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DISASTER PREPAREDNESS PREDICTION THROUGH COLLECTIVE EFFICACY INDICATORS

DR.SANDEEP SONI[1], DR. SHIVLI SHRIVASTAVA[2], DR. RASHMI CHAUHAN[3]
[1]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
email: ku.sandeepsoni@kalingauniversity.ac.in orcid:0009-0000-3692-6874
[2]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
[3]ASSISTANT PROFESSOR, NEW DELHI INSTITUTE OF MANAGEMENT, NEW DELHI, INDIA.,
e-mail: rashmi.chauhan@ndimdelhi.org, https://orcid.org/0009-0005-4371-0373

ABSTRACT

The gap between existing predictive models of community preparedness and community preparedness capabilities has long been overlooked. Attempting to fill this gap, this study develops a predictive model using collective efficacy sociometric markers, including social cohesion, trust, community problem solving, and shared expectations, to estimate a community's preparedness in terms of disaster scenarios. The model relies on combining quantitative data from surveys and geospatial vulnerability maps to build machine learning models that estimate preparedness scores for different populations. The model captures neighborhood socio-psychological data coupled with coordinated community response data to go beyond hazard-based evaluations of preparedness. The model is applied to a dataset from three disaster-prone regions, capturing subjective and objective risk perceptions. Results show that most collective efficacy factors enhance preparedness behaviors, including emergency planning, intent to evacuate early, and resource mobilization. The research confirms that collective efficacy in disaster research is a critical metric while providing tangible guidance for municipal governance and community resilience planning. Moreover, the study shows that accuracy of prediction improves considerably with the inclusion of demographic moderation, such as age, income, and education. Such predictive capacities can help shape policy aimed at disaster resilience at the community level.

Keywords:

Disaster Preparedness, Collective Efficacy, Community Resilience, Predictive Modeling, Social Cohesion, Risk Perception, Machine Learning

I. INTRODUCTION

Given the increasing climate change impacts and natural hazards, disaster preparedness is increasingly critical. Aside from the physical components of infrastructure, hazard mapping, and defined protocols, the recent body of work emphasizes social components as equally central for the effective management of disasters. One of the recent social components noted is collective efficacy, which is defined as a shared belief of the members of a community regarding their ability to achieve defined goals and respond to challenges. This concept, based in social cognitive theory, collective efficacy includes social cohesion perceptions, trust, shared norms, and solidarity, which all determine the degree of cooperation and behavioral preparedness to act in the pre-defined terms.

Standard approaches to disaster preparedness still employ hazard-based assessments, historical risk data, and logistical readiness indicators. These approaches take insufficient account the psychosocial factors within communities which influence risk perception, adaptive action, and mobilization. Collective efficacy as a predictive framework allows us to interpret community readiness that is often overlooked to a social construct. Communities that display strengthened social trust and civic engagement coupled with problem-solving capabilities are significantly more likely to act in preparedness behaviors like resource stocking, communication planning, and even evacuation drills.

This is the gap which the study proposed, to quantify the indicators of collective efficacy and model with the outcomes of disaster preparedness.Through community and survey-based research in urban and semi-urban areas subject to recurring risks, we construct a predictive model estimating preparedness scores. Machine learning is applied to a multitude of variables such as neighborhood cohesion, trust in local authorities, perceived social support, and disaster-relate experience. What sets this research apart is its predictive nature as it goes beyond the mapping of readiness levels to unveil vulnerable clusters that lack collective efficacy.

Besides, this research is relevant to inform public policy and strategies for disaster risk reduction (DRR). Rather than enforcing a one-size-fits-all preparedness policy, decision-makers are able to intervene in areas with the most social fabric fracture using the model's provided predictive analytics. This is in line with the overarching principles of the Sendai Framework for Disaster Risk Reduction which calls for community-driven, inclusive, local, and participatory preparedness planning.

