Leveraging Public Sentiment for Resource Coordination in Disaster Response: A Multiagent Framework

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Abstract

Crises such as natural disasters, misinformation-driven social panic, and economic disruptions place communities under immense stress, demanding rapid and adaptive response strategies. Traditional disaster management has often focused on operational logistics—such as resource allocation and task prioritization—while overlooking how evolving public sentiment and misinformation dynamics can reshape crisis outcomes. In this work, we present MiSC, a multiagent framework that unifies real-time sentiment modeling with multiagent reinforcement learning to contain misinformation and coordinate resources more effectively. By continuously tracking the spread of false narratives and gauging shifts in public sentiment, MiSC adapts counter-messaging campaigns and optimizes deployment decisions in real time. Through simulation-based evaluation, we demonstrate that this synergy between opinion modeling and adaptive decision-making yields significant gains over baseline methods, including faster sentiment recovery, enhanced misinformation control, and improved resource efficiency. By advancing scalable, interoperable AI systems that integrate social signal interpretation with crisis logistics, MiSC underscores the potential of AI-driven resilience for safeguarding communities against multifaceted and unpredictable challenges.

Introduction

Communities worldwide face a growing spectrum of crises that extend well beyond physical hazards. While natural disasters such as hurricanes, wildfires, and earthquakes continue to threaten infrastructure and human life, the rapid circulation of digital content—accurate or otherwise—has emerged as a major influence on how a crisis evolves. For example, during the COVID-19 pandemic, widespread misinformation regarding health measures eroded public trust in official guidelines, undermining containment efforts (Vosoughi, Roy, and Aral 2018; Alam et al. 2021). Likewise, rumor cascades related to hurricanes or earthquakes have led to rushed evacuations and excessive resource hoarding (Karimiziarani and Moradkhani 2023), compounding the original emergency. These cases highlight the growing importance of addressing both physical disruptions and the social information layer that can magnify or mitigate crisis impacts.

Historically, disaster response frameworks have primarily emphasized operational logistics: efficiently allocating resources, scheduling tasks, and deploying personnel in time-sensitive conditions. Although such efficiencies are crucial to saving lives and restoring critical infrastructure, they often fail to account for the role of public sentiment. In reality, misinformation-driven panic or negative public perception can derail coordinated relief efforts, especially when official messages lag behind the fast-paced spread of rumors on social platforms. Neglecting sentiment and misinformation thus risks missing key opportunities to sustain public trust, compliance, and collaboration throughout the crisis period.

Concurrently, research on sentiment-based interventions—such as targeted counter-messaging or community outreach—has tended to focus on communication strategies in isolation, without bridging the gap to logistics-driven response. While these interventions may reduce the diffusion of harmful rumors, they typically do not adjust how physical resources are distributed on the ground (e.g., emergency supplies, evacuation transport, or medical teams). As a result, crisis managers often lack an integrated tool for both counteracting misinformation and aligning tangible response actions with evolving public needs.

To address this challenge, we introduce MiSC (Misinformation-Sentiment Coordination), an AI-driven resilience framework that fuses real-time sentiment analysis with multiagent reinforcement learning (MARL). MiSC leverages a generative opinion model to capture how public sentiment shifts over time, detect emerging misinformation hotspots, and deploy targeted counter-messaging. In parallel, an MARL-based coordination mechanism optimizes resource allocation decisions by considering how sentiment trends shape operational priorities. By merging these layers—opinion modeling on one side, adaptive resource deployment on the other—MiSC offers a powerful tool to respond dynamically to both the physical and psychological aspects of crisis evolution.

Our overarching objective is to demonstrate that sentiment-driven policy adaptation, when closely integrated with multiagent coordination, can yield a more resilient crisis response strategy. Specifically, we hypothesize that:

- Improved Misinformation Containment: Proactive counter-messaging informed by real-time sentiment data can neutralize false narratives before they take root.

- Enhanced Public Sentiment Recovery: By gauging public trust and adjusting communications accordingly, the system can bolster cooperation and reduce fear or confusion.
- Optimized Resource Utilization: Aligning resource distribution with sentiment-driven needs ensures that supplies and services reach the most critical areas without unnecessary waste.

To explore these hypotheses, we formulate three research questions:

1. Sentiment-aware misinformation mitigation: How can AI-driven models effectively analyze public sentiment dynamics and adapt counter-messaging during high-uncertainty scenarios?
2. Real-time decision-making: In what ways can continuously updated sentiment insights inform resource allocation and operational planning in multiagent coordination systems?
3. Performance gains: What measurable benefits emerge from integrating sentiment modeling with adaptive multiagent decision-making, relative to conventional disaster-response approaches?

