An Agent-based Exploration of Information Sharing for Adaptation in Crisis Response

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ABSTRACT

Humanitarian and military organizations face deeply uncertain, continuously changing environments due to disasters and conflict. Information sharing is vital to adapt to these disruptions effectively and ensure the timely availability of essential equipment and supplies anywhere in the world. However, little is known about the role of information sharing in adapting to a changing environment. We use an agent-based discrete-event simulation to study information-sharing mechanisms, specifically delayed information-sharing behavior, and analyze how they impact the adaptation of decision-making structures over time. Drawing upon adaptation models from literature, we develop a model in which agents share information and endogenously create these structures. We experiment with various levels of information delays in dynamically changing environments and assess how this affects adaptation and performance. Our findings unveil that horizontal delays lead to earlier hierarchical expansion and vertical delays slow decision-making in crisis response environments.

Keywords

Adaptation, delayed information, information-sharing behavior, agent-based simulation, coordination

INTRODUCTION

For both military and humanitarian organizations, the timely availability of essential equipment and supplies anywhere in the world is vital. A key challenge herein is adapting to an uncertain, complex and continuously changing environment. Many humanitarian supply chain studies endorse adaptive change and flexibility to manage uncertainty (Baharmand et al., 2017; Oloruntoba & Gray, 2006; Van Wassenhove, 2006). Most of these studies propose that demand can be met by adapting routes, schedules, or facility locations

Effective adaptation relies on information. Humanitarian and military supply chain members must decide what, when, and how to adapt based on the information available to them. In crisis response, this information is often imperfect (Day et al., 2009). For example, it can be inaccurate, delayed, incomplete, or even excessive, leading to information overload. When overwhelmed with information, actors may neglect or discard critical details (Kleinberg & Marsh, 2020).

In addition to the quality of information, the potential for complications or failures can also lie in information behavior. For example, conventionally, it is assumed that if actors have information about improving or adapting, they will act upon it. In emergencies, decision-makers must interpret the information quickly and make decisions rapidly, which has been shown to lead to biases and errors (Paulus et al., 2022). Eisenhardt and Bourgeois (1988) and Tversky and Kahneman (1974) show that time pressure changes information processing and risk preference.

Overall, information is a driver of adaptation, specifically in a humanitarian and military context. However, effectively sharing information for adaptation can be challenging in practice. The Dutch Ministry of Defense faced such challenges. In our collaboration, we observed how information delays and decision-making constraints affect the speed and effectiveness of adaptation. However, most existing studies neglect the behavioral aspects of information sharing. Simulation modeling offers a way to systematically analyze how information sharing affects adaptation. Yet, current models rarely integrate behavioral aspects or consider information delays, even though these factors are critical for understanding adaptation speed.

Therefore, this study aims to develop and use a model to explore the effect of delayed information on adaptations in crisis response management. We draw on simulation models from literature to develop a model in which actors share information to make decisions for adaptations. The actor's information sharing follows behavioral rules (e.g., sharing or not, delaying or not). The modeled environment dynamically changes because the supply needs that must be fulfilled follow a dynamic pattern. Given various levels of information-sharing and delaying behavior, we assess how these dynamic environments lead to adaptations and system's performance.

The remainder of this paper is structured as follows: The section Background discusses related work. The section Methods and Materials describes the agent-based discrete-event simulation model and experimental setup. The section Initial Findings and Future Work presents the preliminary and expected results.

BACKGROUND

Adaptation in a humanitarian and military context

Adaptation refers to adjusting the existing system in response to an actual or expected change or disruption (Wieland et al., 2023). To thrive despite disruptions, actors and organizations must *rapidly* adapt their supply chains to maintain viability (Sardesai & Klingebiel, 2023). Viability for military and humanitarian organizations means being able to keep distributing the supplies anywhere in the world in time despite a changing environment. Thus, these organizations must adapt their supply chains as part of their operations.

Existing literature in humanitarian operations management highlights flexibility, agility, and responsiveness (Jahre & Fabbe-Costes, 2015; Van Wassenhove, 2006). The studies focus primarily on adaptations of locations, routes, or schedules in supply chains. However, these studies overlook the underlying behavioral mechanisms driving adaptation. Policy analysis introduces adaptive planning as a strategy for pre-planned, iterative adaptations (Kwakkel et al., 2015), though this assumes decision making without any biases. Research revealed that decisions under uncertainty and time pressure, as is often the case in crisis response, are prone to biases (Tversky & Kahneman, 1974). Organizational constraints further complicate adaptation. Humanitarian and military organizations are bureaucratic institutions, limiting their capacity for dynamic change. Short operational cycles and rigid structures can lead to delayed or suboptimal adaptations (Baharmand et al., 2017).

