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Designing an Intelligent Earthquake Crisis Management Framework for Megacities Using an Integrated C4ISR System: A Hybrid Approach Based on Mathematical Modeling and Artificial Intelligence

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ABSTRACT

The increasing concentration of population and the growing complexity of megacities have transformed earthquake crisis management into a fundamental challenge. Despite advances in emerging technologies, there remains a gap in developing an integrated framework that combines the dimensions of command, control, communications, and information with intelligent decision-making. The present study aimed to design and validate an intelligent framework for earthquake crisis management in megacities based on an integrated C4ISR system and a hybrid approach combining mathematical modeling and artificial intelligence. Drawing on the paradigm of critical realism and the system dynamics approach, the proposed model simulates the complex interactions among technical, informational, communicational, and organizational components and simultaneously optimizes four key objectives: minimizing human casualties, reducing response time, maximizing resource allocation efficiency, and enhancing situational awareness. To solve the multi-objective optimization problem, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was integrated with a deep neural network model (LSTM-CNN) and self-organizing maps (SOM) to enable prediction, continuous learning, and the identification of hidden crisis patterns. The simulation of three earthquake scenarios in Tehran showed that the proposed framework effectively manages conflicts among objectives and provides optimal strategies for different crisis conditions. Sensitivity analysis indicated that interorganizational coordination and network bandwidth had the greatest impact on system performance and were more influential than many hardware components. Moreover, the system's dynamic learning capability increased its accuracy and response speed across operational cycles. By presenting a framework based on C4ISR, artificial intelligence, and mathematical modeling, this study represents an effective step toward data-driven crisis management and the enhancement of megacity resilience against earthquakes.

Keywords: intelligent crisis management, C4ISR framework, mathematical modeling–artificial intelligence, multi-objective optimization, urban resilience.

Introduction

Earthquake crisis management in megacities has become one of the most complex domains of contemporary public management, urban governance, and disaster risk reduction. The accelerating concentration of population, infrastructure, economic assets, transportation networks, and administrative institutions in metropolitan regions has increased both the probability of cascading disruptions and the scale of potential losses after a major seismic event. In modern megacities, an earthquake is not merely a geophysical shock; it is a systemic crisis that can simultaneously disrupt housing, hospitals, roads, energy grids, water networks, communication systems, public order, and emergency response chains. Therefore, crisis management can no longer be reduced to traditional emergency response or post-disaster relief distribution. It requires anticipatory planning, real-time intelligence, coordinated command structures, adaptive decision-making, and continuous learning from rapidly changing data streams. In this regard, digital transformation and urban resilience have become closely interdependent, as resilient cities increasingly depend on integrated information infrastructures, data-driven governance, and intelligent decision-support systems [1]. The smart city literature has also emphasized that the city of the future is a complex, dynamic, and data-intensive system in which flows of people, information, resources, and services must be continuously monitored and optimized [2]. In this context, the smart city concept provides an important theoretical foundation for rethinking crisis management, because it highlights the role of information and communication technologies, intelligent infrastructure, spatial data, and networked urban management in improving responsiveness and resilience [3-5].

The complexity of disaster management is particularly evident in dense urban environments, where uncertainty, time pressure, resource scarcity, and interorganizational fragmentation converge. Modern cities are characterized by nonlinear interactions among physical infrastructure, social behavior, mobility patterns, institutional capacity, and technological systems. This complexity makes disaster response highly sensitive to delays, incomplete information, weak coordination, and inaccurate prioritization. Disaster management theory has therefore shifted from linear models of response toward integrated and adaptive approaches that consider mitigation, preparedness, response, recovery, and resilience as interconnected phases of a continuous management cycle [6]. Urban disaster studies further show that crisis management in modern cities involves multiple layers of uncertainty, including uncertainty about hazard intensity, damage distribution, population movement, infrastructure functionality, and institutional response capacity [7]. These conditions make intelligent urban crisis management a managerial problem as much as a technical or engineering problem. The growing emphasis on artificial intelligence for disaster risk management and resilient cities reflects this shift, as emerging frameworks increasingly view crisis management as a field requiring predictive analytics, automated classification, real-time data integration, and evidence-based decision support [8]. Earlier work on information and communication technologies in smart cities has similarly indicated that ICT-based urban systems can improve the speed, accuracy, and coordination of crisis management processes when they are embedded in a coherent managerial architecture [9].

Among natural hazards, earthquakes pose a distinctive challenge because they occur suddenly, generate immediate physical destruction, and rapidly create secondary crises such as fires, traffic congestion, communication failure, population displacement, and healthcare overload. Tehran is a critical case in this regard because of its high population density, seismic exposure, heterogeneous urban fabric, aging buildings, and concentration of national administrative functions. GIS-based assessments of seismic vulnerability in Tehran have shown that vulnerability is spatially uneven and depends on multiple factors, including building quality, land use, population distribution, access networks, and proximity to active faults [10]. Seismic hazard analysis using geographic information systems has also demonstrated the importance of spatial modeling in identifying high-risk zones and supporting preparedness planning in the Tehran metropolitan area [11]. However, spatial vulnerability assessment alone is insufficient for real-time crisis management, because decision-makers must also know how damage spreads, where casualties are likely to increase, which routes remain operational, how resources should be allocated, and how organizations should coordinate during the first minutes and hours after an earthquake. The increasing application of spatial machine learning models in hazard susceptibility assessment confirms that risk analysis can be enhanced through data-driven modeling, especially when spatial variables, environmental conditions, and historical patterns are jointly analyzed [12]. Nevertheless, translating such analytical capacity into operational decision-making requires a system-level command, control, communication, intelligence, surveillance, and reconnaissance architecture.

The C4ISR framework—command, control, communications, computers, intelligence, surveillance, and reconnaissance—offers a powerful conceptual and operational architecture for managing complex crises. Originally developed in defense and security contexts, C4ISR provides a structured approach to integrating information collection, situational awareness, decision-making, communication, coordination, and operational execution. Command and control theory emphasizes that effective management of complex operations depends not only on hierarchical authority, but also on information sharing, decision rights, coordination mechanisms, and the ability to adapt to changing conditions [13]. In complex emergency environments, C4ISR interoperability can improve decision superiority by enabling actors to access shared operational pictures, communicate across organizational boundaries, and coordinate actions under severe time constraints [14]. From a crisis management perspective, C4ISR is valuable because it transforms fragmented data into actionable intelligence and connects decision-makers, responders, sensors, communication networks, and analytical models within a unified architecture. Recent studies have explicitly examined artificial intelligence-enabled decision-support systems for urban disaster management from a C4ISR perspective, emphasizing that the integration of AI and C4ISR can strengthen forecasting, prioritization, resource allocation, and real-time operational coordination [15]. Accordingly, C4ISR can serve as a bridge between strategic crisis governance and tactical field response.

