Organisational Resilience and Decision-Making Modes: An Agent-Based Analysis

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Abstract
Organisational resilience, defined as the capacity to absorb and recover from shocks affecting an organisation's operations, becomes increasingly more important in today's environment. While existing research has mainly explored structural and strategic factors contributing to organisational resilience, the role of managerial decision-making modes in this context remains underexamined. This paper addresses this gap by developing an agent-based model that simulates how different modes of decision-making affect resilience. The model captures stylised organisations as collections of interdependent departments operating on performance landscapes with varying complexity. The study compares silo-based, sequential, collaborative, and proposal-based decision-making across 144 simulated scenarios, incorporating shocks of varying severity. The results reveal that collaborative and proposal-based decision-making modes enhance shock absorption and recovery in complex task environments, while simpler modes perform well in settings where tasks are less complex. Proposal-based coordination offers balanced performance.

Keywords: Organisational resilience, decision-making modes, agent-based modelling, disruptions, task interdependence

Paper type: Academic Research Paper

1 Introduction

The growing probability of disruptions, including economic, technological, and operational disruptions, makes it crucial for organisations to respond to crises and develop capabilities, enabling them to anticipate, absorb, adapt to, and recover from shocks. However, how daily business practices affect an organisation's resilience remains largely unknown (Kantabutra and Ketprapakorn, 2021). A large proportion of existing research has focused on coping strategies and how they can be employed during and after shocks. More recently, the focus has shifted to strategies to anticipate shocks and how to prepare organisations to remain effective during crises (Grego et al., 2024). Another stream of research has analysed resilience through the lens of organisational structure, resource allocation, and strategic decision-making mechanisms (Banihashemi et al., 2024; Dahmen, 2023; Garcia-Diaz, 2024; Swaminathan, 2022). For instance, Leitner (2025a, 2023) explores how emergent task allocation affects an organisation's resilience, and You and Williams (2023) conclude that the design of intra-organisational relationships is key to increasing organisational resilience. However, a significant gap remains unexplored: how do models of managerial decision-making – that is, modes of generating and coordinating decisions – shape an organisation's capability to deal with shocks? Even though this dimension appears to be a critical determinant for organisational resilience, it has only received limited attention in research.

This paper addresses this gap by developing an agent-based model of a stylised organisation to analyse how different decision-making modes affect an organisation's ability to absorb and recover from shocks. The model is based on the NK framework (Levinthal, 1997; Wall et al., 2024; Wall and Leitner, 2021) that allows for modelling interdependent decision-making in organisational contexts. Specifically, the stylised organisations are conceptualised as a collection of departments that jointly operate on a performance landscape representing the task environment, whereby the ruggedness of the landscape is externally controlled and shaped by the interdependencies between tasks. Decision-making modes are conceptualised as different modes of how information is shared between departments and how adaptation finally takes place. The key decision-making modes analysed include proposal-based, silo-based, collaborative, and sequential approaches. The results indicate that not all decision-making modes are equally effective, depending on the complexity of an organisation's task. Decision-making modes that facilitate information exchange and mutual adaptation are advantageous in complex task environments, whereas simpler methods work well when organisational departments work on less complex tasks.

The remainder of the paper is structured as follows: Section 2 introduces the model and discusses the scenarios analysed in this paper. Section 3 presents and discusses the results. Section 4 concludes the paper.

2 Model and simulation experiments

This paper's model of a stylised organisation builds on the NK framework (Levinthal, 1997; Wall and Leitner, 2021). The model is populated by $M \in \mathbb{N}$ agents representing departments. Agents operate on a NK-landscape that defines the task environment. More specifically, the task environment captures an N-dimensional binary decision problem ($N \in \mathbb{N}$) with $K \in \mathbb{N}_0$ interdependencies between decisions, shaping the complexity of the decision problem.