Adaptation frameworks from Altay and Pal (2023) and Comes et al. (2020) demonstrate that adaptation is a dynamic process. Altay and Pal (2023) introduce a response-to-disruption framework that includes evaluating resources, which help explain how adaptations evolve from the initial recognition of a disruption to later adaptations. Comes et al. (2020) present a framework in which they picture the feedback loop between information, decision making and adaptation in an evolving crisis environment. They conclude that actors also adapt their own information-sharing and decision-making structures.

Information in humanitarian and military contexts

Information flows are indispensable to functioning supply and distribution disaster relief chains because the actors depend on each other. Therefore, actors must share information inter- and intra-organizationally. Information flows entail the evolving information on the predicted demand from end users and the state of the infrastructure to be matched with the available supplies and capacities. In these contexts, while information is often highly volatile (Van Wassenhove, 2006), the quality of information is critical for the effectiveness of the response (Altay & Pal, 2014).

Information is a driver for adaptation because information is input for coordination decisions on how to adapt the humanitarian supply chains, for example, to reallocate the resources. Comes et al. (2020) argued that the combination of uncertainty and time pressure leads to significant delays in adaptation. They advocate studying how informational use and adaptation behavior on the micro-level lead to the emergence of structures at a systems level.

Apart from the information itself, the information behavior of actors can also lead to non-optimal decisions. In response to disasters and wars, information is collected, checked, processed, and shared to adapt and respond (Zhang et al., 2002). Reliability and verifiability of the information are essential for collecting (Van De Walle & Comes, 2015). Timeliness of the information is vital for using the information and making decisions on time (ibid) as it refers to the availability of information at a time suitable for its intended use (Bailey & Pearson, 1983). Despite its vital role, behavior in each of these steps can be biased. Paulus et al. (2022) show that decision making is hampered by biases in information processing, especially under time pressure.

Recent studies, e.g. (Behl et al., 2023; Day, 2014) have begun exploring information sharing and behavioral factors in humanitarian operations. Adsanver et al. (2024) argues, however, that the behavioral mechanisms of information sharing, particularly those related to information-sharing and coordination, still warrant further investigation.

Conceptualisation

Our conceptual framework (Figure 1) serves as the foundation for our model. With this framework, we build on ideas from the adaptation frameworks of Altay and Pal (2023), Comes et al. (2020) and Ivanov et al. (2010). These frameworks recognize that structures can be endogenously created. Ivanov et al. (2010) developed a conceptual framework in which they addressed various adapting structures (e.g., organizational, informational, and physical). The informational structure determines the structures of information sharing; the organizational one determines the structure of managers and workers. These structures interrelate with each other and change in dynamics (ibid).

In our framework, the environment (input) affects the structures and the behavior (relations within the model), resulting in the performance indicators (output). We conceptualize adaptation as a dynamic process driven by information sharing (Altay & Pal, 2023; Comes et al., 2020). The dynamic environment involves the changing formation of supply needs, which triggers the information sharing to decide about (re)allocation of resources and adaptation of internal structures. The adapted structures influence decision making, shaping performance outcomes that, in turn, drive further adaptations. The performance is measured by reliability, the cost of the structures and the speed of adaptation. Since the amount and characteristics of supply needs vary over time, adaptation remains a dynamic process rather than a one-time change. The effectiveness of adaptation depends on timely information sharing, as timely information enhances effective decision making and resource allocation, while delays or biases hinder it. As visualized in Figure 1, information sharing and decision making moderates the relationship between adaptive changes and system's performance.

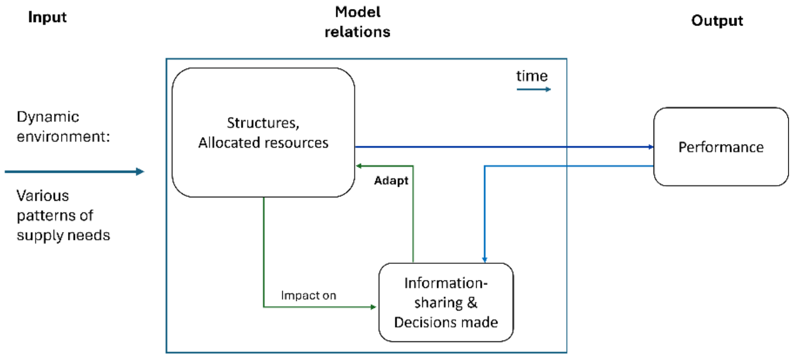


Figure 1 Conceptual adaptation framework

Modeling

Disaster relief networks can be viewed as complex adaptive systems (Day, 2014, Schiffling et al., 2022). Agent-based modeling is considered suitable for simulation of these systems (Epstein, 2006; Gilbert & Troitzsch, 2005). Agent-based modeling is applied in crisis response management for different problems, including collecting information (Altay & Pal, 2014) and dynamic disaster relief distribution (Fikar et al., 2018). Agent-based models capture (i) the dynamic nature of information flows and handling in response to disruptions, (ii) the emergence of phenomena, and (iii) describe systems comprehensively from the micro-level, representing agent behavior, to the macro-level, emerging phenomena at the systems level (Crooks & Heppenstall, 2012). The discrete event simulation technique allows us to efficiently manage the timing and duration of the information activities and delays.

