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Quantifying Support Gaps for Emergency Responders in Baoding, China: A Data-Oriented Case Study

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Abstract: *Sustained emergency response depends on whether responders are protected, trained and supported throughout the mission cycle. Local studies often describe support policies in broad terms, but they rarely identify which support gaps are most consequential or translate field evidence into measurable governance targets. This study examined emergency responder support in Baoding, China, using interviews, questionnaire evidence, case records and policy documents from three types of actors: a social rescue team, an orthopedic hospital, and community-level committees and health stations. Five recurrent support gaps were identified: unstable resource provision, limited scenario-specific training, fragmented coordination, incomplete institutional protection and insufficient recovery-oriented support. A priority index and a medical-psychological-living support index were developed to convert qualitative evidence into quantitative indicators. The results show that resource provision and training are the most visible constraints, whereas psychological support, insurance coverage and liability clarification represent lower-frequency but high-consequence risks. Data from the Baoding Blue Sky Rescue Team, Baoding Orthopedic Hospital and grassroots health institutions further indicate a mismatch between the scale of public service delivery and the level of institutionalized responder support. These findings suggest that city-level responder support should shift from measure listing to data-driven governance, with annual monitoring of equipment, training, health surveillance, psychological services and recovery conditions.*

Keywords: *emergency responders; responder support; support gap; quantitative evaluation; support index; Baoding*

1. Introduction

Emergency response capacity depends on more than plans, command chains and stockpiled materials. It also depends on whether responders can work safely and continuously under hazardous, time-pressured and uncertain conditions. Previous studies have examined emergency support standardization, pre-hospital rescue, training evaluation, logistics response, casualty relief and emergency medical rescue capacity [1-6]. Collectively, these studies indicate that responder support is not a single welfare issue. It is a multi-dimensional governance problem that involves standards, medical preparedness, training, legal protection and resource allocation.

International frameworks reinforce this view. The United States National Response Framework emphasizes coordination, role allocation and resource integration across multiple actors [7]. The National Incident Management System further standardizes command, communication, resource management and information sharing [8]. Health surveillance guidelines from the National Institute for Occupational Safety and Health recommend responder registration, exposure monitoring, health screening and post-deployment follow-up [9]. Research on disaster mental health also shows that responders may develop post-traumatic stress symptoms, anxiety, depression and burnout after exposure to disaster scenes [10-13]. If these risks are not screened and managed, they can compromise return-to-duty safety and long-term participation. People-centred health service frameworks and occupational safety management systems similarly emphasize continuous risk identification, process control, performance assessment and improvement [14,15].

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Two gaps remain in city-level responder support research. First, many local studies focus on what support measures should exist, but they do not identify which gaps should be addressed first. Second, field investigations often contain rich empirical information, yet they are rarely transformed into measurable indicators that can guide budget allocation or annual evaluation. To address these gaps, this study reconstructs field evidence from Baoding into a data-oriented academic analysis. The study asks three questions: what are the main support gaps for emergency responders in Baoding, how do available case data reflect support capacity and remaining gaps, and how can these findings be translated into quantitative indicators for policy optimization?

2. Materials and Methods

2.1. Case Selection and Data Sources

Baoding is exposed to multiple emergency risks, including flooding, geological hazards, traffic accidents, extreme weather and public health events. This study selected three types of local actors to capture different parts of the responder support system. The Baoding Blue Sky Rescue Team represents social emergency rescue forces. Baoding Orthopedic Hospital represents professional medical rescue and pre-hospital-to-hospital linkage. Community committees and health stations represent grassroots mobilization, primary medical support and last-mile recovery services. Together, these cases cover field rescue, medical support and grassroots protection.

Four sources of evidence were used. Field interviews were conducted with personnel from rescue, medical and grassroots organizations. Telephone interviews were conducted with related emergency management and fire rescue actors. A public questionnaire with 200 valid responses was used to assess public awareness and attitudes toward responder support. Policy documents, public reports, institutional records and practice notes were used to supplement case evidence. Only traceable quantitative information and problem-relevant qualitative evidence were retained. Missing questionnaire distributions were not extrapolated.