Artificial intelligence has become increasingly central to disaster management because it can process large volumes of heterogeneous data, identify hidden patterns, support prediction, and optimize decisions in rapidly evolving environments. Systematic reviews of AI applications in earthquake emergency management show that AI techniques are being used for damage assessment, casualty estimation, emergency routing, resource allocation, information extraction, and post-earthquake decision support [16]. Internet of Things technologies and intelligent disaster management systems have also created new opportunities for real-time sensing, automated data collection, early warning, and distributed monitoring of crisis conditions [17]. In smart city management, intelligent systems and AI applications can improve the integration of urban services, enhance predictive governance, and support adaptive resource management [18]. These developments suggest that AI should not be treated merely as an auxiliary analytical tool; rather, it should be embedded within the decision architecture of crisis management systems. In earthquake response, such embedding is especially important because the value of information declines rapidly over time. Data collected after an earthquake must be processed, interpreted, prioritized, and transmitted to decision-makers within minutes. Therefore, the effectiveness of AI depends on its integration with command structures, communication systems, organizational routines, and feedback mechanisms.

Deep learning models are particularly relevant to earthquake crisis management because they can model temporal dynamics, spatial dependencies, and nonlinear relationships among crisis variables. Hybrid architectures such as LSTM-CNN models are well suited to crisis prediction because long short-term memory networks can capture temporal sequences, while convolutional neural networks can extract spatial or structural patterns from multidimensional data. Similar deep learning approaches have been used to predict public opinion crises through social network mining, demonstrating the ability of CNN and LSTM techniques to identify evolving patterns from complex social data [19]. Attention-based BiLSTM and CNN models have also been applied to classify emergency-related tweets for resource management, showing the relevance of social media analytics for emergency response and situational awareness [20]. Beyond supervised prediction, self-organizing maps can support exploratory pattern discovery by clustering complex data and reducing dimensionality. Recent methodological work combining SOM and CNN has shown that hybrid machine learning structures can improve model accuracy and pattern recognition in complex classification problems [21]. Although this application is outside earthquake management, its methodological contribution is relevant because crisis data are also multidimensional, noisy, heterogeneous, and pattern-rich. Integrating LSTM-CNN prediction with SOM-based pattern discovery can therefore provide both forecasting capability and interpretability, enabling decision-makers to recognize hidden crisis typologies and recurring operational configurations.

Despite the growing use of AI, earthquake crisis management remains fundamentally an optimization problem. Decision-makers must allocate limited rescue teams, medical resources, vehicles, communication capacity, temporary shelters, and logistical support across damaged areas while minimizing casualties, reducing response time, maximizing resource efficiency, and improving situational awareness. These objectives often conflict with one another. For example, minimizing response time may require concentrating resources in accessible areas, while minimizing casualties may require sending resources to severely damaged but difficult-to-access zones. Modern optimization theory provides a rigorous framework for managing such trade-offs, and machine learning under an optimization lens has emphasized the importance of combining predictive models with prescriptive decision-making [22]. In post-disaster relief distribution, hybrid NSGA-II algorithms have been used to address bi-objective optimization problems involving relief allocation and short-term network restoration [23]. Similarly, multi-objective optimization models for volunteer assignment in the post-disaster phase have combined fuzzy inference systems with NSGA-II and related evolutionary algorithms to improve assignment decisions under uncertainty [24]. These studies demonstrate that evolutionary multi-objective algorithms are appropriate for crisis contexts because they can generate Pareto-optimal solutions rather than imposing a single objective on a complex decision environment.

However, a purely technical model is insufficient for managing earthquake crises in megacities. Crisis response is shaped by organizational behavior, expert judgment, institutional coordination, interagency trust, and decision-making under uncertainty. Mixed-methods research is therefore valuable because it allows researchers to combine quantitative modeling with qualitative expert knowledge, contextual interpretation, and institutional understanding. Studies of mixed-methods research in disaster management have shown that such designs are useful when complex phenomena require both numerical analysis and contextual explanation [25]. In Iranian social science research, mixed-methods designs have also been discussed as a way to address multidimensional problems that cannot be adequately captured through exclusively quantitative or qualitative approaches [26]. Furthermore, decision-making in uncertain and opportunity-sensitive environments is not always based solely on formal data; experience, intuition, and inspiration can influence how actors interpret ambiguous situations and choose among competing alternatives [27]. In earthquake crisis management, this means that expert knowledge from crisis managers, emergency responders, urban planners, and C4ISR specialists should be incorporated into model development and validation. Such integration strengthens the practical relevance of the model and aligns technical design with real organizational conditions.

The theoretical foundation of the present study is grounded in the assumption that earthquake crisis management in megacities is a complex adaptive system. This means that the behavior of the system emerges from the interaction of multiple subsystems, including seismic hazard, population dynamics, infrastructure vulnerability, communication networks, decision centers, field operations, and social response. In such systems, small delays or coordination failures can generate disproportionate consequences, while improvements in information flow or interorganizational alignment can produce cascading benefits. A system dynamics perspective is therefore appropriate because it can model feedback loops, time delays, accumulations, nonlinear relationships, and dynamic interactions among variables. When combined with C4ISR, system dynamics can help explain how situational awareness evolves, how resources are mobilized, how information is transformed into operational action, and how response effectiveness changes over time. At the same time, AI and optimization algorithms can enhance the model's predictive and prescriptive capacity. This combination responds to a central gap in the literature: many studies focus separately on smart cities, seismic vulnerability, AI-based prediction, disaster optimization, or command-and-control systems, but fewer provide an integrated framework that combines C4ISR architecture, mathematical modeling, multi-objective optimization, and machine learning for earthquake crisis management in megacities.