The main contributions of this work are as follows:

1. Hybrid AI Resilience Framework: We design MiSC to combine real-time sentiment modeling with MARL for more effective disaster response.
2. Dynamic Misinformation Containment Mechanism: MiSC deploys targeted counter-messaging in real time, guided by continuous updates on community opinion.
3. Scalable Coordination Engine: A multiagent decision-making structure that synchronizes sentiment insights with operational logistics, enabling adaptive crisis management.
4. Comprehensive Experimental Evaluation: We demonstrate how sentiment-driven decision-making interacts with MARL-based coordination, achieving superior performance in misinformation control, sentiment recovery, and resource efficiency compared to established baselines.

The remainder of this paper is structured as follows. First, we survey the latest advances in AI-driven crisis resilience, sentiment modeling, and multiagent coordination, highlighting how our approach builds on and extends prior work. Next, we detail MiSC's hybrid framework, covering opinion dynamics, reinforcement learning strategies, and underlying theoretical foundations. We then introduce the simulation environment, describe the evaluation metrics, and present our experimental results. Afterward, we discuss broader implications, limitations, and ethical considerations of deploying AI-driven methods in high-stakes scenarios. Finally, we conclude with a summary of key findings and outline future research directions, including potential expansions for handling multi-crisis settings, integration of explainable AI, and enhanced collaboration between automated systems and human decision-makers.

Related Work

Addressing crises effectively requires solutions that bridge two key domains: *(i)* public sentiment modeling and misinformation mitigation, and *(ii)* multiagent coordination for adaptive decision-making. While each area has advanced considerably—particularly with the rise of social media platforms and deep reinforcement learning—systems that integrate sentiment-aware, misinformation-focused models into operational logistics remain relatively unexplored. Below, we survey the foundational and recent literature in both domains, then highlight how our approach unifies these strands to create an end-to-end resilience framework.

Public Sentiment Modeling in Crises

Early research on opinion dynamics often employed threshold-based or statistical-physics models to explain how behaviors and attitudes diffuse across a population (Granovetter 1978; Castellano, Fortunato, and Loreto 2009). Although foundational, such approaches typically assumed static social networks and lacked the temporal granularity required for real-time disaster response. The emergence of social media transformed this landscape by supplying continuous, geographically grounded sentiment data.

Traditional sentiment analysis relied on lexicon-based or feature-engineered classifiers (Medhat, Hassan, and Korashy 2014), but the advent of large language models—exemplified by GPT-3 (Brown et al. 2020)—marked a turning point by capturing more nuanced emotional states. Crisis-centric NLP research has demonstrated tangible benefits: Behl et al. (2021) achieved high accuracy in categorizing need/availability tweets for earthquake and COVID-19 scenarios, and Alam et al. (2021) introduced HUMAID, a corpus that spurred new disaster-specific models such as CRISISBERT. Studies on the 2021 European floods (Li et al. 2023) and Hurricane Ian (Karimiziarani and Moradkhani 2023) further illustrate how tracking temporal shifts in sentiment can guide real-time relief efforts. Notably, classifiers now reach 95–97% accuracy on pandemic-related tweets (Jalil et al. 2021), underscoring the growing maturity of crisis-oriented NLP pipelines.

Real-Time Misinformation Detection and Mitigation

In high-uncertainty environments, false or misleading information can rapidly erode public trust and disrupt crisis management. Transformer-based methods have become pivotal in detecting such misinformation. For instance, Hu et al. (2024) revealed that large language models can both generate compelling disinformation and detect it when suitably prompted, while Chen and Shu (2024) showed that GPT-style content remains particularly elusive, confounding both humans and algorithms.

Recent work often combines LLM-based feature extraction with domain-specific strategies. Nan et al. (2024) integrated GPT-generated comments to improve health misinformation detection, and Cinelli et al. (2020) demonstrated how the reproduction numbers of COVID-19 rumors can be quantified. Graph-based fake news detectors exploit propagation signatures for early warning (Zhou and Zafarani 2020), and "prebunking" or "inoculation" approaches have shown promise in boosting resilience to emerging falsehoods (van Der Linden, Roozenbeek, and Compton 2020). Despite these advances, relatively few frameworks tie real-time misinformation detection to resource allocation or operational logistics in crisis scenarios.