Agent-based modeling studies in adaptation and information flows

In Epstein's agent-based adaptation model (Epstein, 2006), individual agents share information to make decisions, and adapt to changing patterns of supply needs and endogenously generate structures (e.g., local hierarchies). Though this model originates from organizational adaptation, the dynamics and structures are aligned with Ivanov's multi-structural adaptation framework (Ivanov et al., 2010). However, Epstein (2006) assumes information and information sharing to be perfect, and sharing information does not take time. We incorporate various parameters affecting the duration of information-related activities in our model.

Over the past decade, few agent-based models have been developed that capture information flows in humanitarian and military operations. Altay & Pal (2014) developed a model of post-disaster information diffusion between international and regional NGOs. They concluded that information quality is critical for the effectiveness of the response. They advised incorporating the topology of agents, which we do by using a hierarchical structure of managers and workers. Bateman and Gralla (2017) developed Altay's model further to investigate the effect of individual information-sharing interactions and evaluate strategies on information management in an intra-organizational setting. They found that willingness to share information does not, in their model and in contrast with the findings of Altay's model, significantly affect information acquisition in the focal organization. They conclude that holding regular meetings to collect sufficient information for decision making is advantageous. We incorporate the willingness to share information and team meetings for coordination.

Fikar et al. (2018) developed a support system for aid organizations to decide on the optimal distribution locations and vehicle types, while residents spread information and move to another distribution location. Their results indicate that considering transport disruptions and residential information sharing in planning procedures is essential. They proposed researching information that is shared incorrectly during evolving events to better understand its impacts. We study the effects of imperfect information by considering how delays in information sharing influence adaptation.

Krejci (2015) proposed a simulation model which combined agent-based modeling with discrete event simulation (ABM-DES) for investigating behavior of humanitarian supply chain actors to determine how and whether specific coordination mechanisms enable better effectiveness over time. The model entails two parts. The DES part simulates how the materials and information flow through a supply network. The ABM represents the horizontal and vertical coordination mechanism development process among international and local NGOs. Krejci implemented two coordination mechanisms: transportation coordination and information sharing. We also use a horizontal and vertical mechanism in our model and combine ABM with DES techniques.

In summary, there is a lack of models that examine the impact of information delays on adapting systems operating in crisis response environments. Our model builds on several concepts and extensions suggested in the humanitarian and military literature. It incorporates imperfect information shared within the system, as suggested by Altay and Pal (2014) and Fikar et al. (2018). The model also includes both vertical and horizontal coordination mechanisms (Epstein, 2006; Krejci, 2015). As Bateman and Gralla (2017) proposed, a specific coordination mechanism in our model is meetings. Additionally, our model features a structured topology of agents (Altay & Pal, 2014).

Insights from the Dutch Ministry of Defense

Our collaboration with the Ministry of Defense provided insights into how actors shared information and adapted in response to operational and more strategic disruptions. The first author had the opportunity to observe the distribution and transport command during three military training exercises (operational) and at the Central Staff (strategic). At the strategic level, the Dutch Ministry of Defense faces the challenge of adapting to a severe heightened threat level, after two decades of peace during which budgets declined and a new control and safety system emerged. The Ministry is increasingly focused on understanding how their adaptation speed can be enhanced ensuring a more effective response to significantly more severe crises. The observations highlighted the necessity to model various patterns of disruptions, including a severe crisis causing a regime shift and an environment with peaks. Furthermore we identified adaptation speed as a key metric.

MATERIALS AND METHODS

We use an agent-based model (ABM-DES) to explore the impact of information delays and information sharing behavior on adaptation. It is a pattern-oriented, theoretical model. However, it is inspired by and uses insights gained from the real-world collaboration with Defense. As the crisis response system is such an information-rich complex system, each model will fail to include relevant factors or become over-parameterized and lose power (Grimm et al., 2005). With pattern-oriented modeling, an approach to analyze complex systems, we attempt to focus only on specific critical patterns in the real system. In particular, we isolate the information-sharing and decision-making mechanisms in our crisis response system. Discrete event techniques ensure efficiently manage the timing and sequence of the activities.

Model

The purpose of the model is a theoretical exploration of the effect of information delays on the adaptation of the system's structures and its performance. The idea underlying the model is that managers share information to reallocate workers and adapt their information-sharing and decision-making structures if they consider their performance to be inadequate. We do not focus on the physical supply chain structures but we focus on a pooled dependency of resources. The information involves demand (i.e., arising supply needs) and supply (i.e., the available workers).