2.2. Coding and Quantification

Field evidence was coded into five support-gap categories: resource provision, training system, coordination support, institutional protection and recovery-oriented treatment. A segment was coded only when it indicated a potential effect on responder safety, rescue efficiency, willingness to participate or post-mission recovery. Table 1 summarizes the coding categories, operational definitions and expected governance relevance.

Table 1. Coding framework for responder-support gaps.

Category	Operational definition	Representative evidence	Governance relevance
Resource provision	Equipment, communication, materials or funding constrained mission execution	Equipment renewal relied partly on donations; communication could be unstable in remote terrain	Budget allocation, communication support and equipment renewal
Training system	Training content or certification did not match complex scenarios	Advanced rescue skills were insufficient for chemical, mountain or debris scenarios	Graded training and certification
Coordination support	Information flow or task boundaries were unstable across actors	Field-to-hospital information delay could affect treatment preparation	Dispatch rules and information interfaces
Institutional protection	Insurance, liability, health monitoring or psychological services were incomplete	Insurance coverage and psychological follow-up required further clarification	Insurance expansion, legal protection and referral services
Recovery-oriented treatment	Allowances, rest, family support or post-mission recovery were insufficient	High-risk tasks and long working hours required better recovery support	Mission allowances and return-to-duty safeguards

To rank the urgency of different support gaps, a priority index was constructed. For category j, f_j denotes the observed frequency and $\max(f)$ denotes the maximum frequency across categories. The normalized frequency is $F_j = f_j / \max(f)$. Severity, urgency and policy controllability are denoted by S_j, U_j and C_j, respectively. Equation (1) defines the priority index P_j:

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$$P_j = F_j \times (0.4S_j + 0.3U_j + 0.3C_j) \tag{1}$$

To evaluate the overall support system, a medical-psychological-living support index was proposed. Equation (2) defines the aggregate guarantee index *GI*:

$$GI = w_m M + w_p P + w_l L \tag{2}$$

where M, P and L represent medical support, psychological support and living support. Each dimension can be calculated from standardized secondary indicators, as shown in Equation (3):

$$D_i = \sum_{k=1}^{n_i} \alpha_{ik} x_{ik}, \quad D_i \in \{M, P, L\} \tag{3}$$

The gap for a single indicator is defined in Equation (4):

$$G_k = \frac{\max(0, T_k - A_k)}{T_k} \tag{4}$$

where T_k is the target value and A_k is the observed value. These equations allow broad support problems to be decomposed into measurable gaps, such as equipment availability, psychological service coverage or recovery leave completion. Table 2 lists the indicators and target values used to operationalize the three-dimensional index.

Table 2. Indicators and target values for the medical-psychological-living support index.

Dimension	Indicator	Target value	Evaluation role
Medical	Physical examination coverage	100%	Basic health surveillance
Medical	Chronic disease control	≥85%	Long-term health management
Medical	Equipment availability	≥95%	Field readiness
Medical	Ambulance arrival time	≤10 min	Emergency medical access
Psychological	Psychological service coverage	≥80%	Mental-health accessibility
Psychological	Referral of high-risk personnel	within 24 h	Early intervention
Living	Recovery leave completion	≥90%	Post-mission recovery
Living	Family satisfaction	≥75%	Family-support adequacy

3. Results

3.1. Frequency and Priority of Support Gaps

Five support gaps were identified from interview and case evidence. Resource provision was the most frequent gap, followed by training system, coordination support, institutional protection and recovery-oriented treatment. Figure 1 shows both the observed frequency and the estimated priority index calculated using Equation (1). Frequency alone did not fully represent importance. Resource and training gaps were highly visible because they affected daily operations and field preparedness. Institutional protection, psychological services and liability clarification appeared less frequently, but could produce severe consequences once injury, traumatic exposure or legal disputes occurred.