The significance of such an integrated framework is both theoretical and practical. Theoretically, it advances the management literature by conceptualizing earthquake crisis management as an intelligent, data-driven, and multi-objective decision system rather than a linear emergency response process. It also contributes to crisis management research by linking critical realism, system dynamics, C4ISR, artificial intelligence, and mathematical optimization in a unified analytical structure. Practically, the framework can help crisis managers identify which variables have the greatest effect on casualties, response time, resource efficiency, and situational awareness. It can also support scenario-based planning by simulating different earthquake magnitudes, damage patterns, communication constraints, and coordination levels. For a megacity such as Tehran, where seismic risk and urban complexity intersect, such a model can provide a basis for improving preparedness, prioritizing investments, strengthening interorganizational coordination, and designing more adaptive response strategies. More broadly, the development of intelligent C4ISR-based crisis management systems can support the transition from reactive disaster response to proactive resilience governance.

Accordingly, this study aims to design and validate an intelligent framework for earthquake crisis management in megacities based on an integrated C4ISR system through a hybrid approach combining mathematical modeling, multi-objective optimization, and artificial intelligence.

Methodology

The governing paradigm of this study is critical realism, which is fully compatible with the complex and multilayered nature of the crisis management system within the C4ISR framework. On the one hand, this paradigm acknowledges the existence of objective realities such as fault behavior, urban population dynamics, and the technical capabilities of hardware systems; on the other hand, it recognizes the role of the perceptions and subjective interpretations of human actors in crisis headquarters and their influence on decision-making under uncertainty. The research design is mixed-methods, quantitative–qualitative, with a concurrent approach, implemented in three main phases: formulation, construction, and validation. In the formulation phase, the key system variables are identified through library studies and the Delphi method with the participation of experts. The mixed-methods approach of this study, with its emphasis on expert knowledge and multidimensional analysis of complex problems, is consistent with studies that emphasize the role of experience- and intuition-based decision-making under uncertainty (Bahramfard et al., 2023). In the construction phase, the relationships are formulated within a quantitative model consisting of differential equations and feedback loops. Finally, the model outputs are validated through sensitivity analysis and comparison with historical data.

The statistical population of this study included 16,600 individuals with direct knowledge and experience in earthquake crisis management and C4ISR in Iran. To determine the sample, purposive judgmental sampling was used, and 10 experienced experts were selected based on the criteria of at least 5 years of direct work experience and basic knowledge of C4ISR. These individuals were invited to participate from key relevant institutions, including the National Disaster Management Organization, Tehran Municipality, the Fire Department, academic and research centers, and specialized headquarters. The Delphi process was conducted in three rounds, and the content validity ratio (CVR) for all final indicators was greater than 0.40, while the Cronbach's alpha coefficient of the questionnaire was obtained as 0.85. The proposed mathematical model includes the main state equation, the population evolution equation, and the damage propagation equation.

Main state equation:

$$\frac{dX(t)}{dt} = F(X(t), U(t), \xi(t), t)$$

where $X(t)$is the system state vector, $U(t)$is the decision-making and control vector, $\xi(t)$is the vector of random variables or uncertainties, and $F$is the state transition function.

Population evolution equation:

$$\frac{dP_i(t)}{dt} = -\alpha_i P_i(t) D_i(t) + \sum_j \left[\beta_{ij}(P_j(t) - P_i(t))\right] + \gamma_i R_i(t) - \delta_i P_i(t) G_i(t)$$

where $P_i(t)$denotes the population of region i, $D_i(t)$is the level of damage, $\alpha_i$is the vulnerability coefficient, $\beta_{ij}$is the population displacement coefficient between regions, $\gamma_i$is the rescue coefficient, $R_i(t)$represents relief resources, and $G_i(t)$indicates the secondary effects of the crisis.

Damage propagation equation:

$$D_i(t) = G(M, d_i, S_i, V_i) \times (\quad -e^{-\lambda t}) + \varepsilon A_i(t)$$

where:

$$G(M, d_i, S_i, V_i) = \kappa M \times e^{-\mu d_i} \times (1 + S_i) \times V_i$$

where $M$is earthquake intensity, $d_i$is the distance from the earthquake epicenter, $S_i$is the soil quality coefficient, $V_i$is the structural vulnerability index, $\kappa$is the calibration coefficient, $\mu$is the attenuation coefficient, $\lambda$is the damage propagation rate, and $\varepsilon A_i(t)$represents secondary effects.

The four main objective functions were defined as follows:

1. Minimization of human casualties:

$$J_1 = \int_{T_0}^{T_n} \left[\sum_{i=1}^{k} w_i\,(t) \times P_i(t) \times D_i(t)\right] dt + \rho \times \sum_{i=1}^{k} \int_{T_0}^{T_n} \left[P_i(t) - P_{i,\text{safe}}(t)\right] dt$$

2. Minimization of response time:

$$J_2 = \int_{T_0}^{T_n} \sum_{i=1}^{k} \sum_{j=1}^{m} \left[\delta_{ij}(t) \times T_{ij}(U) \times e^{\beta A_{ij}(t)}\right] dt + \lambda \times \max(T_{ij}(U))$$

3. Maximization of resource efficiency:

$$J_3 = \int_{T_0}^{T_n} \left[\sum_{i=1}^{k} \left(1 - \frac{R_i(t)}{R_{i,\max}}\right) \times C_i(t) \times \eta_i(t)\right] dt + \mu \times \sum_{i=1}^{k} \int_{T_0}^{T_n} \left[R_{i,\min} - R_i(t)\right] dt$$

4. Maximization of situational awareness:

$$J_4 = \int_{T_0}^{T_n} \left[1 - \prod_{i=1}^{k} \left(1 - I_i(t)^{\omega_i(t)}\right)\right] dt - \sigma \times \int_{T_0}^{T_n} \left[\sum_{i=1}^{k} H\,(I_i(t)) \times (1 - Q_i(t))\right] dt$$

To solve the multi-objective optimization problem, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used. This algorithm begins by generating an initial population of random solutions, and in each generation, the solutions are evaluated based on the four main objective functions. A new population is then generated using crossover and mutation operators. The non-dominated sorting mechanism classifies the solutions into different layers based on their degree of dominance. In addition, a deep neural network with an LSTM-CNN architecture was used as the predictive component at the core of the C4ISR system. This network is responsible for predicting crisis kinetics in the initial moments after an earthquake. The network inputs include real-time seismic data, including acceleration, frequency, and duration; spatial parameters, including distance from the fault, soil type, and ground slope; and historical vulnerability data. The network outputs include prediction of the damage propagation pattern during the first 60 minutes, initial estimation of human casualties, and prediction of population density in safe zones. Self-organizing maps (SOM) were used as an analytical tool for discovering hidden patterns in crisis data. This method acts as a complement to the predictive neural network and organizes the complex outputs of previous models into semantic clusters. SOM can identify similar patterns across different crises, reduce data dimensionality, and reveal nonlinear relationships among variables.

