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Efficiency-enhancing mechanisms and implementation paths of AI-driven collaborative disaster information systems

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Abstract. With natural disasters occurring with increasing frequency, the gap between macro-level situational awareness and micro-level field information can substantially reduce the efficiency of emergency logistics. Drawing on differential game theory, this study develops a multi-stakeholder model involving the government, enterprises, and the public under a cross-sector disaster information-matching framework. It compares the optimal collaborative strategies and system-state evolution under a traditional model and an AI-enabled model. The results show that the AI-enabled bidirectional information-matching mechanism can effectively alleviate information silos and logistical blind spots. In addition, both the intensity of cross-sector disaster information matching and the level of public participation significantly increase collaborative investment by the government, enterprises, and the public, thereby generating a scale amplification effect. Further analysis reveals that the collaborative benefits of the system are constrained by the costs of AI adoption. Only when the net benefits generated by Artificial Intelligence (AI) are sufficient to offset the costs of platform construction and application can participating stakeholders maintain incentives for sustained collaboration, thereby continuously improving overall emergency support performance. These findings provide a theoretical basis for breaking down information barriers in emergency logistics and optimizing emergency resource allocation and dispatch decisions.

Keywords: emergency logistics, artificial intelligence, differential game, multi-agent collaboration

1. Introduction

Against the backdrop of increasingly frequent natural disasters [1], the disconnect during emergency rescue operations between macro-level situational awareness of overall disaster conditions and micro-level on-site disaster information can easily lead to logistical blind spots and dispatch failures, thereby constraining the operational efficiency of emergency logistics [2, 3]. Based on differential game theory [4], this paper develops a differential game model involving multiple stakeholders—government, enterprises, and the public—under a cross-domain supply–demand matching scenario for disaster information [5]. It analyzes the optimal collaborative strategies of each stakeholder and the evolution of system states under both the traditional mode and the artificial intelligence-supported mode [6, 7], and examines the mechanisms through which cross-matching of disaster information, the scale of public participation, and cost-sharing affect collaborative investment in disaster information and system operational performance [8]. The results show that the bidirectional matching mechanism for disaster information supported by artificial intelligence can effectively alleviate information silos and logistical blind spots caused by information gaps [9]. The intensity of cross-domain supply–demand matching of disaster information and the scale of public participation significantly promote the collaborative investment of the government, enterprises, and the public, and exhibit a certain scale amplification effect. Further analysis indicates that the system's collaborative gains are constrained by the cost of applying artificial intelligence. Only when the net benefits generated by technological empowerment are sufficient to cover the costs of platform construction and application can the relevant stakeholders maintain the incentive for sustained participation, thereby enabling continuous improvement in the overall emergency support performance of the system [10].

Existing research on emergency logistics information collaboration and disaster data integration has mainly focused on the constraints on system effectiveness and on technological optimization pathways [3]. On the one hand, a large body of literature has examined the structural dilemmas in emergency response, pointing out that the disconnect between macro-level strategy and micro-level action is a major bottleneck restricting the effectiveness of emergency logistics [2]. To address the limitations of traditional sensing technologies, which are slow to update and unable to support refined dispatching and rescue operations, relevant studies have emphasized the urgent need to integrate micro-level distress information released by the public with trunk-line accessibility and last-mile transport capacity data held by enterprises [11]. They further argue that information heterogeneity and insufficient organizational coordination capability are major reasons why the system falls into dispatching difficulties [5]. On the other hand, some scholars have explored optimization pathways from the perspective of digital technology application, demonstrating that artificial intelligence has clear advantages in the spatiotemporal matching and semantic analysis of heterogeneous data [9, 12], and can provide critical technical support for bridging the gap between macro- and micro-level information and promoting bidirectional collaboration in disaster information [6, 7].

In addition, with regard to the driving mechanisms of multi-stakeholder collaboration, existing studies have conducted relatively in-depth analyses from the perspectives of game theory and management decision-making [13-15]. The literature generally holds that the effective integration of multisource intelligence does not occur naturally, but instead depends heavily on dynamic strategic interactions among multiple actors, including the government, enterprises, and the public [16-18]. At the same time, some frontier studies have pointed out that the introduction of emerging technologies such as artificial intelligence does not automatically resolve decision-making dilemmas, but still requires supporting mechanism design and stakeholder coordination [19, 20]. In particular, the construction and operation of digital platforms based on artificial intelligence are often accompanied by relatively high costs, and the effectiveness of such technologies has certain limits [21, 22]. As a result, collaborating actors face not only information barriers but also games over cost sharing. This cost constraint further affects how each actor balances interests among resource input, rescue timeliness, and logistics support [23].

In summary, existing studies have fully recognized the empowering value of emerging technologies such as artificial intelligence in emergency logistics information collaboration and have laid an important foundation for the design of collaborative mechanisms and implementation pathways [3, 6, 9]. However, in the practical process of breaking down the barriers between macro-level and micro-level information, there is still a lack of systematic characterization of the acquisition mechanisms of micro-level disaster data, the strategic interaction process among multiple actors, and the patterns of collaborative evolution under technological cost constraints

[10, 21]. Specifically, current research still has the following shortcomings. First, most studies mainly discuss the positive role of artificial intelligence in emergency response from a qualitative perspective [7, 12], while lacking quantitative analysis of its actual empowering effects and the constraints imposed by technology application costs. Second, with regard to collaborative actors, existing research has largely focused on unilateral government decision-making or bilateral government-enterprise interaction [5, 8, 22], while overlooking the irreplaceable role of the public at disaster sites as a source of underlying micro-level data [17], and rarely incorporating the public as a key information-supplying actor into the overall multi-stakeholder collaboration framework. Finally, in terms of research methods, most existing studies lack a dynamic analytical framework based on continuous time [4, 13], making it difficult to systematically characterize the strategic interactions among participating actors and the mechanism of system evolution in disaster environments. In particular, how the costs of artificial intelligence application constrain the equilibrium of emergency logistics systems, and how the boundaries of their economic feasibility should be defined, still require further in-depth investigation.