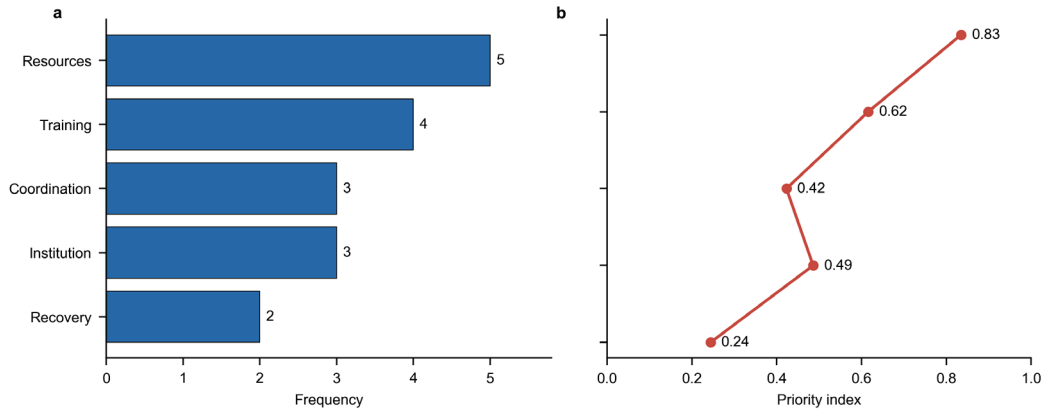


Figure 1. Frequency of support gaps and estimated priority index.

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3.2. Quantitative Profile of the Social Rescue Team

The Baoding Blue Sky Rescue Team had developed substantial service capacity. By 2024, it had approximately 368 formal members and nearly 1,000 volunteers. It had participated in more than 500 rescue missions, accumulated 5,312.2 individual service hours, delivered 1,025 child safety lectures and distributed more than 6,000 yellow wristbands for elderly safety. Figure 2 summarizes these service-capacity indicators. The data show that social rescue forces contribute substantially to local public safety. At the same time, the scale of service provision contrasts with the relatively unstable institutional basis for equipment renewal, funding and advanced training.

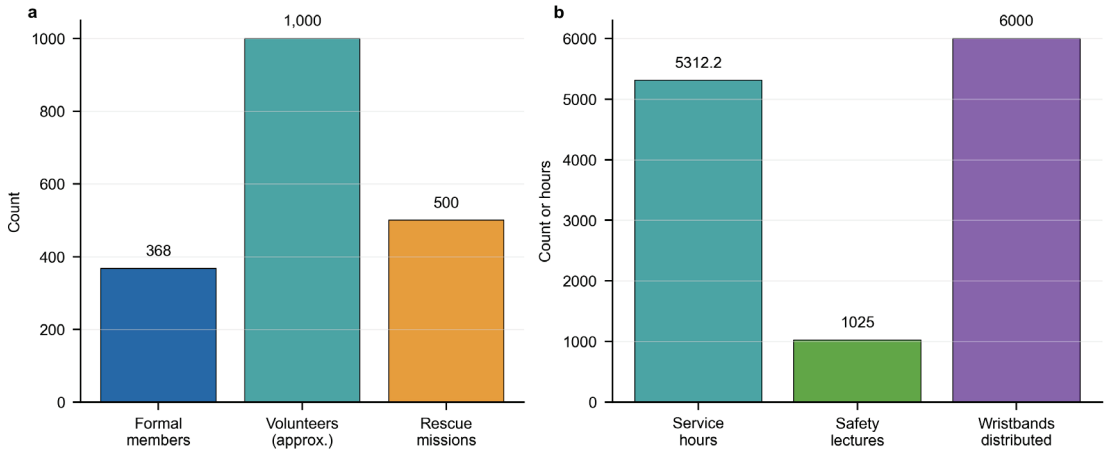


Figure 2. Service-capacity indicators of the Baoding Blue Sky Rescue Team.