The core of our model is based on Epstein's adaptation model (Epstein, 2006) because this model entails critical elements as vertical and lateral information sharing, and managers who adapt by reallocating resources in response to the changing supply needs. We extend this model to capture information delays. To give an overview of the model, we describe the input, i.e., the supply needs, the relations between the managers and workers within the model, and the calculated output. The model entails supply needs, managers, workers and desks. The most important processes of the model are a) a new batch of supply needs flows to the desks, b) each manager with decision authority reallocates the workers within its control and shares information to reallocate outside of its control, c) a team meeting is held in which the actual exchange of workers takes place d) the workers fulfill the supply needs. The processes are repeated according to their agent-dependent time schedule.

Input of the model

The input of the model consists of supply needs. Supply needs arise each time unit and flow to separate desks. Supply needs have state ‘idle’, 'in queue’, 'delayed', 'missed', or 'processed'. Supply needs are generated in batches. The batch size follows a distribution with a maximum value and is much smaller than the number of desks. A probabilistic parameter determines whether a supply need within the batch does not flow to a specific desk which leads to small variations in the batch size each time unit. The batch patterns form the stable (formation 1) and dynamically changing environments (formation 1, 2 and 3): Formation 1 conceptualizes an environment with a disruption during a short period, formation 2 is a gradually evolving, continuously changing environment, and formation 3 is a regime shift. In Formation 0, the stable environment, the batch of supply needs flows to the same set of desks as the previous time unit, see Figure 2. In this figure, a batch is represented as a column of blue balls. Formation 1 is an environment where disruptions occur during short periods, conceptualized by peaks in demand. The peaks are conceptualized by an additional number of supply needs. Each supply need takes priority and flows to desks that are directed to desks next to those used in the stable environment. The gradually evolving environment (Formation 2) is conceptualized by a new batch of supply needs flowing to a set of desks slightly different from the previous time unit. For example, the first batch of supply needs flows to desks 1 to 12, the second to 2 to 13, and so on. Formation 3 is the environment with a regime shift, where an abrupt change occurs. Pre-shift is a stable environment. Post-shift, all supply needs in a batch are queued into the different set of desks, leading to a substantially different but again stable situation. For example, pre shift, the supply needs are used in peace keeping situations, post-shift the supply needs must be used in large-scale conflicts.

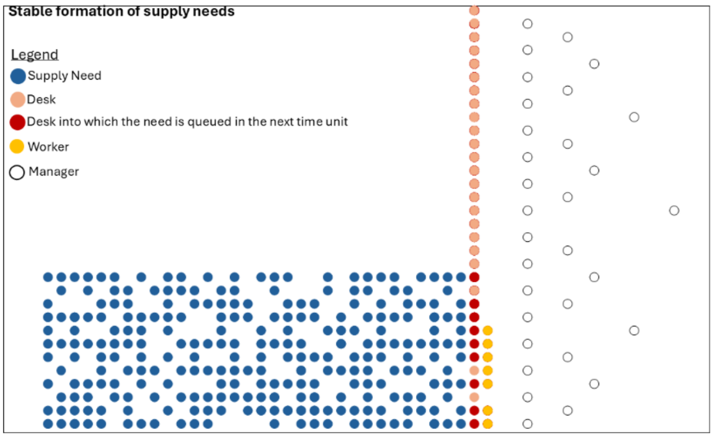


Figure 2 An illustration of the stable environment and the complete hierarchy of potential managers

Relations within the model

Workers have no autonomy; they cannot choose at which desk they operate or which supply need to fulfill. They perform the first supply need in the desk’s queue they are allocated to. Thus, they are treated as resources. The number of workers is smaller than the number of desks, creating a resource allocation challenge.

Desks represent specific control spaces or areas of responsibility where supply needs are collected and managed. Desks each have a queue in which the supply needs wait before being fulfilled by the workers. Each desk is managed by a single manager. If the need remains longer than allowed in the queue (parameter 'max_delay'), its state changes to 'missed'. A supply need is only fulfilled if a worker is at the desk.

Managers reallocate workers across desks within their fixed set of desks (their span of control), share information with managers at the same level to reallocate with others and adapt the information-sharing and decision making structure. Although each desk is managed by one manager, the management structure is organized into a five-level hierarchy, where higher-level managers oversee a progressively larger span of control (2^{level}). For example, managers of level 3 control of a maximum of 8 desks. Figure 2 visualizes this potential hierarchy of managers. The group of managers with decision authority is not fixed – it can change as the decision-making structure adapts through the Upward and Downward mechanisms. To capture this behavior, we use the following four mechanisms (Table 1).