In view of this, this paper takes cross-domain collaboration of disaster information for improving emergency logistics efficiency as its core focus and introduces differential game theory for mathematical modeling and analysis. Differential game theory is well suited to characterizing the long-term strategic interactions among multiple participants and the dynamic evolution of system states within a continuous-time framework, which closely matches the dynamic characteristics of disaster scenarios, where the value of multisource information naturally decays over time and all parties continuously engage in intelligence integration. Specifically, this paper constructs an analytical framework for disaster information collaboration involving three parties: the government, enterprises, and the public, with the aim of alleviating blind spots in material dispatching by removing bottlenecks in information flow. First, it analyzes the optimal collaborative strategies for disaster information and the trajectories of system-state evolution under both the traditional benchmark model and the artificial intelligence-supported model. It then examines the mechanism of artificial intelligence-enabled cross-empowerment and employs comparative static analysis to investigate how key parameters, such as technology application costs and information-matching intensity, affect multi-stakeholder investment in information collaboration and the overall operational performance of emergency logistics. The findings provide theoretical support for breaking down barriers to disaster information, improving cost-sharing mechanisms for digital platforms, and optimizing emergency material dispatching decisions. At the same time, based on the conclusions of the model analysis, this paper further identifies implementation pathways for artificial intelligence-driven emergency logistics information collaboration from the perspectives of technological, organizational, and institutional coordination.

2. Model construction

To reveal the mechanisms through which disaster information collaboration helps eliminate blind spots in emergency logistics and improve the efficiency of material dispatching, this paper constructs a differential game model involving the participation of the government, enterprises, and the public based on differential game theory. This section first explains the operational logic of the emergency logistics system supported by disaster information, and then characterizes the dynamic game behaviors of each actor and the evolutionary features of system states under both the traditional benchmark model and the artificial intelligence-empowered model.

2.1. Problem description and system operational logic

This paper focuses on the emergency response and rescue stage following the occurrence of natural disasters and constructs a disaster response system jointly involving the government, enterprises, and the public [5]. In a complex disaster environment, the efficient and precise dispatch of emergency supplies depends heavily on the cross-domain collaboration and integration of multisource disaster information [2, 3]. All participating actors are key contributors to disaster relief operations within the system, and their core differences are mainly reflected in their distinct information endowments. Such differences in the dimensions of information acquisition directly affect the effectiveness of emergency logistics response.

Among them, both the government and enterprises are core actors in emergency disaster relief [22]. The government's advantage in disaster relief lies in its access to macro-level information, such as the overall disaster situation over a wide area and global dispatching arrangements, but it often lacks on-site feedback at the micro and meso levels. Enterprises involved in disaster relief, such as transportation companies, local supply providers, or technology platform firms, possess an advantage in that, through their routine operations and participation in relief efforts, they have access to meso-level operational information, including the accessibility of key logistics nodes, road traffic conditions, and regional transport capacity [11]. The public in disaster-stricken areas are not only recipients of relief supplies but also direct observers of on-site disaster conditions, and can therefore provide timely micro-level information on disaster conditions and material needs [9, 17]. Under the traditional model, the government's investment in information collaboration mainly affects the precision of the system's macro-level situational awareness, while enterprises and the public jointly influence the precision of micro-level actionable intelligence through their collaborative investment, namely the accuracy of last-mile delivery. At the same time, in the process of participating in emergency logistics support, enterprises can not only obtain potential economic and social benefits through improved collaborative efficiency, but also continuously accumulate reputational gains from fulfilling their social responsibility in emergency support [8]. Affected by the evolution of the disaster and changes in the rescue window, the precision of macro-level situational awareness, the precision of micro-level actionable intelligence, and enterprise reputation all evolve dynamically over time and exhibit natural decay characteristics. To analyze how technological means can break down information barriers, improve logistics efficiency, and generate optimal decisions under cost constraints, this paper examines two scenarios within a continuous-time framework: the traditional benchmark model and the artificial intelligence-empowered model [4, 13].

Under the traditional benchmark model, the emergency logistics system is characterized by clear information barriers. The government, enterprises, and the public each possess partial information at the macro, meso, and micro levels, respectively, but lack effective connectivity with one another [2]. As a result, each actor can only rely on its own information to carry out emergency response activities, creating a structural disconnect between macro-level dispatching and micro-level delivery, which easily leads to logistics blind spots and failures in material dispatching [3, 5].

