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An Evaluation Model for Community Social Service Responsiveness in Public Crises under Resilience Governance

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Abstract. In public crises, community social services are directly related to residents' demand response, vulnerable group protection, resource coordination, and post-crisis recovery. Conventional grassroots service evaluation often relies on post-event summaries and manual assessment. It is difficult to reveal differences among communities in response speed, demand matching, service equity, and recovery feedback in a timely manner. From the perspective of resilience governance, an evaluation model for community social service responsiveness is developed. Publicly available data from 2020 to 2024 are collected, including government service hotline monthly reports, community announcements, emergency management notices, civil affairs information, GDELT event records, and public Weibo texts. Public health emergencies, urban flooding, extreme weather, and temporary control events are transformed into computable community service event units. In terms of method, AHP and the entropy method are combined to generate composite weights and calculate responsiveness scores. An XGBoost regression model is then used for score prediction, while SHAP is applied to interpret key influencing factors. The results show that first response time, demand matching rate, cross-department coordination frequency, and vulnerable group coverage rate are the main variables affecting community service responsiveness. The model can effectively identify governance weaknesses across different crisis scenarios. This evaluation framework provides a quantitative, explainable, and updateable analytical tool for improving grassroots public services.

Keywords: resilience governance, public crisis, community social service, responsiveness evaluation, interpretable machine learning

1. Introduction

Public crises place concentrated pressure on community social services through rising resident demands, resource shortages, and information asymmetry. Communities function as the final space where public services reach residents, while also becoming a key site for crisis recovery and the reconstruction of public trust. Existing studies regard community resilience as an integrated capacity for disaster preparedness, shock absorption, and adaptive recovery, offering a theoretical basis for understanding crisis governance [1]. In practice, grassroots service evaluation still relies heavily on

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post-event assessment, manual summaries, and experiential judgment, which cannot fully capture response speed, demand matching, vulnerable-group coverage, and interdepartmental coordination. Disaster resilience indicator studies emphasize that measurable indicators are necessary for identifying capacity differences across places before and after crisis events [2]. Under the logic of resilience governance, the evaluation of community social service responsiveness mainly involves multi-source public data collection, indicator-system construction, composite score modelling, and key-factor interpretation, providing a data-informed basis for improving grassroots public services during public crises.

2. Literature review

2.1. Resilience governance logic

Resilience governance emphasizes the continuous adaptive capacity of public systems under external shocks. Its core concern extends beyond post-crisis recovery speed and includes pre-crisis resource preparation, organizational coordination during crisis response, and institutional learning after crisis events. Social capital studies show that trust, mutual-aid networks, and public participation within communities can strengthen residents' self-help capacity in disaster environments and influence the actual conversion efficiency of public resources after they enter communities [3]. Urban resilience research further understands resilience as an interactive process among social, institutional, spatial, and technological systems, turning community governance from a purely administrative issue into a matter of multi-actor collaboration and information feedback [4]. This logic requires the evaluation of community social service responsiveness to consider both institutional supply and resident perception. It needs to examine whether government resources are delivered effectively, while also analysing whether the service process can identify needs quickly, organize coordination, and maintain service continuity during recovery.

2.2. Service responsiveness indicators

Service responsiveness indicators are usually developed around speed, coverage, quality, and recovery, and these dimensions become more time-sensitive and group-differentiated in public crises. Quantitative resilience frameworks suggest that the functional maintenance and recovery capacity of community systems can be measured through service disruption, recovery time, and resource substitution capacity [5]. In community social services, first-response time, case-completion duration, demand-category matching rate, and vulnerable-group coverage can reflect how effectively the service system identifies and handles resident needs. Studies on community resilience capacity further indicate that economic conditions, institutional resources, and social connections jointly shape a community's ability to withstand crisis impacts [6]. Therefore, responsiveness indicators should not only record the number of handled cases. They should also include cross-department coordination frequency, volunteer participation, negative-sentiment change, and follow-up update frequency, so that the evaluation can reveal differences among service processes, resource relations, and recovery outcomes.

2.3. Computational evaluation models

Computational evaluation models provide a technical pathway for transforming community service texts into structured indicators. XGBoost can capture nonlinear relationships among

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multidimensional features and maintain strong predictive stability in small and medium-sized structured datasets, making it suitable for modelling composite responsiveness scores [7]. In public service evaluation, AHP can define the indicator hierarchy and initial weights according to governance logic, while the entropy method can adjust weights according to data dispersion, reducing bias caused by purely subjective weighting. SHAP can reveal the marginal contribution of different variables to model outputs, allowing machine learning scores to be converted into interpretable governance evidence [8]. In crisis governance, the value of explainable modelling lies not only in prediction accuracy but also in identifying key links that shape responsiveness, such as early demand recognition, resource coordination efficiency, vulnerable-group coverage, and resident feedback recovery [9].