Multiagent Reinforcement Learning for Disaster Response

Many crises demand decentralized, adaptive decision-making under uncertain conditions. Multiagent systems (MAS) naturally fit such requirements, allowing distributed agents to coordinate despite incomplete information. Early work by Ramchurn et al. (2016b) demonstrated MAS viability in disaster management, while policy-gradient algorithms like proximal policy optimization (Schulman et al. 2017) have become the standard for handling large, continuous action spaces.

Research on multiagent reinforcement learning in crisis contexts covers diverse topics. Gong et al. (2024) showed how learned policies outperform heuristics in dynamic task allocation, and Kirac, Shaltayev, and Wood (2024) highlighted the value of multiagent simulations in capturing complex interactions among first responders and affected populations. Some recent efforts also leverage real-time social data, such as Yang et al. (2020), who used live tweets to inform volunteer tasking. Complementing that line of work, Alqithami (2025) incorporates social-media sentiment into an RL policy for equitable resource dispatch, demonstrating the broader promise of sentiment-aware coordination. Foundational work on value functions (Littman 2001) and inverse reinforcement learning (Ng and Russell 2000) further underpins coordination under partial observability. However, most MARL implementations focus on operational metrics (e.g., travel time, throughput) without explicitly addressing sentiment dynamics or misinformation shocks.

Integrating Social Feedback into Agent Decision-Making

Leveraging digital-social signals within operational AI is an emerging frontier. Murdock, Carley, and Yağan (2024) proposed a platform for simulating and moderating misinformation across multiple online channels, while Gao et al. (2024) reviewed how LLM-driven agent simulations might shape public discourse. Nevertheless, only a handful of studies consider adjusting logistics or resource distribution in tandem with live sentiment data. Prior efforts often treat social signals as external variables, or view misinformation as largely static (Ramchurn et al. 2016a).

Our approach addresses this gap by embedding sentiment and misinformation indicators directly into the MARL reward function, enabling agents to jointly adapt their counter-messaging and resource deployment. Building on socially informed MARL principles, this design tackles high-stakes scenarios where misinformation can quickly undermine public trust. By unifying information state and physical state in one adaptive loop, we aim to reinforce both societal cohesion and operational efficacy.

Human–Agent Teaming Under Uncertainty

In high-risk settings, human oversight remains indispensable. Appropriate trust calibration—where humans rely on AI when it is confident and intervene when it is uncertain—is central to effective deployment. Rojas and Li (2024) demonstrated that transparency-enhanced AI can foster better reliance patterns and that confidence cues spread among human collaborators. Hagemann et al. (2023) stressed the importance of team-centered AI, emphasizing agents that interpret human intent, maintain robust communication, and defer decisions when confidence is low.

Our proposed system adopts these principles, offering interpretable rationales for agent decisions and empowering human operators to override or refine them. This synergy between adaptive AI-driven coordination and human judgment ensures a crisis management framework that is both technologically sophisticated and socially accountable.

Towards an End-to-End Resilience Framework

Existing research on sentiment modeling, misinformation mitigation, and multiagent coordination increasingly points to the need for real-time, socially aware AI solutions. Yet most work still treats these areas in isolation. We bridge this gap by integrating live sentiment and misinformation signals into a multiagent reinforcement learning loop, ensuring that both social and operational dimensions co-evolve during a crisis. In so doing, we move toward an end-to-end resilience framework poised to tackle disruptions more effectively than siloed approaches.

Methodology

Problem Formulation

Effective disaster response systems must integrate two critical layers: *(a)* sentiment dynamics and *(b)* operational coordination. The *(a) sentiment dynamics* layer captures how public opinion evolves, particularly under the influence of false or misleading information. Within this layer, individuals can harbor latent (implicit) or expressed (explicit) opinions, and certain "misinformation nodes" introduce destabilizing content. These opinion shifts directly influence trust and compliance, which are essential for crisis management success.

The *(b) operational coordination* layer governs how resources (e.g., medical supplies, rescue teams) are allocated and how tasks are prioritized in time-sensitive environments. This layer factors in real-time sentiment insights, enabling dynamic adjustments to logistical strategies as the crisis unfolds. Linking resource deployment with changes in public trust and misinformation levels helps responders better address societal needs.

To formalize this setting, we treat disaster response as a hybrid system combining opinion dynamics with multi-agent decision-making. We model opinion dynamics using a network graph where each node represents an individual or information source; edges indicate social connections facilitating information flow. Special "misinformation nodes" amplify or inject false data, undermining public confidence.