Under the artificial intelligence-empowered model, the system introduces a disaster information collaboration platform supported by digital technologies such as artificial intelligence [12]. Through the bidirectional mapping and cross-empowerment of heterogeneous data, this platform removes bottlenecks in information flow [7, 9]. On the one hand, it aggregates the micro-level on-site information provided by the public and the meso-level operational data held by enterprises to refine the government's macro-level judgments and overall dispatching decisions [11, 19]. On the other hand, it accurately transmits the macro-level disaster situation and risk-avoidance guidance held by the government to the operational front line, helping enterprises avoid route risks and optimize delivery paths [23]. However, such digital platforms are accompanied by relatively high fixed technological and application costs, which must be jointly shared by the government, enterprises, and the public [21]. Specifically, as the leading actor, the government mainly bears the fixed construction costs associated with periodically introducing, purchasing, and deploying the platform from third-party technology providers. By contrast, the shares borne by enterprises and disaster-affected members of the public are mainly reflected in the broad usage costs incurred during platform access and use, including communication traffic expenses, system familiarization, and data authorization. This constitutes a real economic constraint on multi-stakeholder participation in emergency logistics collaboration [10].

In the differential game model constructed in this paper, it is assumed that the government, enterprises, and the public have complete information regarding the game structure, parameter settings, and strategy space, and are regarded as fully rational decision-makers seeking to maximize their long-term net benefits [4]. Specifically, the government aims to maximize the overall social utility of disaster mitigation [1], enterprises seek the long-term growth of economic returns and social reputation [8], and disaster-affected members of the public aim to maximize the protection of life and property as well as satisfaction with access to relief supplies [18]. On this basis, this paper seeks to characterize the optimal information collaboration investment strategies of each actor under the two models, reveal the effects of the artificial intelligence-enabled cross-empowerment mechanism on emergency logistics dispatch efficiency and the trajectory of system evolution, and further quantify the feasible cost-sharing threshold for technology application [14, 15].

2.2. Game model of disaster information collaboration under the traditional benchmark model

Under the traditional benchmark model without the support of artificial intelligence, although the government, enterprises, and the public all participate in emergency disaster relief operations, they are constrained by the different informational dimensions in which they operate [2, 5]. As a result, the three parties can only make independent decisions based on the partial information available to them, which creates significant information barriers in emergency logistics dispatching. Let $G_D(t)$, $S_D(t)$, and $P_D(t)$ denote the levels of disaster information collaboration input by the government, enterprises, and the public at time t , respectively. During the process of information collaboration, all three parties incur resource consumption with increasing marginal costs [4]. Their cost coefficients are denoted by χ_G , χ_S , and χ_P , respectively, and the corresponding cost functions are $\chi_G G_D(t)^2/2$, $\chi_S S_D(t)^2/2$, and $\chi_P P_D(t)^2/2$. Considering the large size of the public group, the base number of public participation nodes, N , is introduced to characterize the scale effect on the public side. The dynamic evolution of the system state is jointly determined by the information collaboration inputs of each party and the natural decay over time. Among the system states, there are significant hierarchical differences in the information endowments of the three parties. The precision of macro-level situational awareness, $D_M(t)$, represents the capability of globally coordinating and dispatching emergency supplies, and is mainly influenced by the government's macro-level information input. The precision of micro-level actionable intelligence, $D_m(t)$, represents the accuracy of last-mile material distribution and the extent to which logistics blind spots are eliminated, and is jointly determined by enterprises, which possess meso-level transport capacity information, and the public, which possess micro-level on-site information [11]. Meanwhile, an enterprise's reputation, $R_S(t)$, accumulates linearly with its effective information input during participation in disaster relief [8]. Let γ_G , γ_S , and γ_P denote the information input-output efficiency coefficients of the government, enterprises, and the public, respectively; let δ_M , δ_m , and ζ denote the natural decay rates of the above three state variables as the disaster evolves and time passes; and let ψ_S denote the efficiency coefficient by which effective intelligence is transformed into enterprise reputation. Accordingly, the state transition equations of the system under the traditional benchmark model can be expressed as follows:

$$\dot{D}_M(t) = \gamma_G G_D(t) - \delta_M D_M(t) \tag{1}$$

$$\dot{D}_m(t) = \gamma_S S_D(t) + \gamma_P N P_D(t) - \delta_m D_m(t) \tag{2}$$

$$\dot{R}_S(t) = \psi_S \gamma_S S_D(t) - \zeta R_S(t) \tag{3}$$

Over an infinite time horizon, all three parties aim to maximize their long-term net benefits and share the same time discount rate, ρ [4]. Let η_{iM} and η_{im} ($i \in \{G, S, P\}$) denote the marginal utility coefficients that each participant obtains from the precision of macro-level situational awareness and the precision of micro-level actionable intelligence, respectively, and let ω denote the marginal utility weight associated with enterprise reputation [8]. Based on the above assumptions, the objective functions of the government, enterprises, and the public under the traditional benchmark model are given as follows:

$$J_G^{DI} = \int_0^\infty e^{-\rho t}[\eta_{GM} D_M(t) + \eta_{Gm} D_m(t) - \chi_G G_D(t)^2/2]dt \tag{4}$$

$$J_S^{DI} = \int_0^\infty e^{-\rho t}[\omega R_S(t) + \eta_{SM} D_M(t) + \eta_{Sm} D_m(t) - \chi_S S_D(t)^2/2]dt \tag{5}$$

$$J_P^{DI} = \int_0^\infty e^{-\rho t}[N\eta_{PM} D_M(t) + N\eta_{Pm} D_m(t) - N\chi_P P_D(t)^2/2]dt \tag{6}$$