3.3. Medical Rescue Resources and Response Time

Baoding Orthopedic Hospital showed measurable medical-response capacity during event and emergency support. During the 2023 Baoding Marathon, the hospital deployed 11 medical staff, 3 ambulances and 4 service points, and treated more than 50 injured participants. During the snow emergency on 14 December 2023, the ambulance departed within 5 minutes after the call, arrived at the scene in an average of 15 minutes and initiated preliminary treatment within 10 minutes. Figure 3 compares medical resource inputs with response-time nodes. These data indicate that response time was organized around clear operational milestones. They also imply that information linkage between the scene and the hospital remains critical for protecting the treatment window.

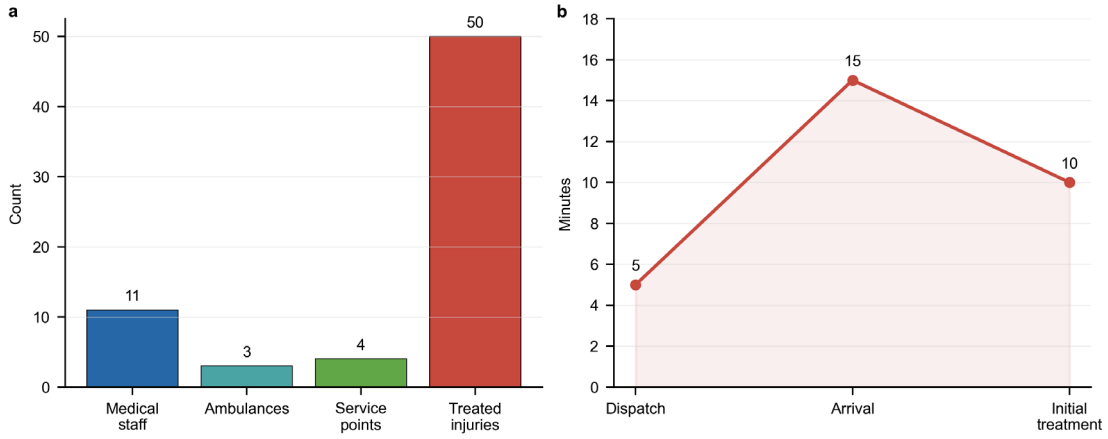


Figure 3. Medical support inputs and emergency response time.

3.4. Grassroots Support Capacity

Grassroots organizations form the terminal layer of responder and community support. Baoding had 35 community health service centres and 133 community health service stations, with a reported

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standardization rate above 90%. In addition, 259 township hospitals and 5,172 village clinics were integrated through unified management, involving 7,758 village doctors. From 2019 to 2022, 3,824 primary medical workers were trained at municipal and county bases. In 2021, more than 89.1032 million yuan was invested to renovate 34 township hospitals. Figure 4 summarizes these grassroots medical and community-support indicators. The results suggest a broad grassroots support base, but they also indicate that facility quality, workforce capability and interdepartmental coordination remain important sources of variation.