Table 1 Manager's information-sharing and decision-making mechanisms

Mechanisms	Description
Reallocation mechanism	Managers reallocate their idle workers to the desks which have need(s) in queue but no worker within their span of control.
Upward mechanism	If after 'upward_inertia' time units, manager i still has performance level P > Tmax (threshold_max), then he informs his direct higher-level manager about the lagging performance and transfers his decision authority to his direct higher-level manager.
Downward mechanism	If after 'downward_inertia' time units, manager i still has performance level P < Tmin (threshold_min), then his direct subordinate managers at the lower level receive back their decision authority and will start to share information with their peers.
Same-level information mechanism	1. If the performance level P is higher than a threshold (threshold_max), the manager calls for resources (workers) considering his 'barrier_to_ask'. 2. Else, if the performance level P is lower than a threshold (threshold_min), the manager supplies its resources (workers), considering his 'barrier_to_give'.

First (the reallocation mechanism), a manager (re)allocates its workers to desks within his own span of control. Then he calculates his current performance level (P), which is the sum of the missed supply needs divided by the manager's memory length. Second, if the performance level exceeds the maximum threshold (Tmax) for 'upward_inertia' periods, he transfers his decision authority to a higher-level manager for further action. Third (the downward mechanism) , if the performance level falls below the minimum threshold for 'downward_inertia' periods, the decision authority is transferred to his subordinate managers. Fourth, the same level information mechanism: If the performance level exceeds the maximum threshold (Tmax), he calls for workers considering his barrier to share information ('barrier to ask') and creates a list of supply needs to be fulfilled. In formation 1, the list is sorted by priority, with prioritized supply needs placed first. If the performance level is lower than the Tmin, he creates a list of his available workers considering his barrier to share information ('barrier to give').

During a team meeting with peer managers, the two lists of a) available workers and b) desks without workers but with supply needs are matched, leading to the actual reallocation of workers. Team meetings can be scheduled aligned with the emergence of supply needs and the manager's schedule, or they can be held at longer intervals—which introduces delays. If managers at different levels each have decision-making authority, team meetings at all levels are held simultaneously.

To account for uncertainties around the barriers of a manager to share information, stochastic elements are introduced. A random value is compared to his 'barrier_to_ask' parameter; if the random value is lower, demand remains unchanged; otherwise, the manager will not ask workers. Similarly, a random value is compared to the barrier_to_give parameter; if it is lower, the number of workers he is able and willing to give to remains unchanged. but if it exceeds the threshold, the manager will not offer his workers.

Output of the model

The model outputs are performance indicators that reflect how effectively the system adapts to a changing environment. We adjusted the adaptation performance indicators from Wu et al. (2009). The first measure defines Reliability, according to Equation 1.

$$R = \frac{\sum_{t=0}^{n} processed\ supply\ needs}{\sum_{t=0}^{n} supply\ needs} \quad (1)$$

The second and third performance indicators relate to the speed of adaptation after a disruption. To quantify the speed of adaptation S_a, we calculate the time from the onset of the disruption to the moment that the performance level is recovered to its level at the disruption moment (Equation 2). The Mean Time to Recover (Equation 3) is the average of the sum of the speed of adaptation (S_a) divided by the number of disruptions.

$$S_a = t_{recovered\ performance\ level} - t_{disruption} \quad (2)$$

$$MTR = \frac{\sum Sa}{\sum disruptions} \quad (3)$$

The Speed of adaptation and Mean Time to Recover indicators will only be calculated in the environment with peaks and the regime shift environment (formations 1 and 3).

The third measure calculates the emerging hierarchical structure of the system. The number of information-sharing managers and the echelons at which the reallocation decisions are made, emerge over time. To translate this into a single metric, we use a cost-like function, the Hierarchy metric (Equation 4). The cost of a manager depends on its level and its state of information-sharing and decision-making or not. To create an insightful metric, we assume that a higher-level manager incurs exponentially greater costs than a lower-level manager.

$$\text{Hierarchy metric} = \frac{\sum cost_{level,state} * manager_{level,state}}{runtime} \quad (4)$$

Initialization and implementation

We initialize the model at t=0 with 7 workers and 32 desks. The workers start at desks 0 - 7 of which only desk 3 is not occupied. The batch of supply needs arises at desks 0 - 11, with a probability of 0.7 that a supply need will be placed in a desk's queue. At t=0, 16 managers of level 1 control each 2 desks. Table 4 in the appendix gives a complete overview of the values of the parameters. The model is implemented in Python using the pydsol library[1,2], which is a Python implementation of the Distributed Simulation Object Library (DSOL) (Jacobs, 2005).

Model verification and validation

Model verification involved testing various model components, all of which functioned as expected. We aligned the core of the model with Epstein's framework (Epstein, 2006). Validation of a pattern-oriented model assesses whether the model is fit for purpose (Grimm et al., 2005). Therefore, we conducted behavior anomaly tests to resolve unexpected behaviors. Furthermore, we engaged in expert consultations with personnel from the Ministry of Defense and academic modelers. Each scenario of 500 time units was run for 10 replications to account for stochastic variation. These efforts confirm that the model satisfies its intended purpose.