Findings and Results

To comprehensively evaluate the performance of the proposed model under different crisis conditions, three earthquake scenarios with different levels of intensity and damage were designed and simulated. These scenarios were selected to cover a wide range of possible earthquake conditions in the megacity of Tehran and to make it possible to examine the efficiency, flexibility, and adaptability of the model under various circumstances. In the first scenario, an earthquake with a magnitude of 6.0 on the Richter scale and a focal depth of 12 km was considered in northeastern Tehran, representing an event with relatively limited intensity and manageable damage. The second scenario involved an earthquake with a magnitude of 6.8 on the Richter scale and a focal depth of 10 km in southern Tehran, simulating a crisis condition with a moderate level of damage and a need for broader mobilization of relief resources. Finally, the third scenario, as the most severe case, modeled an earthquake with a magnitude of 7.4 on the Richter scale and a focal depth of 8 km in northern Tehran, which could lead to extensive damage, disruption of critical infrastructure, and a substantial increase in operational and relief needs.

The selection of these three scenarios makes it possible to compare the performance of the model across different levels of crisis intensity and demonstrates the extent to which the proposed framework can optimize decision-making, resource allocation, and operational coordination under normal, critical, and catastrophic conditions. The results obtained from implementing the model in each of these scenarios, including key performance indicators and the degree of achievement of the intended objectives, are presented in Table 1.

Table 1

Comparison of the Performance of the Four Objective Functions Under Three Different Earthquake Scenarios

Indicator / Scenario	Scenario 1	Scenario 2	Scenario 3
Minimization of human casualties	850 people	8,300 people	54,000 people
Minimization of response time	27 minutes	45 minutes	112 minutes
Maximization of resource efficiency	0.89	0.72	0.51
Maximization of situational awareness	0.85	0.65	0.35

As the intensity and scale of the incident increase, the values of all objective functions deteriorate substantially. This decline is nonlinear and accelerates particularly in Scenario 3. The results reveal the conflicting nature of the objective functions, and the model is capable of providing optimal operational strategies that establish a logical balance among the objectives. A systematic sensitivity analysis was conducted on the key parameters of the C4ISR architecture. The results are shown in Table 2.

Table 2

Sensitivity of Model Outputs to Changes in Key C4ISR Parameters

Key C4ISR Parameters	Applied Change	Effect on Human Casualties	Effect on Response Time	Effect on Resource Efficiency	Effect on Situational Awareness
Spatial accuracy of sensors	20% reduction: 50 to 40 meters	3.2% decrease	4.1% decrease	2.8% increase	8.5% increase
Processing delay at the command center	20% reduction: 45 to 36 seconds	1.8% decrease	6.3% decrease	1.5% increase	3% increase
Effective network bandwidth	20% reduction: 1,000 to 800 Mbps	5.5% increase	7.4% increase	6% decrease	12% decrease
Interorganizational coordination coefficient	20% reduction: 0.60 to 0.48	8.8% increase	11.5% increase	9.7% decrease	7.1% decrease
Failure rate of communication equipment	20% reduction: 0.25 to 0.20	2.1% decrease	2.8% decrease	1.9% increase	4.5% increase

The results show that the system is most sensitive to network bandwidth and interorganizational coordination parameters. A 20% improvement in bandwidth increases situational awareness by approximately 12%, which in turn leads, through a chain effect, to a 5.2% reduction in response time and a 4.1% reduction in casualties. Similarly, improvement in organizational coordination has the greatest effect on reducing response time and casualties.

The chart of normalized key variables, shown in Figure 1, illustrates the trend of four key state variables over the course of the crisis. Between minutes 10 and 30, a critical divergence is observed: the damage curve rises steeply, while the awareness curve remains at its lowest level. After passing through this phase, the curves begin to converge. The key point is the time lag between the inflection point in resource growth, around minute 40, and the inflection point in awareness improvement, around minute 60, indicating the time required to convert the physical presence of resources into operational information within the C4ISR system.

Figure 1

Chart of Normalized Key Variables Over the Crisis Timeline

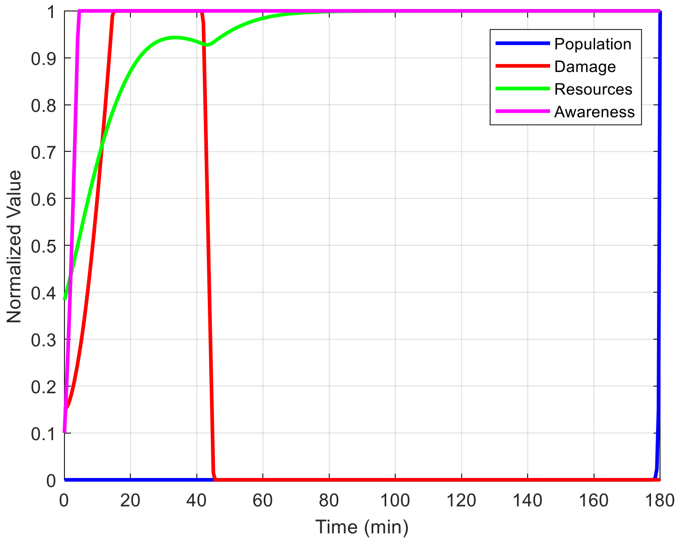
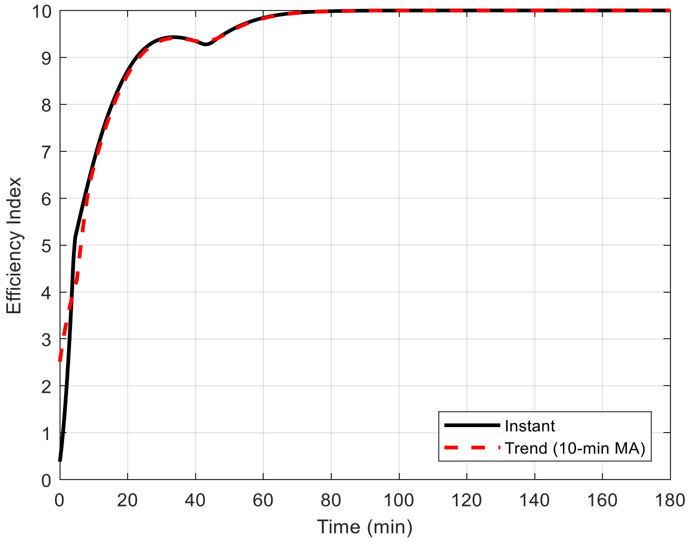