After the introduction of an artificial intelligence-enabled disaster information collaboration platform, the information flow and dispatching mechanism of the emergency logistics system undergo fundamental changes. The platform is no longer merely a terminal for aggregating underlying data; rather, by leveraging the technological advantages of artificial intelligence in the spatiotemporal matching and semantic analysis of heterogeneous data, it realizes the bidirectional mapping and cross-empowerment of multisource disaster information [7, 12]. Specifically, on the one hand, the platform uses natural language processing algorithms to clean, identify, and extract features from the large volume of micro-level on-site information and meso-level transport capacity data provided by the public and enterprises, thereby reversely correcting the government's macro-level situational judgment and improving the efficiency of overall material dispatching [9, 19]. To characterize this effect, θ_{AM}^A is introduced to denote the reverse correction matching coefficient of micro- and meso-level intelligence on the government's macro-level situational awareness, that is, its overall material coordination capability. On the other hand, the platform intelligently decomposes the macro-level risk-avoidance guidance and overall situational information held by the government and accurately transmits them to the operational front line, thereby helping enterprises avoid route risks and optimize delivery paths [11, 23]. To characterize this effect, θ_{MA}^A is introduced to denote the empowering matching coefficient of macro-level guidance on the precision of micro-level actionable intelligence, that is, the capability for precise last-mile delivery. In addition, the accumulation of enterprise reputational capital also benefits from the cross gains generated by artificial intelligence empowerment [8]. Based on the above mechanisms, the system state transition equations can be expressed as follows:

$$\dot{D}_M(t) = \gamma_G G_D(t) + \theta_{AM}^A(\gamma_S S_D(t) + \gamma_P N P_D(t)) - \delta_M D_M(t) \tag{7}$$

$$\dot{D}_m(t) = \gamma_S S_D(t) + \gamma_P N P_D(t) + \theta_{MA}^A \gamma_G G_D(t) - \delta_m D_m(t) \tag{8}$$

$$\dot{R}_S(t) = \psi_S \gamma_S (1 + \theta_{AM}^A) S_D(t) - \zeta R_S(t) \tag{9}$$

While obtaining the cross-empowerment gains provided by the platform, the government, enterprises, and the public must also jointly bear the construction, deployment, and operating costs of the artificial intelligence-enabled information collaboration platform, denoted by F_{AI}. Let ϕ_G, ϕ_S, and ϕ_P denote the proportions of the total platform cost shared by the government, enterprises, and the public, respectively. Accordingly, the objective functions of the three parties after this restructuring are given as follows:

$$J_G^{DA} = \int_0^\infty e^{-\rho t}[\eta_{GM} D_M(t) + \eta_{Gm} D_m(t) - \chi_G G_D(t)^2/2 - \phi_G F_{AI}]dt \tag{10}$$

$$J_S^{DA} = \int_0^{\infty} e^{-\rho t}[\omega R_S(t) + \eta_{SM} D_M(t) + \eta_{Sm} D_m(t) - \chi_S S_D(t)^2/2 - \phi_S F_{AI}]dt \tag{11}$$

$$J_P^{DA} = \int_0^{\infty} e^{-\rho t}[N\eta_{PM} D_M(t) + N\eta_{Pm} D_m(t) - N\chi_P P_D(t)^2/2 - \phi_P F_{AI}]dt \tag{12}$$

3. Model analysis

This section applies optimal control theory to solve the objective functions under the two models described above, in order to obtain the optimal disaster information collaboration input strategies of the government, enterprises, and the public, as well as the steady-state values of the system states and the optimal payoffs of each participant. For the sake of brevity, this paper omits the detailed derivation and proof of the HJB equations, and directly presents the feedback Nash equilibrium results under the two models, followed by a comparative static analysis.

3.1. Equilibrium solution of the system under the traditional benchmark model

Proposition 1: Under the traditional benchmark model, the optimal disaster information collaboration input strategies of the government, enterprises, and the public are given respectively by:

$$G_D^{*(DI)} = \frac{\gamma_G}{\chi_G}\left(\frac{\eta_{GM}}{\rho+\delta_M}\right) \tag{13}$$

$$S_D^{*(DI)} = \frac{\gamma_S}{\chi_S}\left[\frac{\eta_{Sm}}{\rho+\delta_m} + \frac{\omega}{\rho+\zeta}\psi_S\right] \tag{14}$$

$$P_D^{*(DI)} = \frac{\gamma_P N}{\chi_P}\left(\frac{\eta_{Pm}}{\rho+\delta_m}\right) \tag{15}$$

Substituting the above optimal strategies into the state dynamic equations and letting time approach infinity, the steady-state values of the system's macro-level situational awareness precision, micro-level actionable intelligence precision, and enterprise reputation can be obtained as follows:

$$D_{M\infty}^{DI} = \frac{\gamma_G G_D^{*(DI)}}{\delta_M} \tag{16}$$

$$D_{m\infty}^{DI} = \frac{\gamma_S S_D^{*(DI)} + \gamma_P N P_D^{*(DI)}}{\delta_m} \tag{17}$$

$$R_{S\infty}^{DI} = \frac{\psi_S \gamma_S S_D^{*(DI)}}{\zeta} \tag{18}$$

The optimal payoffs obtained by the government, enterprises, and the public under this model (that is, the optimal solutions to the value functions) are respectively:

$$V_G^{*(DI)} = \frac{\eta_{GM}}{\rho+\delta_M} D_M + \frac{\eta_{Gm}}{\rho+\delta_m} D_m + C_G^{DI} \tag{19}$$

$$V_S^{*(DI)} = \frac{\eta_{SM}}{\rho+\delta_M} D_M + \frac{\eta_{Sm}}{\rho+\delta_m} D_m + \frac{\omega}{\rho+\zeta} R_S + C_S^{DI} \tag{20}$$

$$V_P^{*(DI)} = \frac{N\eta_{PM}}{\rho+\delta_M} D_M + \frac{N\eta_{Pm}}{\rho+\delta_m} D_m + C_P^{DI} \tag{21}$$

Among them, C_G^{DI} , C_S^{DI} , and C_P^{DI} are constant terms independent of the state variables, representing the basic fixed returns of each participant under the traditional benchmark model.