FINDINGS OF COMPUTATIONAL EXPERIMENTS AND FUTURE WORK

To better understand the system's performance under varying conditions, we first compared its response to disruptions, conceptualized by formations 1, 2, and 3, with its behavior in the stable condition, represented by formation 0. We used the following settings: the barrier to sharing information is without burden, team meetings do not cause delays between peers, and the managers' decision-making is based on the most up-to-date information, hence without considering that information sharing takes time. Figure 3 shows that, in the (relatively) stable formation, Formation 0, the reliability is higher than in the other environments, which is aligned with our expectations. The reliability percentage of the gradually evolving environment is lower than the environment with peaks and the regime shift.

Experiment – Vertical and horizontal delays

The experiments on vertical and horizontal delays investigate the effects of the various levels of information delays separately, with their values according to Table 2. In Experiment 1a ('horizontal delay'), we vary the interval between the team meetings, in which information at the same level is shared and the managers exchange workers. With the base interval of meetings defined as one time unit, the horizontal delays are 1, 2, and 4 time units when the meeting intervals are set to 2, 3, and 5, respectively. In Experiment 1b, we simulate when upper managers

[1] https://github.com/averbraeck/pydsol-core
[2] GitHub - imvs95/pydsol-model

make decisions based on delayed information ('vertical delay'). We assume that the delay in information sharing is linearly related to the level of managers.

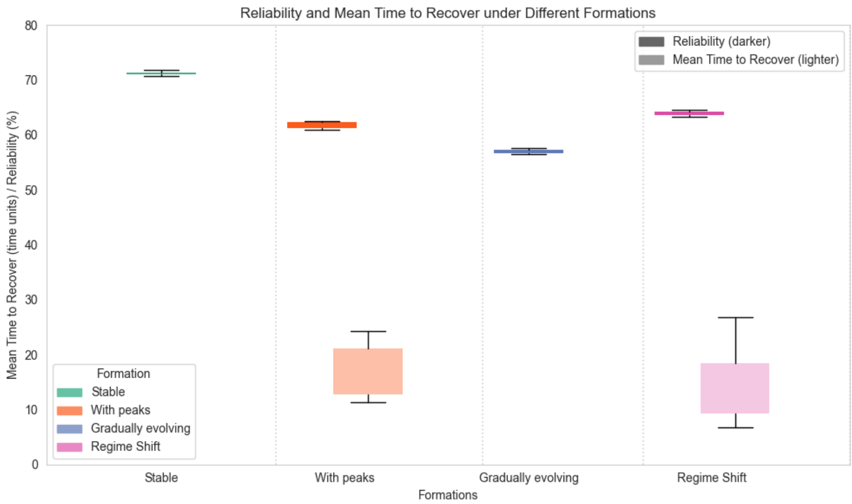
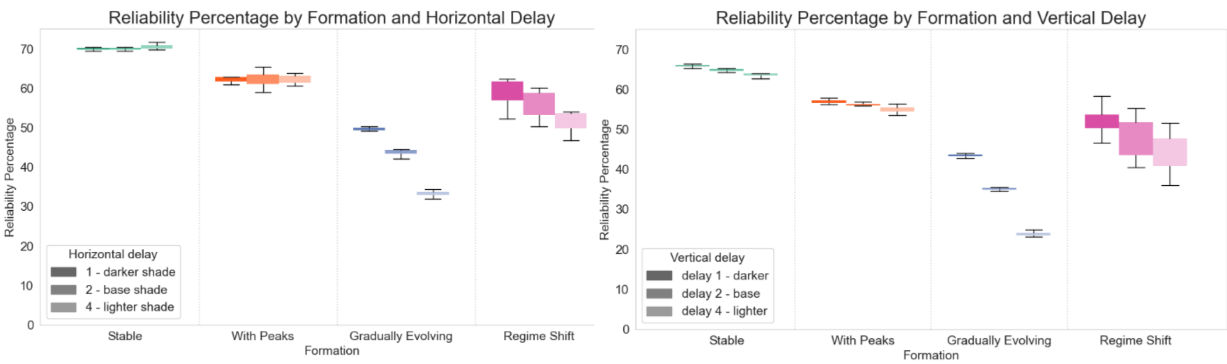


Figure 3 Findings of the baseline scenario by formation

Table 2 The various levels of information delays

Nr	Parameters	Description	Set
1a	*Interval meeting*	Interval between the team meetings, where the managers exchange information on demand and supply of workers.	[1, 2, 4]s
1b	*Vertical_delay*	The delay time of the information between manager levels	[1, 2, 4]