Figure 2

Dynamic Productivity Index

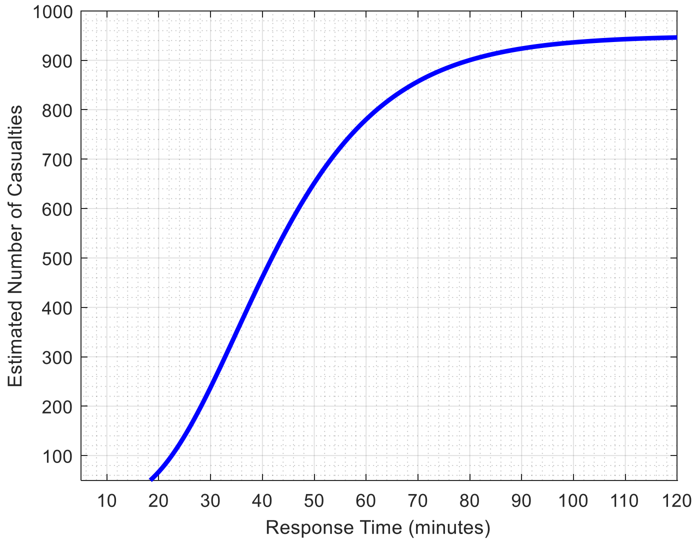


The dynamic productivity index, shown in Figure 2, provides an advanced composite measure. The phase characterized by the lowest efficiency value, around minute 45, represents the deepest point of the efficiency gap or the “moment of maximum system vulnerability.” The gradual but continuous improvement in the productivity index after passing this point provides strong evidence of the cumulative and increasing effect of intelligent C4ISR interventions.

The relationship between casualty rate and response time, shown in Figure 3, exhibits nonlinear behavior that reflects the law of diminishing returns in complex systems. A slight reduction in casualties requires a substantial increase in response time, and vice versa. These results indicate the difficulty and high cost of rescuing the final survivors in hard-to-access areas.

Figure 3

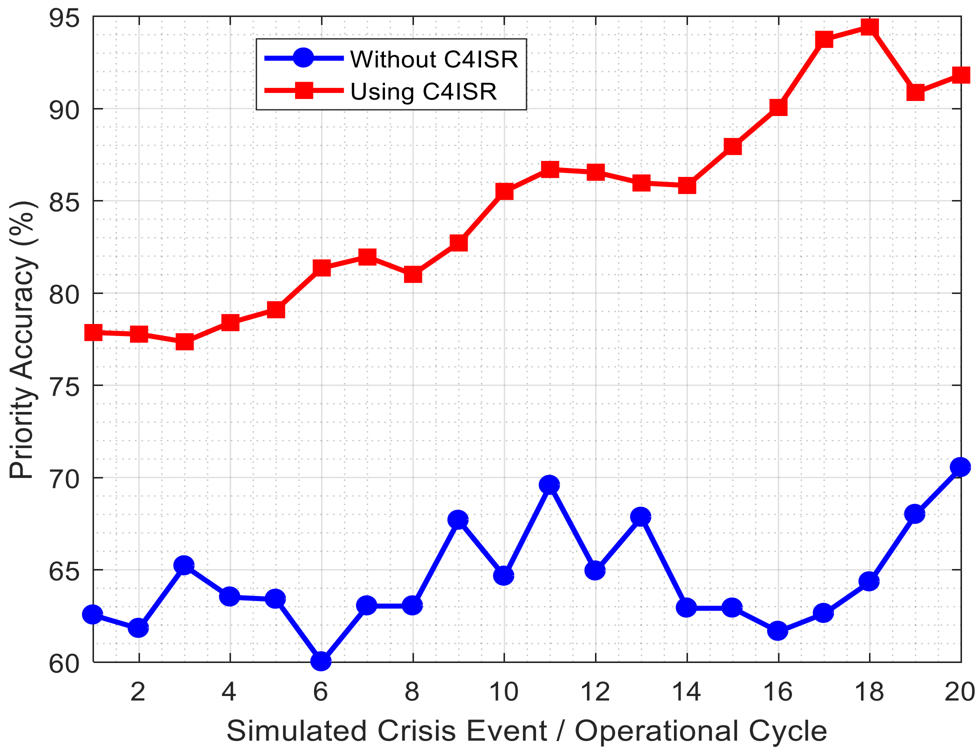
Relationship Between Casualty Rate and Response Time During an Earthquake



The comparison between the performance of the C4ISR-based system and the traditional approach, shown in Figure 4, indicated that the system equipped with C4ISR not only begins with a clear performance advantage at the starting point, approximately 78% accuracy compared with 65%, but also follows a stable and upward improvement trend throughout operational cycles, reaching an accuracy of approximately 95%. By contrast, the traditional system lacks such a systematic learning mechanism, and its performance fluctuates around a fixed mean with random variations.