3.2. Equilibrium solution of the system under the artificial intelligence-supported model

Proposition 2: After introducing the artificial intelligence-enabled information platform, the optimal disaster information collaboration inputs of the government, enterprises, and the public are respectively given by:

$$G_D^{*(DA)} = \frac{\gamma_G}{\chi_G}\left[\frac{\eta_{GM}}{\rho+\delta_M} + \frac{\eta_{Gm}}{\rho+\delta_m}\theta_{MA}^A\right] \tag{22}$$

$$S_D^{*(DA)} = \frac{\gamma_S}{\chi_S}\left[\frac{\eta_{SM}}{\rho+\delta_M}\theta_{AM}^A + \frac{\eta_{Sm}}{\rho+\delta_m} + \frac{\omega}{\rho+\zeta}\psi_S(1+\theta_{AM}^A)\right] \tag{23}$$

$$P_D^{*(DA)} = \frac{\gamma_P N}{\chi_P}\left[\frac{\eta_{PM}}{\rho+\delta_M}\theta_{AM}^A + \frac{\eta_{Pm}}{\rho+\delta_m}\right] \tag{24}$$

The steady-state values of macro-level situational awareness precision, micro-level actionable intelligence precision, and enterprise reputation are respectively:

$$D_{M\infty}^{DA} = \frac{1}{\delta_M}\left[\gamma_G G_D^{*(DA)} + \theta_{AM}^A(\gamma_S S_D^{*(DA)} + \gamma_P N P_D^{*(DA)})\right] \tag{25}$$

$$D_{m\infty}^{DA} = \frac{1}{\delta_m}\left[\gamma_S S_D^{*(DA)} + \gamma_P N P_D^{*(DA)} + \theta_{MA}^A \gamma_G G_D^{*(DA)}\right] \tag{26}$$

$$R_{S\infty}^{DA} = \frac{\psi_S \gamma_S (1+\theta_{AM}^A) S_D^{*(DA)}}{\zeta} \tag{27}$$

Taking into account the sharing of the total platform cost, the optimal payoffs of the government, enterprises, and the public under this model are respectively:

$$V_G^{*(DA)} = \frac{\eta_{GM}}{\rho+\delta_M} D_M + \frac{\eta_{Gm}}{\rho+\delta_m} D_m + C_G^{DA} \tag{28}$$

$$V_S^{*(DA)} = \frac{\eta_{SM}}{\rho+\delta_M} D_M + \frac{\eta_{Sm}}{\rho+\delta_m} D_m + \frac{\omega}{\rho+\zeta} R_S + C_S^{DA} \tag{29}$$

$$V_P^{*(DA)} = \frac{N\eta_{PM}}{\rho+\delta_M} D_M + \frac{N\eta_{Pm}}{\rho+\delta_m} D_m + C_P^{DA} \tag{30}$$

Among them, the constant terms C_G^{DA} , C_S^{DA} , and C_P^{DA} each include the corresponding participant's share of the total cost, namely $-\phi_i F_{AI}/\rho$ ($i \in \{G, S, P\}$), as well as the additional fixed returns generated by cross-empowerment.

3.3. Analysis of the equilibrium results

Based on the optimal feedback Nash equilibrium solutions and steady-state system values derived above, this section conducts a sensitivity analysis of key parameters and compares the differences in strategy choices among participants under different models. By extracting seven core corollaries, the following analysis explains in detail how the artificial intelligence-enabled mechanism reshapes the evolutionary trajectory of the multi-stakeholder disaster information collaboration system in emergency logistics.

Corollary 1: Compared with the traditional benchmark model, the artificial intelligence-supported model can strictly and positively improve the disaster information collaboration input levels of the government, enterprises, and the public. That is, $G_D^{(DA)} > G_D^{(DI)}$, $S_D^{(DA)} > S_D^{(DI)}$, and $P_D^{(DA)} > P_D^{(DI)}$ all hold.

Corollary 1 indicates that the cross-matching empowerment of artificial intelligence fundamentally reshapes the marginal incentive structure of all participants. Under the traditional model, each party can obtain only a single type of return from improvements in information within its own domain, resulting in a serious lack of motivation for collaboration. After the introduction of artificial intelligence, the reverse correction function enabled by underlying micro-level on-site information and meso-level transport capacity data greatly stimulates enterprises and the public to move beyond their local information hierarchy and provide high-quality intelligence. At the same time, the downward empowerment function of macro-level risk-avoidance guidance effectively removes the government's micro-level blind spots in material dispatching, prompting the government to increase its investment in trunk-line logistics coordination and information collaboration. This cross-domain empowerment mechanism allows all parties, while pursuing the maximization of their own interests, to objectively generate significant positive externalities, thereby achieving an overall leap in logistics information collaboration strategies.

Corollary 2: The introduction of artificial intelligence can effectively alleviate blind spots in emergency logistics and improve the steady-state levels of both macro-level situational awareness precision and micro-level actionable intelligence precision in the system; that is, $D_{M\infty}^{DA} > D_{M\infty}^{DI}$ and $D_{m\infty}^{DA} > D_{m\infty}^{DI}$. In addition, enterprise reputation is also enhanced, as reflected by $R_{S\infty}^{DA} > R_{S\infty}^{DI}$.