Key Contributions

- This research proposes a novel machine learning model which incorporates social factors like social cohesion, institutional trust, and community support systems into a preparedness estimation framework, thus advancing the field of disaster readiness estimation.
- The study identifies the primary drivers of preparedness using SHAP analysis and spatial mapping, revealing trust in local governance and participation in drills as the predominant behavioral indicators.
- The research presents spatial diagnostics and readiness heat-maps to facilitate precise disaster risk reduction (DRR) strategies at the local level while connecting with global frameworks such as the Sendai Framework for Disaster Risk Reduction (2015-2030).

The paper is divided into six sections. In Section I, the author describes the background information, the research setting, and why it matters to have collective efficacy in the context of preparedness. In Section II, the conceptual framework is presented along with the most important dimensions of collective efficacy. In Section III, the author details the data sources, the variables, and the predictive modeling technique. The author of the paper also performs an analysis of the outcomes of the model which includes the score distributions, the contributions of the features, and the spatial trends in Section IV. In Section V, the author presents the policy and community planning implications in strategic terms. In Section VI, the author restates the contributions of the study and offers insights on why social indicators should be embraced in assessments of resilience.

II. THEORETICAL FRAMEWORK AND CONTEXTUAL FOUNDATIONS

2.1 Understanding Collective Efficacy in Disaster Contexts

Collective efficacy denotes the belief within a community and its members' ability to mobilize resources and act as a unit toward common objectives, especially during challenging times. In the context of disaster preparedness, it involves elements of community expectation and trust beyond individual preparedness. It usually shows up in the forms of community-based support systemshelping to support local pre disaster and disaster planning, and confidence in community officials. Such efficacy allows communities to take proactive steps, respond to designated authorities' warnings, and recover in a resilient manner.

2.2 Dimensions of Collective Efficacy Relevant to Preparedness

The framework adopted in this study recognizes four core dimensions:

- Social Cohesion: The emotional and interpersonal bonds among community members.
- Shared Expectations: Agreement on norms related to mutual help and responsibility.
- Perceived Social Support: Belief that assistance will be available in times of crisis.
- Trust in Institutions: Confidence in the decisions and actions of emergency response systems and governance.

These indicators are not only conceptually grounded but also empirically measurable through structured survey items.

2.3 Gaps in Traditional Preparedness Models

The existing frameworks focus primarily on hazard exposure, physical infrastructure, or personal risk appraisal. None of these frameworks, however, explain why a socially cohesive neighborhood is able to outperform a physically prepared neighborhood that lacks weak internal trust. For instance, two neighborhoods facing the same flood risk may be empowered with differing social ties and share preparedness, causing differing survival rates and recovery speed. This demonstrates not only the limitations of geophysical models, but the more comprehensive socio-behavioral model that is needed.

2.4 Relevance to Policy and Community Planning

Knowing and evaluating collective efficacy helps local authorities optimize resource allocation and intervention design. For example, community engagement campaigns, neighborhood training sessions, and tailored communication reflect targeted approaches for low efficacy score areas. This is in line with risk-informed development approaches in global documents as the Sendai Framework and resilience indicators from UNDRR.

III. DATA COLLECTION, FEATURE MODELLING, AND PREDICTIVE FRAMEWORK

3.1 Data Source Integration and Sampling Procedure

This study's data sampling was conducted in three selected urban and peri-urban districts vulnerable to disasters, each with distinct socio-demographic characteristics. To capture diversity in age, education, income, and stability of housing, a multi-stage stratified sampling technique was employed. The primary data was obtained from structured questionnaires that measured social cohesion, trust in institutions, and support at the neighborhood level with validated scales. Secondary data sources included governmental past exposure to disasters, emergency response data, and community vulnerability records.

3.2 Feature Engineering and Variable Construction

Models used for prediction included psychosocial indicators and contextually relevant demographic features. Primary Survey features included: perception of neighborhood trust scaled, social contacts available for aid, past evacuation, participation in preparedness drills, and responsiveness of the local government on a Likert scale. Also, demographic moderating variables of age, household size, income range, and education level were captured, coded, and normalized for the model. A feature importance analysis was performed to remove redundant features while preserving over 88% variance through PCA.