Figure 4

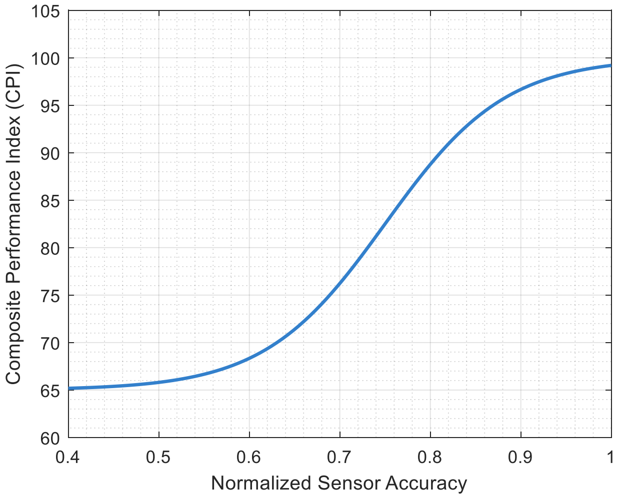
Effect of Implementing the C4ISR Framework on Task Prioritization Accuracy in Urban Crisis Management



The examination of the effect of sensor accuracy on the overall performance index, shown in Figure 5, revealed a sigmoid curve with two distinct functional regions. In the lower range, from 40% to 60% accuracy, the slope is mild and almost linear. From 60% to 85%, the upward slope increases substantially, after which the curve approaches saturation. This indicates that after reaching a sufficient level of accuracy, allocating resources to improving other system components, such as processing speed and interorganizational coordination, can enhance overall efficiency more effectively.

Figure 5

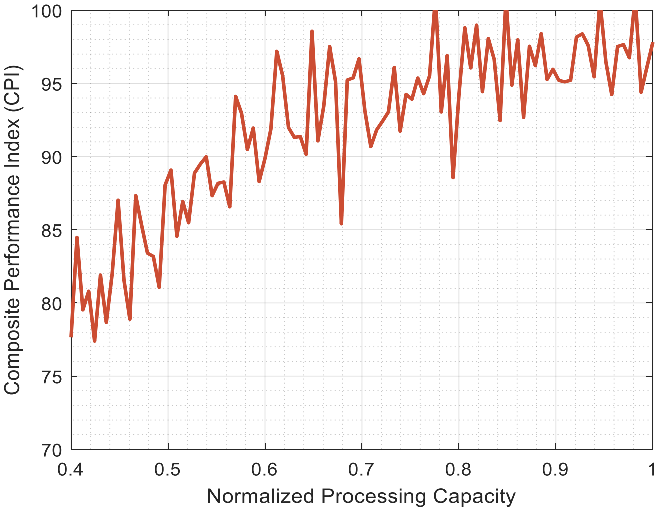
Effect of Sensor Accuracy on the Performance of the Urban Crisis Management System Within the C4ISR Framework



The examination of the effect of central processing capacity, shown in Figure 6, revealed a saturating exponential behavior. In the lower range, with normalized capacities from 0.4 to 0.7, the curve rises with a very steep slope, indicating the critical stage of removing the computational bottleneck. As capacity approaches levels above 0.7, the curve moves toward saturation, and factors such as network bandwidth and data quality become the main constraints.

Figure 6

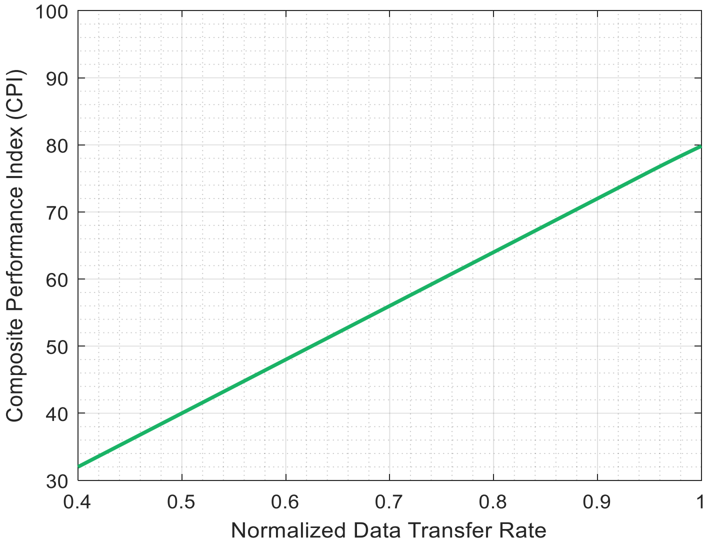
Effect of Central Processing Capacity on C4ISR System Performance in Urban Crisis Management



The relationship between data transmission rate and the performance index, shown in Figure 7, indicated a linear relationship, reflecting the importance of strong and resilient communication infrastructure as the vital artery of the C4ISR framework.

Figure 7

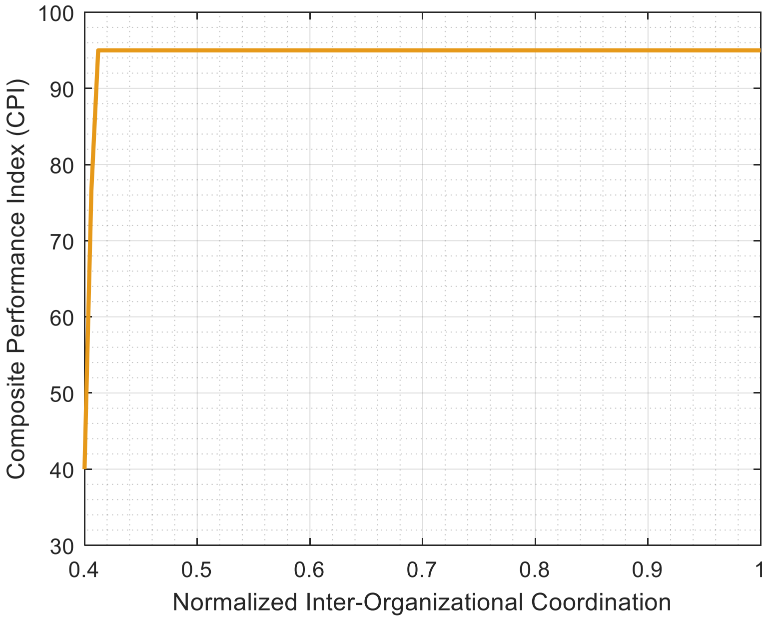
Effect of Data Transmission Rate on the Stability of the C4ISR System in Crisis Management



The examination of the effect of coordination degree on the long-term dynamics of the system, shown in Figure 8, revealed a dynamic and deeply nonlinear pattern. In the initial phase, with coordination values from 0.40 to 0.42, the performance index increases with an accelerating upward slope, indicating the activation of a powerful positive feedback loop. After passing the 0.42 point, improvement in the degree of coordination leads to gradual growth with a mild and almost linear slope, reflecting labor-intensive organizational processes based on initial investment.