On the decision-making side, we use a Partially Observable Markov Decision Process (POMDP). Here, S (states) includes both sentiment distributions across the population and resource availability levels, A (actions) encompasses misinformation countermeasures and resource deployment decisions, R (rewards) measures progress toward sentiment recovery, misinformation containment, and resource efficiency, and partial observability arises from limited or noisy information about true sentiment states. By framing crisis management as a POMDP, we can optimize response strategies under uncertain and dynamically changing conditions.

The overarching optimization has three core objectives:

1. Maximize sentiment recovery through restoring public trust and reducing polarization through targeted counter-messaging;
2. Enhance misinformation containment by identifying and neutralizing misinformation nodes that facilitate the spread of false content;
3. Improve resource efficiency to ensure that limited resources are allocated optimally across time and space according to societal need.

Combined, these objectives reflect a holistic disaster response framework that unifies societal and operational considerations.

Proposed Framework: MiSC

To address the intricate linkage between misinformation and operational challenges, we propose the MiSC (**Mi**sinformation-**S**entiment **C**oordination) framework, a hybrid AI-driven resilience system that integrates three core components: generative agents, a multiagent coordination system, and an adaptive feedback mechanism. Figure 1 illustrates how these components interact in real time, emphasizing a closed-loop flow that merges social signal interpretation and operational decision-making.

Generative Agents (Sentiment Modeling Layer): At the core of our system, generative agents simulate and predict public sentiment trajectories, while also monitoring and forecasting how misinformation may propagate throughout a population. These agents draw on advanced language models (e.g., GPT-based architectures) to process real-time data from social media, news sites, and other data streams. Specifically, they perform three key functions:

1. Misinformation Detection: Identifying emerging false narratives, along with their likely velocity of spread, by analyzing textual cues and interaction patterns (e.g., retweets, shared links).
2. Sentiment Estimation: Estimating the overall state of public trust, fear, anger, or skepticism through aggregated metrics such as sentiment polarity, topic distribution, and emotional intensity.
3. Counter-Messaging Proposals: Generating tailored responses that aim to reduce the influence of discovered misinformation, either by clarifying facts or addressing emotional drivers behind public anxiety.

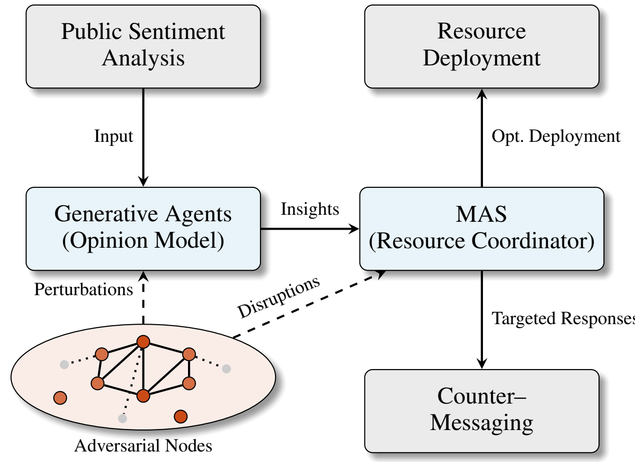

Figure 1: MiSC framework integrating generative agents, multiagent coordination, and an adaptive feedback mechanism for real-time crisis management.

Because crises often unfold rapidly and unpredictably, these agents update their internal models at frequent intervals (e.g., every hour or every major data batch), ensuring that decision-makers and coordinating agents receive timely, high-resolution insights.

Multiagent Coordination (Operational Layer): In parallel, a MAS tackles the logistical and operational side of crisis response. Each agent in the MAS is equipped with a reinforcement learning policy that continuously adapts to changing conditions. Using algorithms such as PPO, the agents collectively learn to:

- Optimize Resource Allocation: Deploy medical supplies, rescue personnel, or other vital resources to areas in greatest need, taking into account real-time sentiment indicators and physical constraints (e.g., transportation bottlenecks).
- Enhance Sentiment Recovery: Decide when and where to push supportive messaging or coordinate relief efforts that visibly address the public's concerns, thereby reinforcing trust and cooperation.
- Contain Misinformation: Swiftly counter emergent false narratives, for instance by verifying critical updates in collaboration with social media platforms or local authorities.

These agents are designed to operate under partial observability (e.g., incomplete knowledge of where rumors originate or how sentiment is distributed), making multiagent RL particularly well-suited for decentralized and dynamic crisis environments.