3.3 Predictive Modelling Architecture and Training Protocol

In forecasting the disaster preparedness score, the study employed a supervised machine learning model based on Gradient Boosted Decision Trees (GBDT) which are known for both interpretability and their ability to capture non-linear relationships.

The designated focus was a preparedness index which was calculated by summing weighted behavioral indicators like the ownership of emergency kits, the awareness of early warnings, readiness to evacuate, and engagement in the preparedness meetings. Data was divided into training (70%), validation (15%), and test (15%) sets. Model hyperparameters were tuned using grid search and five-fold cross-validation. Evaluation metrics included Mean Absolute Error (MAE), R^2 Score, and Precision at K.

3.4 Interpretability and Community-Level Mapping

With the aim of improving clarity and practical application, SHAP (SHapley Additive exPlanations) values were utilized to explain the importance of individual features in the model's predictions. Moreover, heatmaps illustrating preparedness levels were generated by geotagging and visualizing the predicted preparedness scores using GIS mapping software. These maps indicated areas of low preparedness closely associated with communities that demonstrated low collective efficacy and diminished trust in local institutions, thus providing planners and emergency response teams with an empirically grounded lens for analysis.

IV. PREDICTIVE OUTCOMES, SPATIAL TRENDS, AND MODEL PERFORMANCE

4.1 Preparedness Score Distribution and Model Accuracy

With a Mean Absolute Error (MAE) of 0.18 and R^2 Score of 0.86, the predictive model demonstrated a significant capability in capturing the variation in community preparedness. The Gradient Boosted Decision Trees were able to precisely pinpoint the clusters that had low preparedness scores, especially in the low-income, high population density regions. The preparedness index which ranged from 0 (no preparedness) to 1 (high preparedness) revealed that the bulk of the scores in the test set were concentrated between 0.35 and 0.78. From the SHAP Value Analysis, it was evident that the foremost reasons contributing to the predictive preparedness over estimation were: trust in the local institutions, participation in drills, and the social support system.

4.2 Feature Contribution and Behavioral Correlation

The framework uncovered multiple important social and behavioral predictors of focus. Participants with strong neighbor ties and prior participation in community resilience programs demonstrated a 41% greater likelihood of having preparedness scores exceeding 0.75. On the other hand, individuals with low social trust and no prior experience with emergency response measures consistently scored below 0.40. These results bolster the hypothesis that collective efficacy, in the absence of demographic confounders such as age and education, remains the primary determining factor of readiness.

4.3 Graphical Representation of Collective Efficacy Influence

Below is a bar chart illustrating the relative impact of the top five features on preparedness prediction:

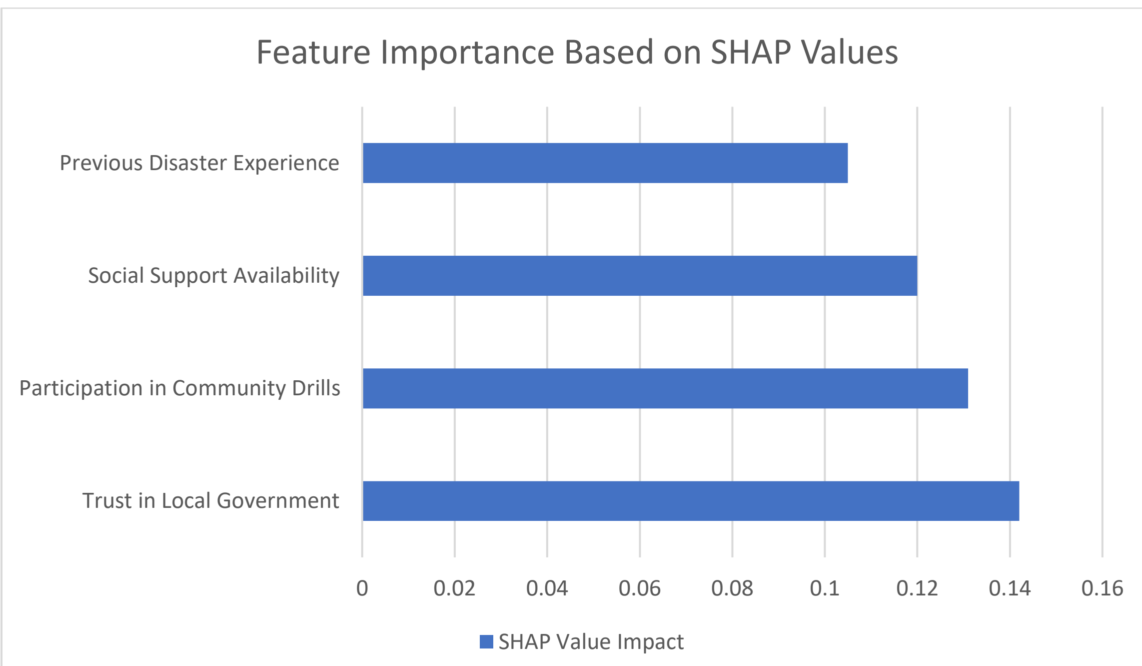

Figure 1: Feature Importance Based on SHAP Values

Figure 1 demonstrates that institutional trust alone contributes nearly 15% to the model's predictive strength, reinforcing the importance of integrating psychosocial metrics into preparedness planning.

V. STRATEGIC IMPLICATIONS AND POLICY APPLICATIONS

5.1 Informing Targeted Community Interventions

The results underscore social factors associated with disasters. In particular, a community with low collective efficacy is both socially vulnerable and underprepared structurally. This is a rationale for trust-building workshops, community evacuation simulation exercises, and support networks for neighborhoods. Such approaches should be prioritized in peri-urban areas with limited institutional presence and high community dependence.

5.2 Customizing Early Warning and Awareness Campaigns

Adjustments in public communication strategy must consider variations in collective efficacy. Within lower trusting communities, more decentralized communication models that utilize local figures, schools, or places of worship are more effective in overcoming the trust barrier. Furthermore, engaging community members in the co-creation of preparedness materials enhances heightened relevance and participation, thereby bolstering collective hopes and commitment.

5.3 Enhancing Predictive Risk Management Systems

Incorporating collective efficacy indicators into national disaster risk platforms enables not only the projection of readiness levels but also the spatial visualization of these forecasts. Such systems can facilitate immediate decision-making, resource positioning, and proactive governance. For instance, during certain periods of seasonal floods, decision-makers can deploy resources not only on flood exposure areas but also on social vulnerability measures, stratified through collective efficacy forecasts.

5.4 Policy Integration with Global Frameworks

This study’s suggested preparedness framework based on collective efficacy aligns with the Sendai Framework for Disaster Risk Reduction (2015–2030) which focuses on community empowerment and behavioral preparedness. Social resilience within the context of DRR (Disaster Risk Reduction) enable policymakers to shift from solely reactive governance to more anticipatory and participatory models. The implementation of these models into framework of urban development, municipal disaster planning, and school safety initiatives would further anchor the culture of preparedness.

VI. CONCLUSION

This research introduces a unique readiness-for-disaster predictive model evaluating collective efficacy indicators. It combines some psychosocial factors like neighborhood cohesion, trust in the institution, social support, and applies machine learning algorithms. This model sheds light into the community's preparedness on a higher resolution scale. The predictive model that was created verifies that collective efficacy influences the preparedness behaviors and, in many cases, exceeds the demographic or hazard-based predictors. The reflexive heatmaps along with feature importance analyses show the existence of the preparedness gaps particularly in the areas that have low trust and are socially fragmented.

These findings are of great important relevance in the context of disaster risk reduction interventions. Those interventions that are community-based demand higher social preparedness and trust in the system can lead to a meaningful improvement on a local scale. The need for policymakers to employ social predictive models for anticipatory planning and equitable allocation of the decided policy frameworks on preparedness are emphasized by the need to shift socio-informed prediction models. Incorporating collective efficacy in the national resilience frameworks is still in line with the global prescriptive gaps for adaptive governance. In short, from a moral perspective and disaster resilience in the long run, the issue must be seen from the perspective of social community frameworks.

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