2.1 Task environment and decomposition

Let us denote the N-dimensional decision problem by $\boldsymbol{d} = [d_1, \ldots, d_N]$, where $d_i \in \{1, 0\}$ and $n = 1, \ldots, N$. Each decision d_i contributes $f(d_i) \sim U(0,1)$ to overall organisational performance. There exist K interdependencies between decisions, which is why the contribution of the decision $f(d_i)$ in addition to d_i is affected by K other decisions. Let us formalise this payoff function by $f(d_i) = f(d_i, d_{i_1}, \ldots, d_{i_K})$, where $\{i_1, \ldots, i_K\} \subseteq \{1, \ldots, i-1, i+1, \ldots, N\}$. The overall performance of a solution vector $\boldsymbol{d}$ to the decision problem is defined as the average of all performance contributions: $P(\boldsymbol{d}) = 1/|\boldsymbol{d}| \sum_{i=1}^{N} f(d_i)$.

The decision problem $\boldsymbol{d}$ is sequentially and symmetrically divided into M disjoint sub-problems, and every department oversees one sub-problem, each consisting of $Q = N/M$ decision-making tasks. The allocation follows the following rule: $d_m = [d_{\{Q\cdot(m-1)+1\}}, \ldots, d_{\{Q\cdot m\}}]$. In consequence, when there are $N = 15$ decisions and $m = 5$ departments, every department oversees 3 decisions.

2.2 Shocks to the task environment

The task environment might be affected by shocks. Specifically, the performance contributions $f(d_i)$ can change due to disruptions in the organisation's environment. Consequently, the shape of the NK-landscape might change as well. The model considers correlated shocks using a method proposed by Demirtas (2014) that uses a correlation parameter $\rho \in \{-1, 1\}$ *to* control the severity of shocks. To do so, first two random numbers $v_i \sim U(0,1)$ and $w_i \sim B(a, 1)$ are drawn, where the shape parameter of the Beta distribution is a function of the correlation parameter, $a = 1/2\left(\sqrt{49 + \rho/1 + \rho} - 5\right)$. Then, the two random numbers are used to compute the correlated performance contribution according to the following rule:

$$f^c(d_i) = \begin{cases} |w_i - f(d_i)|, & v_i < 0.5\,, \\ 1 - |1 - w_i - f(d_i)|, & v_i \geq 0.5\,. \end{cases}$$

2.3 Utility function and decision-making modes

Departments are modelled to be myopic utility maximisers, meaning they aim to immediately increase their utility (without considering long-term effects). Let us denote the utility of the department m as follows:

$$U(\boldsymbol{d}_{mt}, \boldsymbol{d}_{-mt}) = \lambda \cdot P(\boldsymbol{d}_{mt}) + (1-\lambda) \cdot P(\boldsymbol{d}_{-mt})\,,$$

where $\boldsymbol{d}_{mt}$ and $\boldsymbol{d}_{-mt}$ denote the department m's own and residual decisions, respectively, and departments are characterised by a linear incentive mechanism where the parameter λ is used to weight the department's own and residual performance.

Over time, departments can change their decisions at every time step, and departments can exchange information during this adaptation process according to the following decision-making modes (see also Blanco-Fernández et al., 2025; Siggelkow and Rivkin, 2005).

2.3.1 Silo-based decision-making

In silo-based decision-making, departments gather information independently and do not share it with their colleagues. This means that departments are unaware of their colleagues' decisions at a specific point in time and rather rely on their colleagues' behaviours $\boldsymbol{d}_{-m(t-1)}$ that have been observed in the previous period. In every period, every department identifies an alternative set of actions within their area of responsibility and in the neighbourhood of the currently implemented actions. Please note that the neighbourhood is defined by a Hamming Distance of 1 around $\boldsymbol{d}_{mt}^*$. In every period, every department must choose between either sticking with the status quo or adopting the newly discovered alternative. They do so according to the following rule:

$$\boldsymbol{d}_{mt} = \underset{\boldsymbol{d}' \;\in\left(\boldsymbol{d}_{m(t-1)},\, \boldsymbol{d}_{mt}^*\right)}{\arg\max} \; U\left(\boldsymbol{d}' \;, \boldsymbol{d}_{-m(t-1)}\;\right).$$

Then, the collective solution to the overall decision problem in period t is the combination of all actions taken by departments: $\boldsymbol{d}_t \;= \bigcup_{m=1}^{M} \boldsymbol{d}_{mt}$.