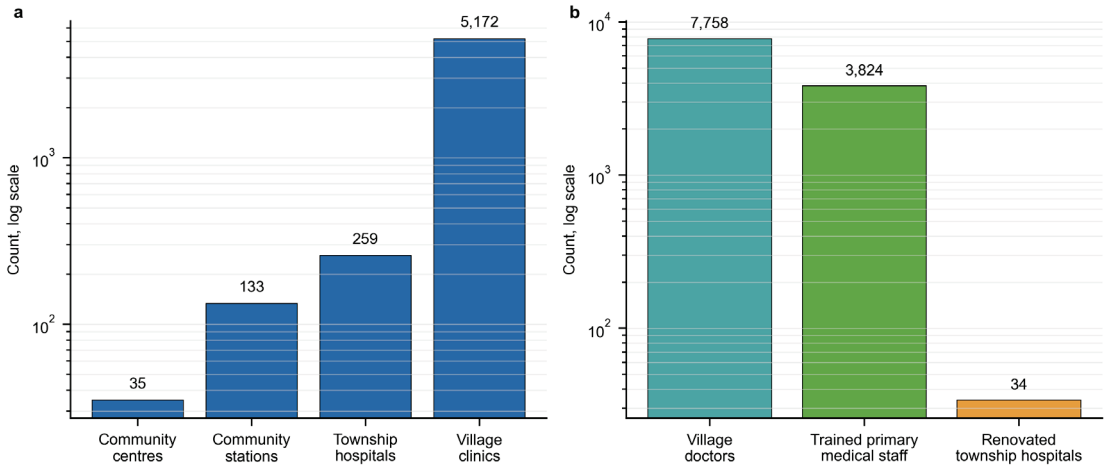


Figure 4. Grassroots medical and community support indicators.

3.5. Public Awareness Gap

The questionnaire results indicated that public recognition of responder support was generally positive, but a clear awareness gap remained. Approximately 15% of respondents reported that they were completely unaware of emergency responder support. In a sample of 200 respondents, this corresponded to about 30 individuals. Figure 5 visualizes this awareness gap. Public awareness is not merely a communication outcome. It can influence donations, volunteer participation and cooperation at rescue scenes, thereby indirectly affecting responder support.

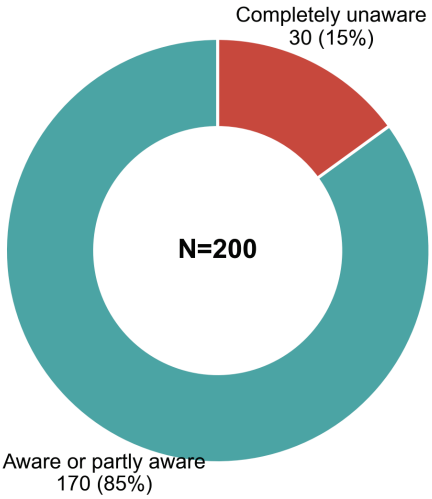


Figure 5. Public awareness gap regarding emergency responder support.

3.6. Target Values for the Three-Dimensional Support Index

The medical-psychological-living index was converted into target values for annual evaluation. Medical targets included 100% physical examination coverage, a chronic disease control rate of at least 85%, equipment availability of at least 95% and an average ambulance arrival time of no more than 10 minutes. Psychological targets included psychological service coverage of at least 80% and referral of high-risk personnel within 24 hours. Living-support targets included recovery leave completion of at

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least 90% and family satisfaction of at least 75%. Figure 6 shows the percentage-based target values, while Table 2 defines their evaluation role. These values provide a practical starting point for monitoring support quality and identifying specific improvement gaps.

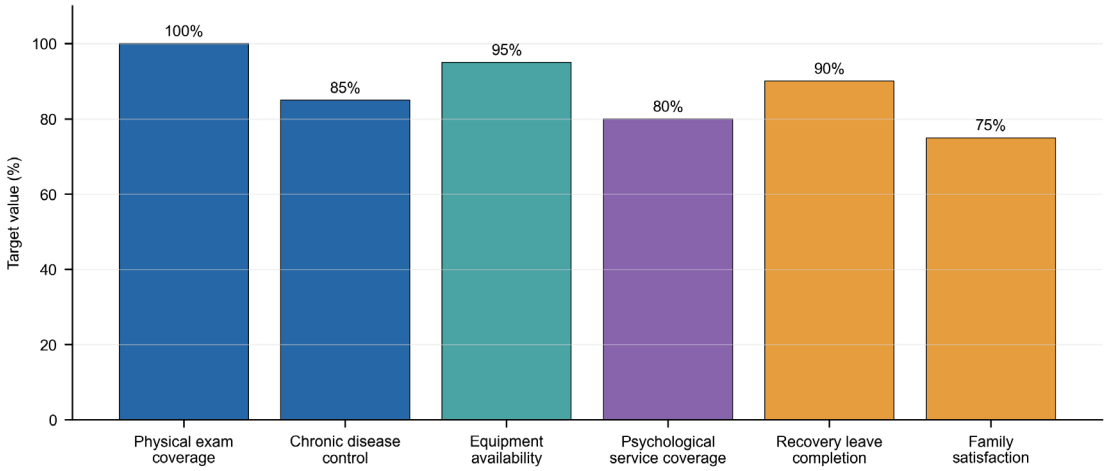


Figure 6. Suggested target values for the three-dimensional support index.