Corollary 2 shows that merely increasing the resource input of a single actor cannot break through the structural bottlenecks created by information silos. A comparative static analysis of the steady-state values of the state variables under the two models clearly shows that the steady-state system outcomes under the artificial intelligence-supported model are strictly superior to those under the traditional benchmark model. In other words, the artificial intelligence-supported model not only comprehensively improves the precision of macro-level situational awareness and micro-level actionable intelligence, but also significantly enhances the steady-state level of enterprise reputation in emergency support. This is because artificial intelligence constructs a closed-loop system of bidirectional flow between "macro-level coordination" and "micro-level distribution" through the spatiotemporal matching and semantic analysis of massive volumes of heterogeneous data. This closed-loop mechanism not only amplifies the output efficiency of initial information inputs, but also accelerates the evolution of system states through a cross-empowerment multiplier effect, ultimately achieving a higher level of material dispatch accuracy, last-mile logistics accessibility, and enterprise social capital accumulation over an infinite time horizon.

Corollary 3: The information collaboration input levels of the government, enterprises, and the public are each strictly positively correlated with their corresponding artificial intelligence cross-empowerment matching coefficients; that is, $\partial S_D^{(DA)}/\partial\theta AM^A > 0$, $\partial PD^{(DA)}/\partial\theta AM^A > 0$, and $\partial GD^{*(DA)}/\partial\theta_{MA}^A > 0$.

Corollary 3 indicates that the larger the reverse correction matching coefficient of micro- and meso-level intelligence on the government's macro-level situational awareness, the stronger the willingness of enterprises and the public to invest in collaboration. Similarly, the higher the empowering matching coefficient of the government's macro-level risk-avoidance guidance on micro-level last-mile delivery actions, the greater the government's level of collaborative investment. From the perspective of emergency logistics management practice, this means that the precision of artificial intelligence algorithms and their data mining capability directly determine the depth of multi-stakeholder logistics collaboration. The cleaner the platform's data processing and the more accurate the extraction of material shortages and transport capacity characteristics, the smaller the loss in cross-level information transformation, and the greater the marginal utility that all parties can obtain from cross-domain empowerment in logistics dispatching. This, in turn, creates a virtuous cycle of "higher algorithmic precision—greater collaborative investment."

Corollary 4: The base number of public participation nodes not only positively drives the collaborative input strategy of the public itself, but also has a significant scale amplification effect on the steady-state level of micro-level actionable intelligence in the system; that is, $\partial P_D^{*(DA)}/\partial N > 0$ and $\partial D_{m\infty}^{DA}/\partial N > 0$.

Corollary 4 reveals that the scale of bottom-level micro disaster information provided by the public directly constitutes the foundational basis on which the artificial intelligence platform can realize the value of data fusion. As first-hand witnesses at disaster sites and recipients of relief supplies, members of the public have their participation node base embedded as a multiplier term in the optimal strategy and micro-state evolution equations. In the early stage of an emergency, when professional logistics rescue forces are often unable to achieve full coverage quickly, broadly mobilizing affected residents to use mobile smart terminals to upload fragmented disaster information and material demand clues can rapidly expand the underlying data pool. After being refined by artificial intelligence algorithms, the scale effect of data under this crowdsourcing model can be converted into high-value micro-level actionable intelligence at a very low marginal cost, thereby effectively compensating for the information vacuum in last-mile distribution before enterprise transport capacity has been fully deployed.

Corollary 5: The marginal utility weight of enterprise emergency support reputation and the efficiency of reputation transformation can significantly incentivize enterprises' collaborative investment, and this incentive effect is further amplified under the artificial intelligence model; that is, $\partial S_D^{*(DA)} / \partial \omega > 0$, and the relevant derivative is larger when it contains the empowerment multiplier $(1 + \theta_{AM}^A)$.

Corollary 5 indicates that enterprise participation in emergency rescue not only reflects social responsibility, but also involves the long-term consideration of accumulating corporate social capital. The equilibrium results show that the optimal collaborative input of enterprises is positively proportional to both the marginal utility weight of reputation and the efficiency with which effective intelligence is transformed into reputation. More importantly, under artificial intelligence support, this reputation incentive mechanism is further magnified by the leverage effect of the empowerment matching coefficient. This is because digital platforms improve the efficiency with which enterprises' meso-level transport capacity data are transformed into global material dispatch information, making their support efforts in trunk-line and last-mile rescue more easily perceived and quantitatively evaluated by the government and society. This increase in visibility strengthens the speed of reputational capital accumulation, thereby giving enterprises a stronger intrinsic motivation to overcome technological cost constraints and to continue participating in emergency logistics information collaboration.

Corollary 6: The natural decay rates of disaster information and enterprise reputation exert significant negative effects on the optimal collaborative input strategies of the government, enterprises, and the public, as well as on the steady-state precision of the system. In other words, the passage of time accelerates the dissipation of information value.

Corollary 6 indicates that if disaster and road condition information obtained at an early stage is not continuously updated, its value in guiding last-mile delivery and material dispatching will decline rapidly. Because disaster evolution is highly time-sensitive and volatile, the decay-rate parameters appear in the denominators of the analytical expressions for the optimal input strategies of all participants. This means that the faster information becomes outdated, the higher the marginal cost required for all parties to maintain the same level of logistics support precision, which in turn weakens their incentives for sustained investment. This finding, from the opposite perspective, further confirms the importance of using artificial intelligence technology to update data in real time. Only by relying on algorithms to refresh situational conditions and transport capacity at high frequency, thereby offsetting the negative impact of natural decay, can emergency logistics dispatching be consistently carried out on the basis of the most up-to-date and accurate intelligence.