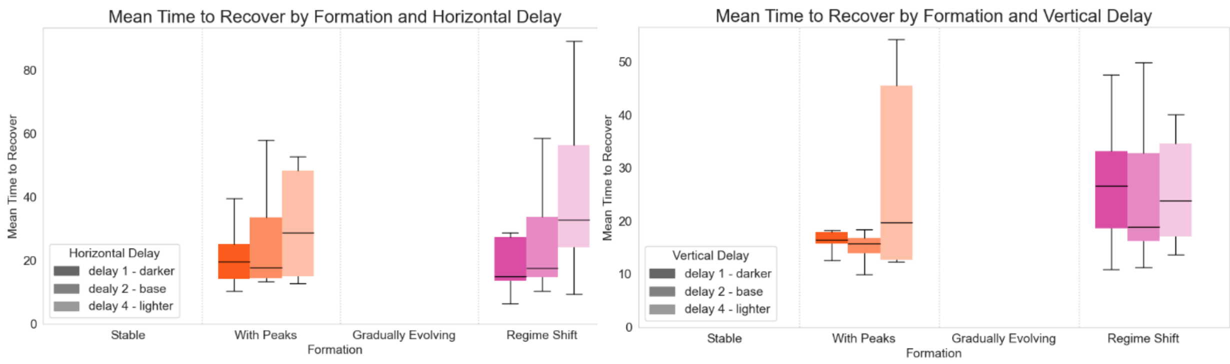
Figure 4 shows that both the scenarios with longer horizontal and vertical delays cause lower reliability. Despite the intended positive adaptation actions, the system's reliability declines due to delays. Comparing Figure 4a to 4b reveals that vertical delays have a more severe effect on reliability than horizontal delays, suggesting that slow decision-making at higher levels weakens adaptation.



(a) Experiment 1a - Horizontal delays (b) – Experiment 1b – Vertical delays

Figure 4 Findings from Experiment 1a and 1b: Reliability percentage by formation and by horizontal and vertical delays

Figure 5 depicts that the spread of the boxplots increases with longer delays, reflecting greater variance in adaptation speed (measured by the mean time to recover). As delays increase, their effects on the speed of adaptation become less predictable. In some scenarios, longer delays resulted in significantly worse adaptation speeds.

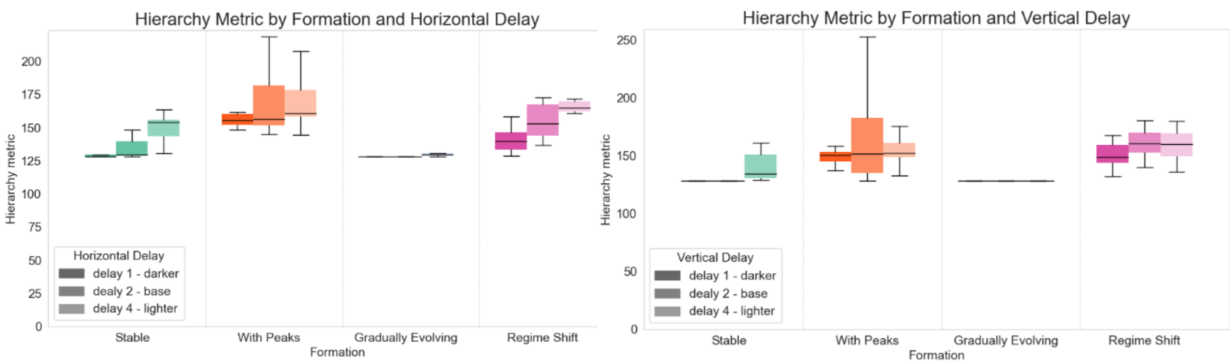


(a) Experiment 1a - Horizontal delays

(b) – Experiment 1b – Vertical delays

Figure 5 Findings from Experiment 1a and 1b: Mean Time to Recover by formation and by horizontal and vertical delays

Figure 6 provides insight into how the structures emerge in response to disruptions under delayed information scenarios. Each boxplot represents the hierarchy cost when information flow is delayed. In both figures, performance issues in disrupted environments escalate to higher levels more quickly. Longer delays particularly increase hierarchy costs in the 'With Peaks' and 'Regime Shift' formations. In Figure (a), which represents horizontal delay scenarios, all formations exhibit higher median hierarchy costs compared to those in vertical delay scenarios (see Figure (b)). With horizontal delays, the reallocation of workers is blocked until the next team meeting, reducing performance and causing triggering earlier escalation to higher levels. In the gradually evolving environment, no new hierarchical levels emerge, suggesting that small, continuous changes do not trigger escalation and structural adaptations. This indicates that while hierarchy helps manage disruptions, it may not be necessary for environments with incremental change.



(b) Experiment 1a - Horizontal delays

(a) Experiment 1a - Vertical delays

Figure 6 Findings from Experiment 1a and 1b: The Hierarchy Metric by formation and horizontal and vertical delays

DISCUSSION AND CONCLUSIONS

Information is a driver for adaptation because decisions on how and what to adapt are based on information. This study examines delayed information sharing in decisions on resource allocation and information-sharing structures. In this study, adaptation refers to changes in hierarchical structures and resource allocation prompted by disruptions and delayed information flows.