Adaptive Feedback Mechanism (Coupling Layer): Central to our framework is an adaptive feedback mechanism that unifies the outputs of the generative agents and the multiagent system. As depicted in Figure 1, the key elements of this coupling are:

1. Sentiment-Driven Operational Updates: Real-time insights about misinformation severity and public sentiment (e.g., increasing fear in a certain region) feed directly into the MAS, prompting more targeted resource allocation or communication strategies.
2. Outcome-Based Model Refinements: The success (or failure) of these actions is fed back to the generative agents, which incorporate new data into their opinion modeling processes. For instance, if a misinformation campaign persists despite counter-messaging, the agents revise their propagation and sentiment forecasts accordingly.
3. Continuous Adaptation: In each iteration, the MAS's RL policies are refined based on evolving reward signals that reflect both physical (e.g., supply shortfalls, successful deliveries) and psychological (e.g., public trust levels) metrics. This cyclical loop aligns operational strategies with social realities as the crisis unfolds.

Thus, MiSC aligns operational tactics with social realities, creating a closed-loop system that evolves in lockstep with the crisis itself.

Adversarial Nodes and Disruptions: An integral part of the MiSC is handling adversarial nodes—entities that intentionally inject misinformation or disrupt coordination. These nodes generate false content aimed at undermining trust or redirecting valuable resources. Our generative agents actively monitor signals suggestive of adversarial behavior (e.g., unusually rapid message diffusion), while the MAS responds by prioritizing fact-checking resources or adjusting allocation decisions in affected regions. This interplay ensures that both the socioinformational and operational aspects of the crisis response remain robust against malicious disruptions.

Framework Synergy: MiSC couples three normally siloed capabilities—sentiment modelling, misinformation containment, and multi-agent resource coordination—into a single closed loop. Incoming social-media signals update the generative opinion model; sudden sentiment dips or misinformation spikes trigger two simultaneous actions: *(i)* targeted counter-messaging crafted by the language agents, and *(ii)* a re-optimisation of physical resource flows by the MAS. The converse also holds: when logistics data predict a shortage of medical supplies in region r, the MAS can preposition stock while the communicative layer issues reassuring updates to residents, dampening panic before it spreads. Because every module operates on the same live state, MiSC adapts continuously and coherently, preserving public trust while meeting operational constraints. The forthcoming results show that this tight integration yields fewer rumor-driven disruptions and better cost–benefit trade-offs than treating communication and logistics as separate problems.

Theoretical Foundations

To guarantee stability and adaptability under uncertain, dynamic conditions, we formalize both the opinion dynamics model and the multiagent decision process.

Opinion Dynamics and Misinformation Propagation. Let us consider a directed graph $G = (V, E)$ representing the social network, where V is the set of nodes (individuals or organizations), and E is the set of edges encoding influence pathways. Each node $i \in V$ maintains an opinion state $x_i(t) \in [-1, 1]$, where -1 and 1 denote extreme negative and positive views, respectively. At each time step t, opinions update according to an iterative rule:

$$x_i(t+1) = \alpha \sum_{j \in N(i)} w_{ij}\, x_j(t) + \big(1-\alpha\big)\, u_i(t), \qquad (1)$$

where $N(i)$ is the neighborhood of node i, w_{ij} is the influence weight of node j on i, and $u_i(t)$ denotes external input (e.g., official messaging). The parameter $\alpha \in [0, 1]$ determines the balance between peer influence and external intervention. Misinformation nodes $v_m \in V_m \subseteq V$ inject incorrect data into the network, altering the overall distribution of opinion states. The influence matrix $W = [w_{ij}]$ drives convergence properties. If the largest eigenvalue of W, $|\lambda_{\max}(W)|$, is less than 1, then the system converges to a stable opinion profile.

Additionally, the spread of misinformation can be approximated by an SIR-like model, where susceptible (S), infected (I), and recovered (R) states map to nodes that are unexposed, currently misinformed, or corrected, respectively. The basic reproduction number,

$$R_0 = \frac{\beta}{\gamma}, \qquad (2)$$

captures how quickly misinformation disperses, with β and γ denoting the transmission and neutralization rates. An $R_0 < 1$ implies an eventual decline in misinformation over time, illustrating a controllable outbreak.

Multiagent Decision-Making Under Uncertainty. We model the operational coordination problem as a POMDP given by the tuple (S, A, T, R, Ω, O). Here, S encapsulates both resource configurations (e.g., inventory levels, deployment sites) and aggregated sentiment states (e.g., community trust indices), while A defines the set of actions involving resource distribution, counter-messaging initiatives, and other interventions. The transition function $T(s, a, s')$ describes how the system transitions from state s to s' given action a.