2.3.2 Collaborative decision-making

In the collaborative decision-making mode, departments are connected in a ring network, and with fixed probability P, they perform collaborative decision-making as described below. In contrast, with the likelihood of $(1-P)$, they perform silo-based decision-making.

Collaborative decision-making is implemented as adjacent hill-climbing (Yuan and McKelvey, 2004). Specifically, if departments m and n engage in collaborative decision-making, each of them identifies their alternatives $\boldsymbol{d}_{mt}^*$ and $\boldsymbol{d}_{nt}^*$ in the neighbourhood of $\boldsymbol{d}_{m(t-1)}$ and $\boldsymbol{d}_{n(t-1)}$, respectively. They share information during decision-making, which is why their joint residual decisions (i.e., the actions taken outside of department m's and n's areas of responsibility) are denoted by $\boldsymbol{d}_{-(mn)(t-1)} = \boldsymbol{d}_{t-1} \setminus \left(\boldsymbol{d}_{m(t-1)} \cup \boldsymbol{d}_{n(t-1)}\right)$.

Then, the two departments make a decision that maximises their joint utility according to the following rule:

$$\left(\boldsymbol{d}_{mt}, \boldsymbol{d}_{nt}\right) = \underset{\substack{\boldsymbol{d}'_m \in\left(\boldsymbol{d}_{m(t-1)},\, \boldsymbol{d}_{mt}^*\right) \\ \boldsymbol{d}'_n \in\left(\boldsymbol{d}_{n(t-1)},\, \boldsymbol{d}_{nt}^*\right)}}{\arg\max} \; U^{adj}\left(\boldsymbol{d}'_m,\, \boldsymbol{d}'_n,\, \boldsymbol{d}_{-(mn)(t-1)}\;\right),$$

where the joint utility function $U^{adj}(\cdot)$ is defined as the mean of the two individual utilities: $U^{adj}\left(\boldsymbol{d}_{mt},\, \boldsymbol{d}_{nt},\, \boldsymbol{d}_{-(mn)(t-1)}\right) = \frac{1}{2}\left(U\left(\boldsymbol{d}_{mt},\, \boldsymbol{d}_{-m(t-1)}\;\right) + U\left(\boldsymbol{d}_{nt},\, \boldsymbol{d}_{-n(t-1)}\;\right)\right)$.

2.3.3 Sequential decision-making

In the sequential decision-making mode, departments make decisions one after another, with each department passing on information about its choices to those that have yet to decide, thereby reducing uncertainty for subsequent decision-makers. For simplicity, let us assume that the decision-making order follows the department indices. This means that the department $m = 1$ starts with the decision-making procedure and informs departments 2 to M about their decisions and, thereby, reduces the uncertainty about their residual actions. Let us redefine the vector of residual decision for the sequential decision-making mode as follows:

$$\boldsymbol{d}_{-mt}^{seq} = \left(\boldsymbol{d}_{1t}, \dots, \boldsymbol{d}_{(m-1)t}, \boldsymbol{d}_{(m+1)(t-1)}, \dots, \boldsymbol{d}_{M(t-1)}\right).$$

As in the previous decision-making modes, department m identifies an alternative course of action $\boldsymbol{d}_{mt}^*$ in the neighbourhood of $\boldsymbol{d}_{m(t-1)}$, and next, the department assesses the two choices according to

$$\boldsymbol{d}_{mt} = \underset{\boldsymbol{d}' \;\in\left(\boldsymbol{d}_{m(t-1)},\, \boldsymbol{d}_{mt}^*\right)}{\arg\max} \; U\left(\boldsymbol{d}' \;, \boldsymbol{d}_{-mt}^{seq}\;\right).$$