Figure 8

Effect of Coordination Degree on the Long-Term Dynamics of the Crisis Management System



Discussion and Conclusion

The findings of this study showed that the proposed intelligent C4ISR-based framework can provide a structured, adaptive, and data-driven model for earthquake crisis management in megacities. The simulation of three earthquake scenarios in Tehran demonstrated that as earthquake magnitude, spatial extent of damage, and operational pressure increased, the performance of all four objective functions deteriorated substantially. In Scenario 1, the model estimated 850 casualties, a response time of 27 minutes, resource efficiency of 0.89, and situational awareness of 0.85. In Scenario 2, these indicators changed to 8,300 casualties, 45 minutes of response time, resource efficiency of 0.72, and situational awareness of 0.65. In Scenario 3, as the most severe condition, casualties increased to 54,000 people, response time reached 112 minutes, resource efficiency declined to 0.51, and situational awareness decreased to 0.35. These results indicate that the crisis management system behaves nonlinearly under increasing pressure, meaning that a moderate increase in earthquake intensity can lead to a disproportionate increase in human loss, operational delay, and systemic inefficiency. This pattern is consistent with the literature on urban complexity, which argues that modern cities function as highly interconnected systems in which disruptions in one subsystem may rapidly affect other subsystems [2, 7]. The findings also support the view that disaster management in metropolitan areas should be understood not as a linear response process, but as a complex adaptive system requiring continuous information processing, coordination, and feedback-based decision-making [6].

The scenario-based results are particularly important in relation to Tehran, because previous studies have repeatedly emphasized the seismic exposure and spatial vulnerability of the Tehran metropolitan area. The sharp increase in casualties and response time in the third scenario is aligned with studies showing that Tehran's seismic risk is intensified by its population concentration, heterogeneous land-use patterns, vulnerability of urban structures, and uneven distribution of emergency accessibility [10, 11]. The present model extends these studies by moving beyond static vulnerability assessment and introducing a dynamic crisis management framework capable of simulating damage propagation, population movement, resource allocation, and situational awareness over time. While GIS-based seismic vulnerability studies provide essential spatial diagnosis, they do not fully explain how crisis response evolves during the first operational minutes after an earthquake. The present findings therefore complement spatial risk studies by showing that seismic vulnerability becomes more critical when combined with weak communication bandwidth, delayed processing, and insufficient interorganizational coordination. This conclusion is also compatible with studies that emphasize the role of smart city infrastructure, land-use planning, and ICT-based urban management in reducing crisis consequences [3-5, 9].

Another important finding was the conflicting nature of the four objective functions. The model showed that minimizing casualties, reducing response time, maximizing resource efficiency, and improving situational awareness cannot always be achieved simultaneously at their maximum levels. In severe crisis conditions, improving one objective may impose costs on another objective. For instance, reducing casualties in highly damaged and inaccessible areas may require longer response times and heavier resource consumption, whereas maximizing resource efficiency may conflict with immediate deployment to low-access, high-risk zones. This result supports the necessity of multi-objective optimization in disaster management. Previous studies have shown that post-disaster relief distribution, volunteer assignment, and network restoration require optimization models that can manage trade-offs among competing operational goals [23, 24]. The use of NSGA-II in the present study is consistent with this research stream, because evolutionary multi-objective algorithms are able to generate a set of Pareto-optimal solutions rather than forcing the decision-maker to accept a single deterministic answer. This is especially important in crisis management, where decisions are shaped by time pressure, uncertainty, ethical priorities, and incomplete information. From a methodological perspective, the findings also support the argument that machine learning and optimization should be integrated, because prediction alone is not sufficient unless it is connected to prescriptive decision-making and operational prioritization [22].

The sensitivity analysis revealed that the system was most sensitive to two key parameters: effective network bandwidth and interorganizational coordination. A 20% reduction in network bandwidth increased casualties by 5.5%, increased response time by 7.4%, reduced resource efficiency by 6%, and reduced situational awareness by 12%. Similarly, a 20% reduction in the interorganizational coordination coefficient increased casualties by 8.8%, increased response time by 11.5%, reduced resource efficiency by 9.7%, and reduced situational awareness by 7.1%. These results indicate that in a C4ISR-based crisis management architecture, the most decisive factors are not necessarily hardware quantity or isolated technical capacity, but the quality of information flow and organizational synchronization. This finding is strongly aligned with command-and-control theory, which emphasizes that effective command depends on shared awareness, information distribution, decision rights, and coordination across actors [13]. It is also consistent with studies on C4ISR interoperability, which argue that decision superiority in complex emergency environments depends on the capacity of different units and organizations to exchange, interpret, and operationalize information in real time [14]. Therefore, the present study confirms that the effectiveness of C4ISR is not limited to technological deployment; rather, it depends on the integration of communication infrastructure with institutional coordination mechanisms.

The results further showed that improving bandwidth can produce cascading effects across the system. The model indicated that a 20% improvement in bandwidth increased situational awareness by approximately 12%, which then contributed to reductions in response time and casualties. This finding is consistent with current studies on digital transformation and urban resilience, which emphasize that resilient cities require robust data infrastructure, interoperable platforms, and fast information exchange among crisis actors [1]. It also corresponds with studies on IoT-based disaster management systems, which highlight the importance of sensor networks, real-time data transmission, and connected devices in improving emergency response capacity [17]. The linear relationship between data transmission rate and system performance observed in this study further strengthens the argument that communication infrastructure functions as the vital artery of an intelligent crisis management system. In the absence of stable and high-capacity communication networks, even advanced AI models and decision-support systems may lose their operational value because data cannot reach the command center or field units in time. This finding is also consistent with research on AI-enabled decision-support systems for urban disaster management from a C4ISR perspective, which emphasizes that artificial intelligence can improve decision-making only when embedded in a reliable command, communication, and information architecture [15].