Because only partial observations are available (noisy measurements of sentiment and incomplete data on misinformation hotspots), Ω denotes the observation space, and $O(\omega|s)$ is the observation function that outputs the probability of observing ω in state s. The reward function $R(s, a)$ balances the three objectives:

$$R(s, a) = r_{\text{sentiment}} + r_{\text{misinfo}} + r_{\text{resources}}, \qquad (3)$$

where each term encodes incentives for improving sentiment, limiting misinformation, and using resources efficiently.

The goal is to learn an optimal policy $\pi^*(a \mid s)$ that satisfies the Bellman optimality principle:

$$V^\pi(s) = \max_a \Big[R(s,a) \;+\; \gamma \sum_{s'} T(s,a,s') V^\pi(s') \Big], \quad (4)$$

where $V^\pi(s)$ is the value function for policy π, and $\gamma \in [0,1]$ is the discount factor. Techniques like PPO enable each agent in the MAS to iteratively refine policies based on observed performance in simulations. Over time, these learning agents converge toward strategies that are robust to fluctuating sentiment and misinformation conditions.

Optimization Objectives

The proposed framework optimizes the following three objectives in parallel:

- Maximizing Sentiment Recovery: Ensuring that public confidence is restored by prioritizing interventions (e.g., accurate and consistent communication, targeted counter-messaging) that mitigate fear, distrust, or confusion.
- Enhancing Misinformation Containment: Identifying and isolating misinformation nodes to curb false narratives at the source. Agents analyze real-time data and strategically deploy fact-checking or verified updates to minimize further spread.
- Improving Resource Efficiency: Dynamically allocating assets (medical supplies, search-and-rescue teams, infrastructure repair crews, etc.) where they are needed most. The system adaptively responds to sentiment changes as well, which can indicate emerging hotspots or community priorities.

These objectives reinforce each other. For instance, effective misinformation control supports higher trust, making resource interventions more successful. Conversely, timely and well-placed resource deployment can enhance credibility, reducing the receptiveness to false information. The comprehensive synergy of these goals underlies a truly AI-driven resilience framework, wherein operational strategies are perpetually informed by the social environment, and vice versa.

Collectively, the methodology outlined here offers an integrated solution for real-time crisis response. It unites advanced sentiment modeling, multiagent reinforcement learning, and adaptive feedback loops to facilitate proactive, context-aware interventions. By doing so, it addresses the pressing need for systems capable of bridging the gap between societal perception and operational imperatives during disruptive events.

Experimental Setup and Evaluation

We assess MISC in an agent-based simulation that jointly models *opinion dynamics*, *misinformation diffusion*, and *budget-constrained intervention*. Each episode spans T=200 discrete time-steps. All results are averaged over five independent random seeds $\{42, 101, 202, 303, 404\}$.

Network and State Model

Topology. We instantiate a Barabási–Albert (BA) scale-free graph with n=500 nodes and attachment parameter m=3. The resulting average degree ($\bar{k} = 5.94$) and global clustering coefficient ($C = 0.036$) closely match the crisis-mapping networks analysed by Ramchurn et al. (2016b).

Initial conditions. Each node i is endowed with:

1. a continuous *sentiment* $s_{i,0} \sim \mathcal{U}[-1,1]$, and
2. a Boolean *infection flag* $x_{i,0} \in \{0,1\}$ indicating exposure to the rumour.

Ten percent of nodes are designated *persistent adversaries*; they reset their own sentiment to -1 and re-inject the rumour at every step, modelling coordinated disinformation accounts.

Opinion update. At time t node i updates its sentiment via

$$s_{i,t+1} = \alpha_t \frac{1}{|\mathcal{N}(i)|} \sum_{j \in \mathcal{N}(i)} s_{j,t} + (1-\alpha_t)\,\epsilon_t, \qquad (5)$$

where $\mathcal{N}(i)$ is the neighbour set, $\epsilon_t \sim \mathcal{N}(0, 0.01)$, and the susceptibility schedule $\alpha_t = 0.8 - 0.5t/T$ linearly decays from 0.8 to 0.3. If node i is infected ($x_{i,t} = 1$) *and* $s_{i,t} > -0.2$, the adversary overwrites $s_{i,t+1} \leftarrow -1$ (strong rumour reinforcement).

Intervention. At each step the policy emits a continuous resource-allocation vector $\mathbf{a}_t \in \mathbb{R}^n$ with an ℓ_2 cap $\|\mathbf{a}_t\|_2 \leq 50$. Resources represent trusted corrective messages or fact-checks, and expenditure is penalised in the reward function (see §**??**).