To explore adaptations, we developed an agent-based discrete-event simulation model, inspired by adaptation mechanisms observed in crisis response settings and grounded in the literature. We modeled a hierarchical structure of managers, where higher-level managers have a broader overview to ensure that resources are reallocated quickly. However, when information sharing is delayed, the conventional benefits of hierarchy are challenged. Our computational experiments reveal that if horizontal delays occur, they cause a growing hierarchy earlier than vertical delays. As the hierarchy expands, vertical delays slow decision-making, counteracting the intended conventional benefits.

The model describes indeed a human resource allocation process in response to fulfilling arising supply needs in a crisis setting. In a more traditional crisis setting the needs of the affected victims will be fulfilled using a push based supply chain. In contrast, we use a pull based supply chain. However, several core characteristics are shared with the traditional crisis supply chain settings. Among these characteristics, we view the limited resources (workers, stock) that must be dynamically reallocated, the unpredictability of the arising supply needs (various dynamically changing formations) and the delayed information. Furthermore, we believe that in the traditional humanitarian setting, the hierarchical and horizontal coordination with delays and barriers to share are also present.

In our collaboration with the Dutch Ministry of Defense, we observed several instances of the adaptation process, reflecting the adaptation dynamics identified in our model. During military exercises, operational workers responded quickly and introduced an additional meeting and another information sharing procedure to address perceived lagging performance. These adaptation actions intended to improve coordination but they increased complexity and created horizontal delays. This observation mirrors the model's finding that horizontal delays accelerate hierarchy growth and reduce flexibility. Interestingly, this operational response directly conflicted with strategic aims of increasing flexibility. At the strategic level, during a regime shift triggered by heightened threats, we saw how challenging it was to adapt after two decades of accumulated procedures to discuss and ensure careful resource allocation. The established procedures and ingrained hierarchical inertia delayed responses, consistent with our computational results that vertical delays and high hierarchy slow overall adaptation and recovery.

Despite adaptations, our experiments indicate that the system's overall reliability declined due to delays, highlighting the trade-offs between reliability, the cost of structures and the speed of adaptation. Understanding these trade-offs better requires further investigation into how multiple delay factors interact within crisis response operations. Therefore, we recommend that future studies explore scenarios where multiple information delay parameters vary simultaneously to understand their nonlinear interactions and combined effects better.

The findings challenge the conventional view that adaptation inherently strengthens the system's performance: the short-term individual adaptations can have adverse outcomes due to inertia. Moreover, our results indicate that when hierarchical information sharing in crisis response systems is time-consuming or delayed, a hierarchical structure may not always be the most effective strategy to respond and adapt quickly to disruptions.

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Table 3 Constants and Parameters with their initial settings

Parameters	Actor	Description	Value
Nr of workers	Worker	Determines the number of workers that can be deployed to fulfil the supply needs	7
Processing time	Worker	The time the worker takes to fulfill a need	1
Batch size needs	Supply Need	The number of supply needs per batch	12
Prob_create_need	Supply Need	The probability that a need will be placed in a desk's queue.	0.70
Duration_stable	Supply Need	The number of time units without peaks (used in formation 1).	40
Duration_unstable	Supply Need	The number of time units without peaks (used in formation 1).	12
Priority_inflow_ratio	Supply Need	Determines the maximum number of additional needs that flow into the system, expressed as a percentage of the initial batch size. All these additional needs are automatically assigned a priority (formation 1)	0.7
Regime_shift_time	Supply Need	Duration before and interval between regime shifts occur (formation 3)	52
Max_delay	Supply Need	The maximum time that a Supply Need remains in the queue before it is removed. We assume that, in a crisis response setting, such delays are often not allowed.	1
Nr_Managers_Level_1	Manager	The number of managers at level 1	16
Length_memory	Manager	The number of time units a manager uses to calculate his penetration level.	10
Down	Manager	Downward inertia: Number of periods that the penetration level is below the threshold before the control is reverted to the managers on the lower hierarchical level	15
Up	Manager	Upward inertia: Number of periods that the penetration level is above the threshold before the upward manager is informed, i.e., the escalation procedure starts	15
Tmax	Manager	When the penetration level exceeds the T_max threshold, the manager will demand for worker(s).	See 'threshold'
Tmin	Manager	When the penetration level is lower than T_min, the manager will supply worker(s)	See threshold
Threshold	Manager	The threshold to compare the penetration level to	[0.7, 1.4, 2, 4, 20]
Barrier to ask	Manager	The barrier to ask for workers. Ranges between [0 -1]. 0 means no barrier, 1 means a full barrier.	0
Barrier to give	Manager	The barrier to share information on available workers. Ranges between [0 -1]. 0 means no barrier, 1 means a full barrier.	0