3. Experimental methods

3.1. Data collection scheme

Data collection focuses on community social service records during public crises from 2020 to 2024. The sample scope is set as publicly available materials from three to five prefecture-level cities in China. The main sources include monthly reports from the 12345 government service hotline, announcements from community service centers, local emergency management notices, public information from civil affairs departments, GDELT event records, and public Weibo posts. The collected content includes crisis type, event time, street or community level, demand category, first response time, case completion cycle, service target, coordinating actors, feedback text, and follow-up update records. Public health emergencies, urban flooding, extreme weather, and temporary control events are coded as community service event units. During data processing, personal names, phone numbers, and detailed addresses are removed. Only service process variables that can be used for statistical analysis are retained. Text data are processed through deduplication, word segmentation, sentiment identification, and topic classification. They are then merged with structured fields to form the data matrix required for indicator calculation and model training.

3.2. Indicator system construction

The indicator system is built around five primary indicators, namely response timeliness, demand matching, resource coordination, service equity, and recovery feedback. The secondary indicators include first response time, case completion cycle, demand category matching rate, vulnerable group coverage rate, cross department coordination frequency, volunteer participation, negative sentiment reduction, and follow-up service update frequency. AHP is first used to set the indicator hierarchy and initial weights according to the logic of resilience governance [10]. The entropy method is then used to revise the weights according to sample dispersion. In this way, expert judgment and objective data variation are both included in the evaluation process. The combined weight is shown in Formula 1, where w_j^{AHP} represents the AHP weight, w_j^{E} represents the entropy weight, and α is set as 0.5.

$$w_j=\alpha w_j^{AHP}+(1-\alpha)w_j^{E}, \quad \sum_{j=1}^{m} w_j=1 \tag{1}$$

After the weights are determined, the standardized indicator values of each community event unit are weighted and summed to obtain the composite responsiveness score of community social

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services, as shown in Formula 2 [11]. In this formula, z_{ij} represents the standardized value of the jth indicator for the ith community event unit, and R_i represents the composite responsiveness score.

$$R_i = \sum_{j=1}^{m} w_j z_{ij} \tag{2}$$

3.3. Model training procedure

Model training is based on the indicator matrix and composite responsiveness scores formed in Section 3.2. Python 3.11 is used to complete data cleaning, missing value processing, outlier checking, and feature standardization. Text fields are segmented with jieba. Resident feedback sentiment is identified by Chinese-RoBERTa-wwm-ext and converted into positive, neutral, and negative probabilities. Structured indicators, sentiment variables, and event type variables are jointly input into the XGBoost regression model. The training set, validation set, and test set are divided at a ratio of 7:1.5:1.5. Model parameters are adjusted through grid search. The main parameters include tree depth, learning rate, subsample ratio, and number of estimators. Prediction performance is tested by MAE, RMSE, R^2, and Spearman correlation coefficient. This avoids judging model stability with a single error index. After model training, SHAP is used to calculate the contribution of each indicator to the composite score. Global importance ranking and single event explanations are then generated.

4. Results

4.1. Responsiveness score distribution

Based on the trial calculation of 216 community service event units, the responsiveness scores of public health emergencies, urban flooding, extreme weather, and temporary control events show clear differences. As shown in Table 1, the average responsiveness score of public health events is 76.4. This result is mainly supported by a higher demand matching rate and vulnerable group coverage rate. Urban flooding events have the highest coordination frequency, with an average of 4.1 cross actor collaborations per event. This indicates that spatial disasters rely more on on-site coordination among streets, communities, property management units, and volunteers. Temporary control events have the lowest composite score, at 66.9. Their first response time reaches 6.4 hours, while the vulnerable group coverage rate is only 61.3%. This shows that low scores do not simply result from insufficient resources. They are also closely related to the pace of information release, the completeness of service closure, and the number of coordinating actors.

