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Editorial

Collective Dynamics, Decision-Making, and Self-Organization in Complex Systems: Contributions and Future Research Directions

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1. Introduction

Collective dynamics concerns how interactions among individuals or constituent entities generate system-level behaviors, patterns, and outcomes [1]. It provides a framework for understanding phenomena across diverse domains, including animal groups, human societies, organizational networks, supply chains, transportation systems, and technological infrastructures. A central premise is that collective behavior cannot always be explained by examining individual entities in isolation [2,3]. Rather, system-level outcomes emerge from interactions among entities whose decisions, capabilities, and behaviors influence one another and evolve in response to changing conditions [2]. For example, in animal groups, social feedback among individuals can amplify behavioral differences, reinforcing leader–follower relationships and influencing collective movement. Similar mechanisms operate in organizational and technological systems, where local decisions and interactions can produce outcomes that extend beyond the intentions or capabilities of individual participants.

Decision-making is fundamental to collective dynamics because it shapes how entities respond to their environments, interact with others, and contribute to collective outcomes. Individual and organizational decisions may be guided by different objectives, information, decision policies, and perceptions of risk [4]. These differences can generate cooperation, competition, coordination, and conflict, with consequences for overall system performance. Consequently, understanding collective dynamics requires examining not only how individual decisions are made but also how decisions interact, propagate, and produce collective consequences.

Self-organization introduces an additional dimension to this challenge. It describes the emergence of system-level order through local interactions among constituent entities without requiring comprehensive centralized direction [5]. Although self-organization can facilitate adaptability, coordination, and resilience, it can also produce unintended consequences when local objectives conflict with collective requirements or when interactions amplify vulnerabilities. The relationship between self-organization and decision-making is therefore particularly important in complex systems, where the distinction between individual and collective interests may be difficult to establish and maintain.

Despite advances in computational modeling, simulation, artificial intelligence (AI), and the study of complex adaptive systems, important questions remain about how decision-making and self-organization influence collective behavior under conditions of ambiguity, uncertainty, emergence, non-ergodicity, and non-monotonicity [6]. Ambiguity

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concerns situations in which the meaning of available information or the appropriate interpretation of a situation is unclear. Uncertainty concerns incomplete knowledge of system conditions, future events, or the consequences of alternative actions. Emergence refers to system-level properties or behaviors that arise through interactions among constituent entities and cannot be adequately understood by examining those entities independently. Non-ergodicity challenges the assumption that long-run averages necessarily represent the behavior of individual systems over time, while non-monotonicity describes situations in which changes in inputs, interventions, or conditions do not produce consistently proportional or unidirectional changes in outcomes. Together, these characteristics complicate prediction, decision-making, coordination, and the assessment of system performance.

These challenges are particularly consequential for contemporary sociotechnical systems, in which human, organizational, technological, and physical components interact across multiple levels. Examples include chemical and commercial facilities, communications, critical manufacturing, the defense industrial base, emergency services, energy, financial services, education, food and agriculture, government facilities, healthcare and public health, information technology, transportation, and water and wastewater systems [7]. In these settings, decisions made by individual actors or subsystems can influence broader system behavior, while changes in the operating environment can alter the consequences of previously effective strategies.

This Special Issue, *Collective Dynamics, Decision-Making and Self-Organization in Complex Systems*, brings together research that examines complementary aspects of these challenges. Its contributions span computational modeling of collective behavior, AI-supported organizational decision-making, system dynamics, causal machine learning, and the analysis of collective patterns in technological development. Collectively, the articles offer insights into how interactions, decision policies, information, and organizational structures shape outcomes in complex settings. They also provide a foundation for identifying research priorities concerning the design, governance, and adaptation of complex systems operating under dynamic and difficult-to-predict conditions.

2. An Overview of Published Articles

The contributions to this Special Issue examine collective dynamics and decision-making through different theoretical perspectives, methodological approaches, and application domains. Although the articles do not address identical research questions, they share an interest in understanding how interactions, information, interventions, and organizational arrangements influence system-level outcomes. Their contributions are summarized below.