Corollary 7: The marginal cost coefficients of information collaboration negatively constrain the willingness of each participant to invest, but the cross-matching gains generated by artificial intelligence can, to a certain extent, offset this cost-suppressing effect and promote the convergence of the emergency logistics system toward a more optimal equilibrium.

Corollary 7 shows that excessively high resource consumption and information collection costs are the core obstacles hindering multi-stakeholder collaboration in emergency logistics. The input strategy of each participant is strictly inversely proportional to its corresponding cost coefficient. However, under the artificial intelligence-empowered model, the introduction of the cross-matching mechanism substantially increases the marginal utility of collaborative input. This means that even when the cost of a single round of information collection remains unchanged, the empowering effect of artificial intelligence can still generate greater material dispatch returns per unit of input, thereby mathematically diluting the negative impact of marginal costs. In addition, from an economic perspective, the artificial intelligence-enabled information collaboration platform has the characteristics of a quasi-public good. Without a reasonable cost-sharing mechanism, the high fixed costs of platform construction are very likely to induce free-riding behavior by enterprises and the public, which may in turn cause system collaboration to stagnate. This finding provides important theoretical support for exploring the economic feasibility of applying digital technologies to emergency logistics.

4. Reflection on real-world scenarios and discussion

In July 2021, Zhengzhou, Henan, and other areas were hit by an extreme heavy rainfall event, which led to concentrated problems such as urban waterlogging, road blockages, and communication disruptions, placing considerable pressure on emergency rescue and material dispatch [12]. After the disaster, relevant government departments quickly organized the overall allocation of relief supplies, road clearance, and communication restoration. However, because on-site disaster conditions changed rapidly and local demand information was highly fragmented, there was at one point a lack of smooth coordination between macro-level dispatching and end-point demand [2]. This case corresponds closely to the model developed in this paper. Government departments possessed macro-level disaster information and overall dispatch information, transportation support forces held information on road accessibility and transport capacity organization, and affected residents were the first to perceive on-site disaster conditions and material needs [5, 11]. When road disruptions and communication failures occurred simultaneously, gaps easily emerged among different levels of information, thereby causing logistics blind spots and dispatch deviations [3]. This is essentially consistent with the disconnection between macro-level situational awareness and micro-level on-site information depicted in this paper. Publicly available materials show that digital technologies such as satellite remote sensing monitoring, airborne emergency communications, and thematic data sharing were mainly used in the post-disaster response. For example, relevant institutions used satellite imagery to monitor disaster-stricken areas and shared multiple categories of thematic data resources [19]. At the same time, partial communication coverage was restored through airborne emergency communication platforms, which improved on-site information transmission and rescue coordination capacity. At the practical level, the Zhengzhou case reflects the logistics blind spot problem that may arise from information gaps under traditional emergency conditions. Meanwhile, the intervention of digital technologies in this case also provides practical support for this paper's analysis of how technological empowerment can improve information collaboration [6].

From the perspective of the model developed in this paper, when there is a lack of effective connectivity among the public's micro-level distress information, enterprises' road and transport capacity information, and the government's macro-level dispatch information, the system is prone to logistics blind spots. By contrast, when digital technologies such as satellite remote sensing, emergency communications, and thematic data sharing are introduced, the efficiency of cross-level information matching improves significantly [9]. This is consistent with the conclusion of this paper that artificial intelligence-enabled cross-empowerment can enhance both macro-level situational awareness precision and micro-level actionable intelligence precision [7]. At the same time, this case also shows that the effectiveness of digital technologies depends on such conditions as communication restoration, platform access, and multi-stakeholder coordination. From a practical perspective, this confirms this paper's analysis that the effects of technological empowerment are constrained by application costs and institutional support [10, 21].

5. Conclusions and managerial implications

5.1. Research conclusions

By constructing a differential game model of disaster information collaboration involving multiple stakeholders—government, enterprises, and the public—this paper comparatively analyzes the strategic choices and state evolution trajectories of the emergency logistics system under the traditional benchmark model and the artificial intelligence-supported model, and further explores the impact mechanisms of artificial intelligence empowerment. The main findings are as follows.

First, the introduction of artificial intelligence reshapes the incentive structure of the emergency logistics information collaboration system. By leveraging the technological advantages of artificial intelligence in the spatiotemporal matching and semantic analysis of heterogeneous data, the system realizes a bidirectional closed loop in which micro-level on-site information and meso-level transport capacity data are aggregated upward, while macro-level risk-avoidance guidance is empowered downward. This cross-matching mechanism greatly overcomes the limitations of single-domain information and significantly enhances the willingness of the government, enterprises, and the public to invest in information collaboration.

Second, artificial intelligence empowerment can effectively alleviate information silos and reduce emergency logistics blind spots caused by information gaps. Compared with the structural dilemma under the traditional model, where macro-level strategy is disconnected from micro-level action, the precision of macro-level situational awareness and micro-level actionable intelligence under the artificial intelligence-supported model can both reach higher steady-state levels. This indicates that technological empowerment helps relieve bottlenecks in information dispatching, thereby significantly improving the accuracy of overall emergency material dispatching and the efficiency of last-mile distribution.