2.3.4 Proposal-based decision-making

In the proposal-based method, departments explore and rank alternative lines of action locally and propose their ranked alternatives to a central authority. The central authority aggregates the proposals and makes the final decision, assuring global coherence of actions. Specifically, every department m identifies an alternative $\boldsymbol{d}_{mt}^*$ in the neighbourhood of the status quo $\boldsymbol{d}_{m(t-1)}$. The two options (the alternative and the status quo) are ranked concerning expected utility (using the utility function introduced in Section 2.3.1). Then, the ranked options $\left(\boldsymbol{d}_{mt}^{(1)}, \boldsymbol{d}_{mt}^{(2)}\right)$ are forwarded to a central coordinating unit. The central unit combines the proposals of all M departments by concatenating all proposals ranked first and second, respectively, according to the rule $\boldsymbol{d}_t^{(j)} = \bigcup_{m=1}^{M} \boldsymbol{d}_{mt}^{(j)}$, where $j \in \{1, 2\}$. Finally, the coordinating unit evaluates the combined proposals concerning the highest performance and makes the final decision as follows:

$$\boldsymbol{d}_t = \underset{\boldsymbol{d}' \in \{\boldsymbol{d}_t^{(1)}, \boldsymbol{d}_t^{(2)}\}}{\arg\max} P(\boldsymbol{d}') .$$

2.4 Simulation experiments

The following four parameters of the model are considered variables to construct scenarios:

- The performance landscape on which departments operate follows the logic of the NK model introduced above. Specifically, landscapes with two levels of complexity are considered, whereby the interactions follow the patterns in Figure 1. Specifically, in the case of (i) small diagonal blocks, tasks are organised into modular structures, meaning interdependencies exist within departments but not between them. This structure simplifies decision-making and is referred to as *decomposable tasks*, as each department operates independently. In the case of (ii) *reciprocal interdependencies*, tasks assigned to departments are highly interconnected, with interdependencies both within and between departments. This pattern requires coordinated decision-making across departments to manage complexity effectively (Leitner, 2024).
- Four decision-making modes, namely (i) silo-based decision-making, (ii) collaborative decision-making (with different probabilities of *joint* decision making), (iii) sequential decision-making, and (iv) proposal-based decision-making, are considered. For details on the decision-making modes, see Sections 2.3.1 to 2.3.4.
- Two configurations are considered for the incentive mechanism: $\lambda \in \{0.25, 1\}$ for group-based and individualistic incentives, respectively. For details on how the incentive parameter affects utility, see Section 2.3.
- Shocks of different severity are considered, ranging from severe ($\rho = -0.5$) to moderate ($\rho = 0$) and slight shocks ($\rho = 0.5$). For details on how shocks are implemented, see Section 2.2.

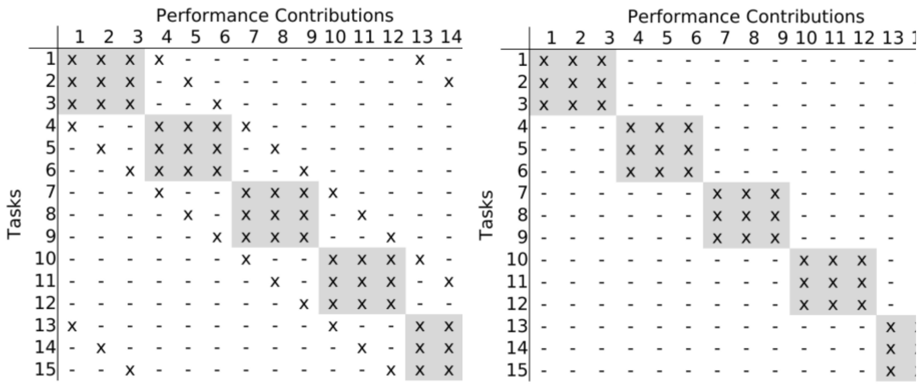

Figure 1: Interdependence patterns
Left: reciprocal interdependencies, right: decomposable tasks

The dimensionality of the decision problem is fixed at $N = 15$, and the number of departments is set to $M = 5$. The parameter variations yield a total number of 144 scenarios. For these scenarios, simulations per scenario have been performed, whereby based on the coefficient of variation, the number of simulations per scenario is set 150. Each simulation run spans 500 timesteps, with shocks occurring after 250 timesteps. Statistical tests confirm that the performance time series (both before and after a shock) reaches stationarity after approximately 240 timesteps. The simulation model is implemented in Python.