Table 1. Group statistics of community social service responsiveness

Crisis type	Event units	First response time/hour	Demand matching rate/%	Vulnerable group coverage rate/%	Coordination frequency /times	Composite responsiveness score
Public health	78	4.6	82.4	71.8	3.2	76.4
Urban flooding	56	3.9	79.6	68.5	4.1	74.8

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Table 1. (continued)

Extreme weather	46	5.1	75.2	64.9	3.6	70.3
Temporary control	36	6.4	72.8	61.3	2.7	66.9

4.2. Key factor interpretation

The test results show that the XGBoost model achieves an MAE of 4.82, an RMSE of 6.37, an R^2 of 0.781, and a Spearman correlation coefficient of 0.806 on the test set. This indicates that the predicted scores are highly consistent with the weighted evaluation results. As shown in Figure 1, the SHAP interpretation results indicate that first response time has the highest average contribution value, at 0.23. The demand matching rate is 0.19. Cross department coordination frequency is 0.17. Vulnerable group coverage rate is 0.14. Front-end response and demand identification variables are located in the core contribution area. This shows that community crisis service capacity first depends on whether resident demands can be quickly identified and handled. The contribution values of negative sentiment reduction and follow-up service update frequency are 0.11 and 0.09. Although they are lower than timeliness and matching indicators, they still have a continuous effect on the stability of the composite score. This suggests that information updates and emotional recovery in the recovery stage have become important variables in resilience governance evaluation.

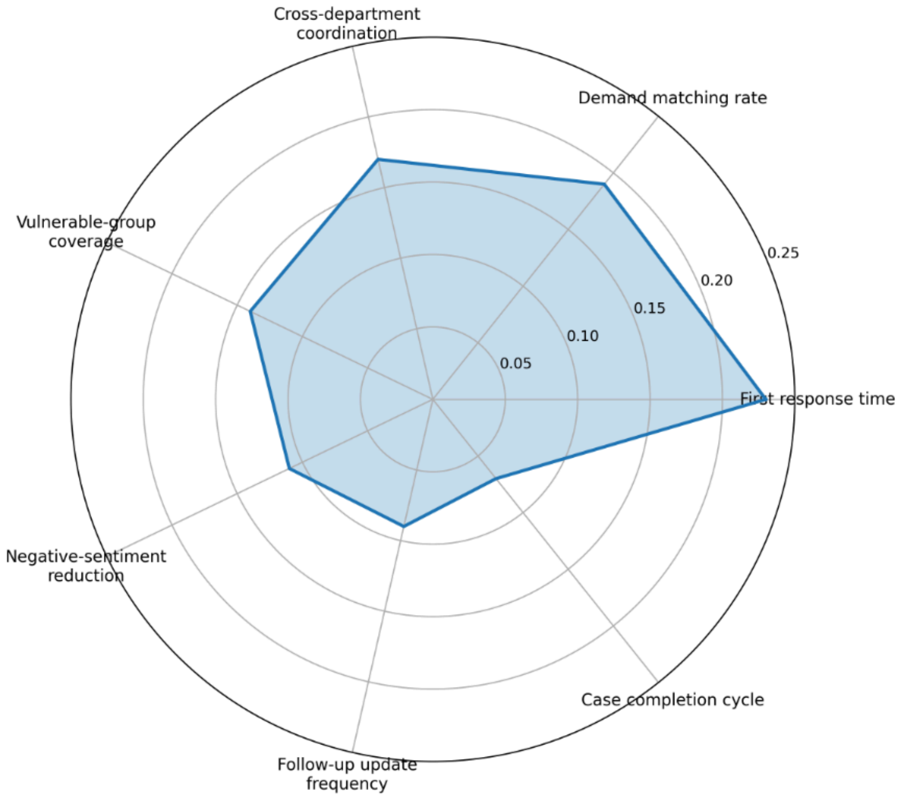

Figure 1. Radar chart of SHAP contribution of key indicators

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5. Discussion

The results indicate that differences in community social service responsiveness are not only determined by the scale of resource input. They are more directly reflected in the speed of demand identification, the accuracy of service matching, and the efficiency of cross-actor coordination. Public health events receive higher scores, which suggests that routinized service procedures and vulnerable group management can improve service stability. Temporary control events receive lower scores. This reflects that insufficient information updates and incomplete service closure can weaken residents' perceptions. SHAP results further show that first response time and demand matching rate occupy the core influence positions. Recovery feedback indicators have lower contributions, but they still affect the long-term stability of service evaluation.

6. Conclusion

An evaluation model is developed to assess community social service responsiveness under resilience governance. The model consists of public data collection, indicator system construction, composite weighting, machine learning prediction, and explainable analysis. It transforms scattered hotline records, community announcements, emergency notices, and online feedback into structured indicators. XGBoost and SHAP are used to identify key influencing factors. The results show that community service improvement should focus on rapid response, accurate matching, coordinated linkage, and recovery feedback. Future work can include more city samples and more crisis types to test the applicability and stability of the model.

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