The performance comparison between the C4ISR-based system and the traditional approach showed that the intelligent system started with higher task-prioritization accuracy, approximately 78% compared with 65%, and improved gradually across operational cycles until reaching about 95% accuracy. By contrast, the traditional system fluctuated around a fixed average and lacked systematic learning capacity. This result indicates that the main advantage of the proposed framework is not merely initial superiority, but its ability to learn dynamically from incoming data and improve operational decisions over time. This finding is compatible with systematic reviews of artificial intelligence in earthquake emergency management, which show that AI can support damage assessment, casualty estimation, emergency routing, and decision support in rapidly evolving earthquake conditions [16]. The use of LSTM-CNN architecture in the proposed framework is also supported by previous studies showing that CNN and LSTM techniques are effective for modeling complex temporal and spatial patterns in crisis-related data [19]. Moreover, the relevance of deep learning for emergency information processing is reinforced by research using attention-based BiLSTM and CNN models for classifying emergency tweets and supporting resource management [20]. These studies collectively support the present finding that intelligent crisis systems must be capable of real-time prediction, classification, and prioritization.

The use of self-organizing maps in the proposed framework also proved conceptually important because crisis data are multidimensional and often contain hidden patterns that cannot be easily detected through conventional statistical procedures. SOM-based analysis allows complex outputs from seismic, spatial, demographic, and operational models to be organized into meaningful clusters, thereby supporting pattern discovery and decision interpretation. This aligns with recent work suggesting that combining SOM with CNN-based structures can improve model accuracy and pattern recognition in complex analytical environments [21]. In the present study, SOM complements the predictive function of the LSTM-CNN model by helping identify similarities among crisis patterns and reducing the cognitive burden on decision-makers. This is particularly relevant for C4ISR systems, where the command center must not only receive data but also transform data into understandable operational intelligence. The findings also support broader arguments that artificial intelligence applications in smart city management can enhance governance capacity when they are designed as decision-support mechanisms rather than isolated computational tools [18]. Accordingly, the proposed model demonstrates how AI can be connected to command architecture, optimization logic, and crisis management objectives.

The dynamic productivity index provided further evidence of the cumulative effect of intelligent C4ISR interventions. The lowest level of efficiency occurred around minute 45, representing the deepest point of the operational efficiency gap or the moment of maximum system vulnerability. After this point, the gradual but continuous improvement in productivity indicated that the accumulation of data, resource mobilization, improved awareness, and coordinated action gradually strengthened system performance. This result is consistent with the logic of critical realism and mixed-methods disaster research, because it shows that crisis outcomes are produced through the interaction of objective conditions, technological capacity, organizational interpretation, and human decision-making. Mixed-methods research is particularly relevant in this context because it allows mathematical modeling to be informed by expert judgment and practical knowledge [25, 26]. Moreover, the role of expert interpretation and experience in the Delphi phase is consistent with studies emphasizing that decision-making under uncertainty is often shaped by tacit knowledge, judgment, and intuitive recognition of opportunity or risk [27]. Therefore, the present framework gains strength from combining quantitative modeling with expert-based validation rather than relying exclusively on technical simulation.

The analysis of sensor accuracy and central processing capacity revealed additional managerial implications. The effect of sensor accuracy on overall performance followed a sigmoid pattern, meaning that improvements in accuracy had limited effects at low levels, strong effects in the medium range, and diminishing effects after reaching a sufficient threshold. Similarly, central processing capacity showed a saturating exponential pattern: performance increased sharply when computational bottlenecks were removed, but after a certain level, other factors such as data quality, bandwidth, and coordination became more influential. These results indicate that investment in crisis management technology should not follow a one-dimensional hardware-centered logic. Instead, system designers should identify threshold points and allocate resources to the weakest bottleneck at each stage of system development. This interpretation is aligned with the European emphasis on AI for disaster risk management and resilient cities, which highlights the need for integrated technological, institutional, and governance capacities rather than isolated adoption of advanced tools [8]. Overall, the findings suggest that the proposed C4ISR-based framework can improve earthquake crisis management by combining real-time data collection, predictive modeling, multi-objective optimization, organizational coordination, and adaptive learning within a unified system architecture.

The present study has several limitations. First, although the model was developed using expert judgment and scenario-based simulation, its outputs depend on the assumptions, parameters, and available data used in the modeling process. Second, the three earthquake scenarios were designed to represent different levels of crisis intensity in Tehran, but they cannot cover all possible combinations of fault rupture, infrastructure failure, weather conditions, population mobility, and secondary hazards. Third, some variables, such as public behavior, institutional trust, informal volunteer activity, and real-time political decision-making, are difficult to quantify precisely and may influence actual crisis outcomes. Fourth, although the model integrates artificial intelligence, mathematical modeling, and C4ISR logic, its real-world implementation would require access to high-quality real-time data, interoperable institutional platforms, and stable communication infrastructure, which may not be fully available in all operational contexts.

Future research should expand the proposed framework by testing it in other megacities with different seismic, infrastructural, demographic, and governance conditions. Researchers can also develop more detailed submodels for hospital surge capacity, traffic disruption, emergency shelter allocation, public communication, and secondary hazards such as fire, landslide, and hazardous material release. Future studies may incorporate agent-based modeling to simulate individual and collective behavior after earthquakes and combine it with system dynamics to capture both macro-level and micro-level processes. In addition, future research should evaluate the model using real operational drills, historical earthquake datasets, and live crisis-management exercises. Comparative studies between traditional command systems, partially digital systems, and fully integrated C4ISR-based systems would also help determine the practical added value of each technological and organizational component.

From a practical perspective, crisis management authorities should prioritize the development of integrated command-and-control platforms that connect sensors, field units, emergency organizations, communication networks, and decision-support algorithms. Investment should not be limited to purchasing advanced hardware; equal attention must be given to interorganizational coordination, data-sharing protocols, communication bandwidth, personnel training, and operational interoperability. Municipalities and national crisis management agencies should design scenario-based exercises that test the system under different levels of earthquake severity and identify bottlenecks before a real disaster occurs. Emergency managers should also establish standard procedures for converting raw data into operational intelligence, prioritizing tasks, allocating resources, and updating decisions as new information becomes available. The most important practical implication is that urban earthquake resilience depends on the joint strengthening of technology, management capacity, institutional coordination, and continuous learning.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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