3 Results and Discussion

At the core of this paper is the organisation's ability to absorb and recover from shocks. Before shocks occur in the task environment, decision-making modes already shape an organisation's position within that environment, influencing whether it operates near a global or local maximum when a shock occurs (Leitner, 2025b). In task environments with (nearly) decomposable tasks, most decision-making modes lead to organisations (almost) achieving the global maximum. In contrast, when task decomposition is characterised by reciprocal interdependencies, the global maximum cannot be reached in most cases, whereby proposal-based and collaborative decision-making modes lead to higher task performance compared to silo-based and sequential modes (Siggelkow and Rivkin, 2005). These findings align with existing literature, and the proposed model successfully replicates them (Rand and Wilensky, 2006). This replication confirms that the model has a relatively high construct validity, indicating that the model is capable of capturing core features of organisational adaptation theorised using NK model and complex system approaches.

During the simulations, organisations experience a shock to their task environment after 250 timesteps and are modelled to resume operations immediately afterwards. Shock absorption is assessed by comparing performance immediately before and after the shock, while recovery is evaluated based on performance after 250 additional time steps. Differences are evaluated using the Mann-Whitney U test, and the U statistic is used to compute the rank-biserial correlation as an effect size measure. To efficiently report the results, k-means clustering was applied to group the 144 scenarios into nine distinct clusters. The optimal number of clusters was determined using the Davies-Bouldin and Caliński-Harabasz indices. Clustering of scenarios allows for detecting structural patterns rather than merely reporting isolated scenarios. A log-likelihood ratio test assessed the significance of different parameters for the clustering solution. In consequence, the analysis approach allows for the interpretation of resilience as emerging from interactions with the organisational context. The results indicate that *interdependence pattern*, *decision-making mode*, and *shock correlation* significantly influence the clustering structure; the results are organised along these dimensions.

Table 1 presents the cluster profiles for organisations operating in environments with decomposable tasks, while Table 2 focuses on environments with reciprocal interdependencies. Scenarios are further grouped within each table based on shock severity (slight vs. moderate to severe shocks). Both tables report two primary outcomes: (i) the capability to absorb shocks, comparing performance immediately before (period 249) and immediately after the shock (period 250), and (ii) the capability to recover from shocks, comparing performance before the shock (period 249) and after a recovery period (period 500). For each cluster, the average rank-biserial correlation (as a measure of effect size) and its standard deviation are reported. Additionally, the dominant decision-making modes characterising each cluster are indicated.

Table 1**:** Results for decomposable tasks

# Scenarios	Absorbing shocks (period 249 vs. 250)		Recovering from shocks (period 249 vs. 500)		Decision-making mode
	Average	Std	Average	Std	
Slight shocks:					
8	-0.6092	0.0705	0.1618	0.0284	Collaborative (low/mean probability) Proposal-based
18	-0.6401	0.0975	0.0755	0.0212	Collaborative (high probability) Sequential Silo-based
Moderate to severe shocks:					
30	-0.8831	0.0580	-0.0065	0.0258	Collaborative (low/mean probability) Proposal-based
19	-0.9061	0.0575	0.0202	0.0202	Collaborative (high probability) Sequential Silo-based

The results indicate that organisational resilience – more specifically, an organisation's capability to absorb and recover from shocks – is contingent on both the decision-making mode that is effective in the organisation and the complexity of the task environment. In low-complexity task environments, where tasks assigned to departments have minimal interdependencies and are perfectly decomposable into disjoint areas of responsibility, organisations exhibit higher overall performance, and decision-making modes play a lesser role in resilience. When a shock disrupts the task environment, organisations using proposal-based and collaborative decision-making modes experience a smaller initial performance drop than those relying on silo-based or sequential decision-making mechanisms in environments with decomposable tasks (see Table 1). This observation is driven by almost independently operating departments (on smooth performance landscapes), leading to even simple decision-making rules performing well. However, the cost of uncoordinated action increases as the task environment becomes more complex and the performance landscape becomes more rugged (see Table 2). Here, organisations employing collaborative or sequential decision-making modes experience a more pronounced drop in performance. This observation can be explained by the fact that the proposal-based and collaborative decision-making modes facilitate mutual adaptation. Specifically, these modes allow departments to align their decisions, leading them to favourable positions in the landscape, i.e., positions that are likely also viable after a shock.