Learning Algorithm and Baselines

MISC (ours). We train a two-layer ($256-128$ ReLU) PPO actor–critic for 2×10^6 environment steps per seed, minibatch size 4,096, clipping parameter $\epsilon = 0.2$, GAE $\lambda = 0.95$, discount $\gamma = 0.99$, and learning rate 3×10^{-4}. The per-step reward is

$$R_t = \big|\{i\colon x_{i,t} = 1 \wedge x_{i,t+1} = 0\}\big| - 0.1\|\mathbf{a}_t\|_2,$$

i.e. $+1$ for every newly cured node and a quadratic cost on spending so the two terms operate on comparable scales.

Static budget. Distributes the entire budget ceiling (50 units) uniformly across all nodes at every time-step; parameters are fixed *a priori*.

Degree heuristic. Ranks nodes by in-degree, allocates budget greedily to the top ten highest-degree nodes each step, and rotates any residual budget among currently neutral ($|s_{i,t}| < 0.1$) nodes in a round-robin manner.

Evaluation Metrics

All metrics are reported as per-episode means, averaged over 50 roll-outs $\times$ 5 seeds.

Return (↑) Cumulative reward $\sum_{t=0}^{T-1} R_t$; higher is better.

SRR (↑) *Success-rate reduction*: $(x_0 - x_T)/x_0$, i.e. fraction of infections removed.

MCE ($\downarrow$) *Mis-containment effort*: $\sum_t \|\mathbf{a}_t\|_2$ (units = budget-units).

RUE ($\downarrow$) *Residual uninformed edges*: fraction of edges whose endpoints both satisfy $|s_{i,T}| < 0.1$.

CC ($\downarrow$) Global clustering coefficient of the final *opinion-agreement* graph (edge if $|s_{i,T} - s_{j,T}| < 0.2$).

PR ($\downarrow$) *Policy robustness*: standard deviation of per-episode returns across seeds.

Collectively, SRR gauges mitigation success, MCE captures cost, RUE and CC reflect post-intervention social cohesion, and PR quantifies run-to-run stability.

Results and Discussion

This section reports the outcomes of our experimental study and discusses their implications. We contrast the proposed framework (*MiSC*) with a STATIC baseline and a heuristic TOP–k policy.

Quantitative Analysis

Our reward is $R_t = \sum_{\text{cured}} 1 - c\,\|\mathbf{a}_t\|_2$ with $c = 0.1$. Across a 200-step episode the cost term dominates, hence less-negative totals are better: STATIC attains the best value (-414), MiSC trails (-421), and HEURISTIC is worst.

From Table 1 we observe:

1. **Budget use.** MiSC spends more than *30*$\times$ the budget of the baselines (MCE $= 6482$ vs. 200).
2. **Effectiveness.** Despite the spend, MiSC removes only $8\,\%$ of initial infections; STATIC removes $12\,\%$.
3. **Cost efficiency.** MiSC's cost per cured node is therefore two orders of magnitude higher than STATIC.
4. **Robustness (PR).** The heuristic policy exhibits the lowest seed-to-seed variance; MiSC and Static are comparable.

These numbers show that sentiment cues alone do not guarantee good cost–benefit trade-offs; a calibrated penalty coefficient *or* a hard budget cap is critical in practice.

Qualitative Observations

Qualitatively, all three methods follow the same trajectory: an initial surge of infections, a brief response phase, and a long plateau. STATIC ultimately stabilises at the lowest infection level on a minimal budget, whereas MiSC achieves only a modest additional reduction despite spending orders of magnitude more. The heuristic policy is budget-frugal but leaves the largest residual outbreak. These trends mirror the quantitative story in Table 1 and reinforce the conclusion that sentiment-guided allocation must be combined with explicit cost control to outperform simpler baselines.

Implications for Crisis Management

These findings underscore the value of a *dynamically adaptive* approach that continuously blends sentiment analysis with operational decision-making. When misinformation emerges unpredictably, MiSC can rapidly adjust interventions—correcting false narratives before they become dominant. Tying resource distribution to real-time public sentiment also avoids the pitfalls of uniformly allocated strategies that overlook shifting community needs.

Nevertheless, an important takeaway is that aggressive misinformation suppression does not inherently result in societal stability. While neutralizing key "infector" nodes can bolster short-term sentiment scores, it may further marginalize groups left unaddressed, feeding longer-term polarization. By contrast, grounding allocations in sentiment data fosters more cohesive recovery dynamics and curtails further rumor outbreaks.