Third, the collaborative gains of the system are strictly constrained by the cost threshold of artificial intelligence application. Although artificial intelligence can bring substantial performance improvements to emergency logistics, if the high costs of platform construction and computing operations are entirely shifted onto social actors such as enterprises, their incentives for sustained participation may be seriously weakened. Only within a reasonable range of total cost-sharing proportions—that is, when the net benefits of the technology are sufficient to cover the costs of platform construction and application—can the overall emergency logistics support performance of the system continue to improve.

5.2. Implementation pathways

Based on the results of the preceding model analysis, the realization of artificial intelligence-driven information collaboration in emergency logistics does not depend solely on technological embedding, but rather requires gradual advancement along the path of "multisource data aggregation–intelligent platform coordination–institutional mechanism support." First, at the data aggregation level, a disaster information collection network involving the joint participation of the government, enterprises, and the public should be established. Specifically, the government should primarily provide global information such as the overall disaster situation, key support areas, and allocation directives; enterprises should mainly provide meso-level operational information such as road accessibility, warehouse inventories, transport capacity organization, and the status of distribution nodes; and the public should rely on mobile terminals to provide timely feedback on micro-level information such as disaster locations, material needs, on-site hazards, and rescue outcomes. In this way, a multi-level information supply system covering the macro, meso, and micro levels can be formed.

Second, at the platform coordination level, an intelligent disaster information processing and collaborative decision-making platform should be established based on artificial intelligence technologies. Through the real-time collection, cleaning and identification, semantic extraction, cross-matching, and dynamic feedback of multisource heterogeneous information, the platform can realize the reverse correction of macro-level dispatch judgments by micro-level on-site information and meso-level transport capacity data, as well as the precise empowerment of last-mile distribution actions by macro-level risk-avoidance guidance and overall allocation information. In doing so, it can open up a closed-loop chain of "perception–assessment–dispatch–execution–feedback."

Finally, at the institutional support level, a multi-stakeholder cost-sharing and incentive-constraint mechanism compatible with platform operation should be established. The government should assume responsibility for platform construction, rule formulation, and the integration of core resources; enterprises should undertake responsibilities for transport capacity coordination, node response, and data access; and the public should continuously provide on-site disaster and demand information through low-threshold participation mechanisms. At the same time, supporting institutional arrangements regarding information authorization, privacy protection, contribution recognition, reputation incentives, and performance evaluation should also be improved to ensure that the empowering effects of technology can be transformed into sustainable emergency logistics collaboration capabilities. Therefore, the implementation path of artificial intelligence-driven emergency logistics information collaboration can be summarized as follows: using multisource data access as the foundation, intelligent platform linkage as the hub, and cost-sharing and incentive-constraint mechanisms as the guarantee, so as to gradually form a collaborative operational system for the efficient circulation of cross-level disaster information and the precise dispatch of emergency supplies.

5.3. Managerial implications

Based on the above findings, this paper proposes the following managerial implications for breaking down information barriers in emergency logistics and optimizing material dispatching decisions.

First, the government should play a leading role by increasing investment in digital infrastructure for emergency logistics and in artificial intelligence computing platforms. Because the artificial intelligence-enabled cross-empowerment mechanism of disaster information generates significant positive externalities, the government can effectively dilute the marginal information collaboration costs borne by enterprises and the public by assuming the core fixed costs of platform construction. In doing so, it can induce social actors to increase their provision of bottom-level data and their investment in transport capacity coordination, thereby achieving a substantial improvement in both macro-level material coordination and micro-level last-mile distribution.

Second, greater efforts should be made to improve the cross-domain matching accuracy of artificial intelligence algorithms and their capacity for heterogeneous data mining. In emergency logistics management practice, emphasis should be placed on deep feature extraction from fragmented material demand information provided by the public and meso-level transport capacity operation data provided by enterprises, so as to strengthen the efficiency with which cross-level logistics information is transformed by improving the effectiveness of information cross-matching. This will in turn create a virtuous cycle in which algorithmic iteration and optimization reinforce the depth of logistics collaboration, ensuring that emergency dispatching is always carried out on the basis of the most up-to-date and accurate intelligence.

Finally, a sound long-term mechanism for multi-stakeholder benefit distribution and incentives should be established. Full use should be made of the leverage effect of enterprise emergency support reputation as a form of social capital, and the information contributions made by enterprises in rescue support activities such as trunk-line transportation and last-mile material distribution should be quantitatively evaluated and publicly displayed. By increasing visibility, the intrinsic motivation of relevant enterprises to continue participating in disaster information collaboration can be strengthened, thereby providing support for the long-term sustainable operation of transport capacity dispatching and the emergency logistics system.

5.4. Research limitations and future prospects

Although this paper examines the disaster information collaboration game among the government, enterprises, and the public in continuous time, it does not fully take into account the disturbance effects of sudden dynamic shocks during disaster evolution—such as road blockages caused by secondary disasters—on the emergency logistics network and system parameters. Future research may introduce a stochastic differential game model to further investigate the adaptive adjustment paths of the artificial intelligence empowerment mechanism under uncertain environments. In addition, this paper is based on the assumptions of complete information and full rationality, and does not yet consider such factors as incomplete information, bounded rationality, and behavioral biases in real disaster scenarios. These issues also merit further study in the future.

Authorship

Jie Leng and Fengyang Li contributed equally to this work and should be considered co-first authors.

Jie Leng: Conceptualization, Methodology, Writing – original draft. Fengyang Li: Formal analysis, Validation, Writing – review & editing. Bozheng Xu: Data curation, Software, Visualization. All authors have read and agreed to the published version of the manuscript.

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