AUC of 0.795, PR-AUC of 0.821, F1-score of 0.746, and Brier score of 0.186. Model 3 achieved 0.834, 0.858, 0.765, and 0.167, respectively. The improvement in ROC-AUC was reported as 0.039, with a bootstrap confidence interval that remained above zero.

A. Model Comparison

The results indicate that environmental perceptions added predictive information beyond demographic, professional, training, and emergency-exposure variables. In the leave-one-facility-out test, Model 3 achieved ROC-AUC 0.830 and

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F1-score 0.770, compared with ROC-AUC 0.791 and F1-score 0.745 for Model 2. This suggests that the benefit was not limited to the standard cross-validation results, although the test still used the same overall study dataset.

TABLE I. COMPARISON OF THE MAIN PREDICTION MODELS

Model	Predictor group	ROC-AUC	F1-score	Brier score
Model 1	Demographic / professional	0.653	0.683	0.237
Model 2	Model 1 + training / exposure	0.795	0.746	0.186
Model 3	Model 2 + built environment	0.834	0.765	0.167

Note: Lower Brier score indicates lower probabilistic prediction error.

B. Important Predictors

The SHAP analysis identified previous disaster training as the leading predictor, followed by perceived built-environment resilience, profession, participation in drills, and work area. These factors are understandable in practice: training and drills provide preparation experience, profession and work area reflect different responsibilities, and environmental conditions may make emergency tasks easier or more difficult. The findings do not prove that the environment causes preparedness; the environmental score was based on participants' perceptions.

C. Practical Use

A hospital or healthcare facility could use a secure dashboard to review de-identified or unit-level questionnaire data. If the explanation points to limited disaster training or low drill participation, the institution could arrange focused training and simulation exercises. If environmental concerns are prominent, the facility could review evacuation access, wayfinding, circulation, visibility, crowding, and staff-support areas. The model should support improvement planning, not punishment or automatic decisions about employees.

D. Calibration and Reliability

Although Model 3 performed better on several metrics, its calibration was not perfect. The reported calibration slope was 0.769, and the authors recommended recalibration before operational deployment. This means that the model may rank risk reasonably well but its predicted probabilities should not yet be treated as fully reliable real-world probabilities.

VI. ADVANTAGES AND LIMITATIONS

A. Advantages

The approach combines multiple readiness factors rather than relying on one survey score. It compares predictor groups in a structured way, uses validation procedures, provides explanations for predictions, and can connect findings with possible actions such as staff training, drills, or environmental review.

B. Limitations

The study is cross-sectional, so it cannot establish cause and effect. Preparedness was self-reported rather than measured through observed emergency performance. Built-environment variables were based on staff perceptions rather than objective architectural measurements. The data came from one national context and 12 facilities, and internal validation does not replace independent external validation.

VII. FUTURE SCOPE

Future work should test the framework with independent data from more healthcare facilities and different countries. Researchers could combine staff perceptions with objective building information, evacuation-route measures, occupancy data, environmental sensors, emergency-drill results, or digital building models. Prospective studies could also examine whether recommendations generated from model explanations lead to measurable improvements in preparedness.

Before practical deployment, the model should be externally validated, recalibrated, and monitored for changes in performance over time. Researchers should examine whether the model performs fairly across professions, facility

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types, and staff groups. Any dashboard should protect staff privacy, explain how outputs are used, and keep human decision-makers involved.

VIII. CONCLUSION

This paper describes an explainable machine-learning approach for estimating healthcare workers' self-reported emergency preparedness. In the source study, adding perceived built-environment resilience improved prediction results beyond workforce, training, and emergency-exposure information. The most influential factors included previous disaster training, environmental resilience, profession, drill participation, and work area. These findings support the idea that preparedness is shaped by both people and the places where they work.

The framework may help healthcare institutions identify possible gaps and plan targeted improvements. However, the current results should be treated as promising internal evidence rather than proof that the model is ready for use. External validation, recalibration, and further evaluation are needed before it is used to guide real operational decisions.

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REFERENCES

[1] B. Obeidat, "Explainable Machine Learning for Predicting Healthcare Workers' Emergency Preparedness Using Disaster-Readiness and Built-Environment Indicators," IEEE Access, accepted for publication, 2026, doi: 10.1109/ACCESS.2026.3730327.

[2] G. S. Collins et al., "Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD): The TRIPOD Statement," Annals of Internal Medicine, vol. 162, no. 1, pp. 55–63, 2015.

[3] S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in Advances in Neural Information Processing Systems, 2017.

[4] R. D. Riley et al., "Evaluation of clinical prediction models (part 1): From development to external validation," BMJ, vol. 384, 2024.