Table 2: Results for non-decomposable tasks

# Scenarios	Shock absorption (period 249 vs. 250)		Recovering from shocks (period 249 vs. 500)		Decision-making mode
	Average	Std	Average	Std	
Slight shocks:					
15	-0.2273	0.0731	-0.0993	0.0377	Collaborative (low probability) Silo-based
19	-0.3563	0.1023	0.0331	0.0360	Collaborative (mean/high probability)
Moderate to severe shocks:					
6	-0.4361	0.0676	-0.2344	0.0483	Silo-based
19	-0.5680	0.0833	-0.0134	0.0312	Collaborative (mean/high probability)
110	-0.5698	0.1034	-0.1209	0.0243	Sequential

Recovering from shocks depends on shock severity and an organisation's capability to coordinate actions after the shock. In complex environments, collaborative decision-making modes facilitate better recovery because they facilitate coordinated adaptations across departments. In contrast, organisations using silo-based and sequential decision-making modes often struggle to regain previous performance levels, leaving them trapped in suboptimal positions. In task environments of low complexity, organisations regain pre-shock performance in all cases. The relationship between task complexity and effectiveness of the decision-making mode is further moderated by shock severity: Slight shocks only result in moderate shifts in the performance landscape, enabling recovery over time in all decision-making modes. Interestingly, when the task environment is of low complexity and shocks are moderate, collaborative and proposal-based decision-making modes can help organisations achieve significantly better performance post-shock. In contrast, severe shocks lead to drastic performance drops, and when there is a lack of coordination across departments, as in silo-based modes, recovery is difficult. On the other hand, collaborative and proposal-based decision-making modes support tight coordination, allowing for effective recovery.

These findings are relevant for the design of real-world organisations. The results confirm that decentralising decisions to the department level can achieve high performance and strong recovery capability in modular and relatively stable environments, such as traditional manufacturing lines or standardised service operations. In more complex and volatile environments, such as emergency response coordination and digital product development, cross-departmental coordination and joint action (as in the collaborative mode) become increasingly essential. The results also indicate that organisations are better off in dynamic environments when they not only support communication between departments but also facilitate joint exploration and mutual adjustment.

4 Conclusion

This paper presents an agent-based model of a stylised organisation operating in a dynamic task environment subject to external shocks. The model investigates how different decision-making modes influence an organisation's ability to absorb and recover from such shocks. The findings suggest that specific decision-making modes offer advantages depending on the complexity of the environment. Complex task environments characterised by reciprocal interdependencies benefit from decision-making structures that support information exchange and mutual adaptation. In contrast, simpler decision-making modes may work efficiently in less complex settings. These results highlight the importance of aligning decision-making structures with environmental complexity. The study contributes to resilience research by incorporating an organisation's pre-shock positioning within the task environment into the resilience analysis. It highlights that crisis response mechanisms do not solely determine resilience but are also influenced by the decision-making architecture in place before the shock.

Future research could account for the fact that firms differ in their ability to respond to crises. Prior performance plays a critical role: organisations that perform well before a shock can often accumulate slack resources, enabling a more immediate and effective response, while less successful organisations may lack this capacity (Smallbone et al., 2012). Extending the model to incorporate this dynamic would enhance its realism. Moreover, to increase the generalizability of results, future studies should explore additional interdependence patterns and examine whether consistent behavioural patterns emerge across different organisational contexts. Future research could also examine how decision-making modes evolve and investigate the influence of additional contextual factors such as organisational culture and leadership.

Ethics declaration

No ethical clearance was required for the research presented in this paper.

AI declaration

No AI tools were used for the creation of this paper.

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