4. Discussion

4.1. Interpretation of the Main Findings

The data indicate that responder support in Baoding is constrained by a mismatch between increasing service demand and uneven institutionalized support. Figure 2 shows that social rescue forces already provide substantial public services, yet their equipment, funding and advanced training still require more stable support. Figure 3 shows that medical institutions have measurable response capacity, but the value of rapid response depends on timely field-to-hospital information transfer. Figure 4 shows broad grassroots coverage, while also suggesting that workforce quality, facility conditions and coordination efficiency remain uneven. Figure 5 shows that public support is incomplete, as a measurable share of respondents had no awareness of responder support.

The equations proposed in the Methods section provide a way to move from descriptive evidence to decision-oriented evaluation. Equation (1) helps rank support gaps by combining frequency with severity, urgency and controllability. Equations (2) and (3) organize support capacity into medical, psychological and living dimensions. Equation (4) further translates target-performance differences into indicator-specific gaps. Together with Tables 1 and 2, these equations define how a local government could convert field observations into annual monitoring indicators.

4.2. Implications for Data-Driven Governance

The figures are not only descriptive. They can organize policy decisions. Figure 1 identifies the most urgent categories for annual intervention. Figure 2 can inform government procurement of services, equipment support and training subsidies for social rescue teams. Figure 3 can be used to refine pre-hospital triage and transfer protocols. Figure 4 can identify weaknesses in last-mile support. Figure 5 can guide communication strategies and volunteer recruitment. Figure 6 can support annual performance reporting and resource allocation across medical, psychological and living-support dimensions.

4.3. Policy Recommendations

First, Baoding should establish dedicated support for rescue equipment and emergency communication. Water rescue, mountain rescue, traffic accidents and extreme weather response should receive priority. Second, a graded training and certification system should distinguish basic rescue, professional rescue and complex-scenario rescue. Certification results should be linked to dispatch eligibility and role allocation. Third, social rescue forces should be included in a classified resource database that records team size, equipment, insurance coverage, training certification and response

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areas. Fourth, medical and psychological support should be embedded into the full mission cycle, including pre-mission screening, post-mission assessment, referral when necessary and return-to-duty confirmation. Fifth, an annual responder-support data report should be established. It should integrate equipment, training, insurance, health surveillance, psychological services, mission allowances and injury-related absence.

5. Conclusion

This study provides a data-oriented assessment of emergency responder support in Baoding, China. By integrating interview coding, questionnaire evidence and case-based quantitative indicators, it identifies resource provision and training as the most visible support gaps. It also shows that coordination, institutional protection and recovery-oriented support are deeper determinants of responder safety and long-term team stability. The priority index in Equation (1) and the medical-psychological-living support index in Equations (2)-(4) convert field observations into measurable governance tools.

The main contribution of this study is to move local responder-support analysis beyond descriptive lists of measures. The framework enables support gaps to be ranked, monitored and linked to annual policy adjustment. This is particularly relevant for cities where social rescue teams, hospitals and grassroots organizations share emergency-response responsibilities, but differ in resources, professional capacity and institutional protection.

This study has limitations. The quantitative indicators were derived from available field records and public materials, rather than from a fully standardized longitudinal database. Some dimensions, especially psychological outcomes and recovery quality, require individual-level responder data. Future research should collect longitudinal health, training, exposure and post-mission recovery data from responders. Such data would allow the proposed support index to be validated across cities, disaster types and organizational models.

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