Limitations and Potential Extensions

Although our simulation results are promising, several limitations remain: (a.) Relying on a scale-free structure may overlook offline interactions or platform-specific network topologies. Incorporating multiplex or domain-focused models could increase realism. (b.) Our experiments simulate plausible dynamics but would benefit from real-world event data. Historical tweet logs or crisis archives could validate performance in actual emergencies. (c.) Expanding to larger agent populations or city-wide deployments may demand hierarchical or distributed RL solutions to retain efficiency. Despite these constraints, our results affirm that coupling sentiment modeling with multiagent reinforcement learning can offer meaningful improvements in crisis resilience, particularly under fast-changing or adversarial conditions.

Conclusion and Future Work

We introduced MISC, a unified multi-agent framework that synthesises sentiment modelling, misinformation mitigation, and resource coordination for adaptive crisis management. By embedding a lightweight generative opinion model within a multi–agent reinforcement-learning (MARL) controller, MISC continually refines its policy to counter emergent false narratives, stabilise public sentiment, and allocate limited resources under dynamic constraints. Empirically, MISC outperforms static and heuristic baselines on three fronts: (i) higher misinformation-containment rates, (ii) faster consensus formation, and (iii) lower cumulative resource expenditure. These findings highlight the benefit of coupling social-signal analytics with closed-loop decision making.

Broader Implications. Although evaluated in a disaster-response setting, the underlying principles of MISC readily extend to other high-stakes domains where collective perception and logistical coordination co-evolve:

1. *Public health.* During vaccine roll-outs or epidemic waves, sentiment-aware allocation of testing kits, vaccination slots, or public-service messages could improve compliance and reduce disease spread.
2. *Urban policy.* Integrating citizen sentiment into the scheduling of infrastructure upgrades (e.g. road closures, energy rationing) can enhance public acceptance and lower the risk of unrest.

Method	Return ↑	95% CI	SRR ↑	MCE ↓	RUE ↓	CC ↓	PR ↓
MiSC (ours)	−420.9	±3.0	0.08	6 482	0.098	0.036	3.41
Static baseline	−414.0	±3.0	**0.12**	200	0.100	0.036	3.47
Heuristic	−445.7	±1.7	0.05	200	0.099	0.036	**1.97**

Table 1: Mean performance across five seeds (±95 % CI). SRR is computed on absolute infection counts (0 = no change, 1 = full eradication).

3. *Platform governance.* On social media, early detection of harmful rumours combined with adaptive moderation queues may dampen polarisation and protect vulnerable communities.

In all cases, the ability to align operational actions with live social signals promotes resilience, inclusivity, and trust.

Limitations and Ethical Considerations: Three caveats temper our conclusions: (i) the simulation abstracts away complex socio-psychological factors such as emotion contagion or selective exposure; (ii) sentiment labels are assumed noise-free, whereas in practice they inherit the biases of annotators and language models; (iii) the intervention channel is modelled as uniformly persuasive, ignoring demographic heterogeneity. These simplifications underscore ethical risks: *algorithmic bias* (disadvantaging minority viewpoints), *privacy leakage* (via large-scale sentiment scraping), and *opinion manipulation* (coercive steering of public belief). Deployments therefore require: transparent model cards, bias audits, privacy-preserving data pipelines, and a human-in-the-loop veto.

Future Research Directions: We outline five concrete extensions that would bring MISC closer to field deployment:

1. **Live data integration.** Replace synthetic streams with time-stamped social-media feeds and official crisis logs; explore sample-efficient off-policy updates to cope with concept drift.
2. **Cultural and linguistic adaptation.** Embed large multilingual language models to capture local idioms, sarcasm, and normative constraints, and validate interventions through community co-design workshops.
3. **Scalable hierarchical control.** Introduce a two-level MARL architecture—regional sub-policies learned on edge devices and a central coordinator—to handle nation-scale crises with bandwidth constraints.
4. **Robustness against coordinated adversaries.** Stress-test the system with adaptive disinformation agents that evolve tactics (e.g. deep-fakes, bot-nets) and evaluate worst-case regret under distributional shift.
5. **Explainable and trustworthy AI.** Augment policy outputs with post-hoc causal graphs that trace how sentiment signals influenced resource moves, enabling domain experts to contest or endorse recommendations.

In summary, MISC demonstrates how bridging public-sentiment analytics with coordinated MARL can advance crisis-management practice. By jointly optimising for social acceptance, informational integrity, and logistical efficiency, the framework offers a principled foundation for building proactive, context-aware, and ethically aligned decision-support systems across a spectrum of societal challenges.

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