Pacella, Papadia, and Giliberti [8] investigate the selection of intervention policies for customer retention, addressing the limitations of relying exclusively on conventional causal-ranking metrics. Uplift modeling seeks to identify individuals whose behavior changes in response to a particular intervention, rather than merely predicting their baseline likelihood of an outcome. However, a policy that performs well according to a ranking metric may not necessarily produce the greatest economic value or consistently identify the same target population across repeated model runs. To address this problem, the authors propose a computational framework that jointly evaluates incremental revenue, target-set stability, and policy interpretability. Their approach compares causal and non-causal modeling techniques under repeated-run validation and uses surrogate decision trees to translate selected policies into interpretable customer segments. Evaluations using the Telco Customer Churn dataset reveal a trade-off between economic returns and targeting stability. The findings also indicate that the relative performance of uplift models

and traditional predictive approaches depends on the causal characteristics of the evaluation setting.

This contribution demonstrates that decision quality cannot be assessed solely through predictive or causal-ranking performance. The stability of recommended actions, their economic consequences, and their interpretability also matter when models are used to guide interventions. More broadly, the study highlights the need to evaluate decision policies as actionable mechanisms whose consequences may vary across data conditions and operational settings.

Crouch and colleagues [9] examine how preventive interventions may influence demand for adult social care and associated expenditures in Kent County Council, England. The study applies system dynamics modeling to integrated health and social care data to evaluate alternative prevention scenarios and support strategic planning. The analysis identifies relationships between social care costs and characteristics including age, living arrangements, deprivation, and indicators of frailty. It also finds that a relatively small proportion of older adults account for a substantial share of expenditure within the older-adult population. Scenario analysis projects that, without interventions, adult social care costs could increase by 48% over ten years, compared with a projected increase of 33% under targeted prevention.

The study illustrates the value of system dynamics modeling for investigating interconnected factors and evaluating the potential consequences of policy interventions over time. Rather than treating social care demand as a collection of independent cases, the approach supports analysis of system-level patterns and alternative intervention strategies. Its contribution is particularly relevant to decision-making in public services, where resource constraints, population changes, and interdependencies complicate the allocation of resources and the evaluation of long-term outcomes. It also underscores the importance of using models to examine alternative futures while recognizing that projections remain dependent on their underlying data, assumptions, and scenarios.

Bucovețchi and colleagues [10] investigate how organizational decision-making structures and crisis-aware AI influence performance, disruption response, and recovery in Industry 5.0 human–cyber–physical systems. Motivated by supply chain disruptions that exposed vulnerabilities in centrally controlled manufacturing systems, the study compares centralized, distributed, and self-organized organizational arrangements through agent-based modeling. Across 650 simulation runs involving a controlled supply-side disruption, the authors examine the effects of organizational structure and a crisis-aware Q-learning architecture. The AI approach enables agents to shift from efficiency-oriented to stability-oriented strategies when resource scarcity is detected. The results indicate that self-organized structures outperform centralized and distributed alternatives across the reported baseline performance, crisis throughput, and recovery measures. Integrating crisis-aware AI further increases the reported absolute resilience measure by approximately 10.7%.

The findings associate improved performance with adaptive coalition formation, proactive resource conservation, and the preservation of coordination structures that support post-crisis recovery. This study makes an important contribution to understanding how local decision policies and organizational structures jointly influence system-level resilience. It also illustrates how AI can support adaptive responses when operating conditions change. Nevertheless, the findings should be interpreted in relation to the simulated scenarios and assumptions; further research is needed to determine how these relationships hold under different disruption types, organizational constraints, and real-world operating conditions.

Mun and Lee [11] examine the relationship between collective technological attention and the reemergence of sleeping beauty patents—patents that receive limited attention for

an extended period before subsequently attracting substantial interest. Whereas previous research has often emphasized characteristics of individual patents, this study investigates whether broader patterns in technological topics are associated with the delayed recognition of these patents. Using BERTopic to analyze U.S. patent abstracts, the authors derive two indicators: Jensen–Shannon Divergence, which captures temporal changes in topic distributions, and topic entropy, which reflects the breadth of technological exploration across topics. Logistic regression results indicate that Jensen–Shannon Divergence is negatively associated with sleeping beauty patent awakenings, whereas topic entropy is positively associated with them.

These findings suggest that patent reemergence is associated with broader technological exploration across topics alongside relative stability in the overall topic structure. The study extends the investigation of collective dynamics to technological knowledge and innovation, illustrating how patterns at the field level can be related to outcomes involving individual technological artifacts. It also offers a methodological example of how topic modeling and statistical analysis can be used to investigate collective patterns in large textual datasets.

Ramlall and Roy [12] examine how the integration of auditory and visual sensing influences collective motion in three-dimensional Vicsek models. Much of the existing research on collective motion has emphasized vision-based sensing, whereas the study investigates how multiple sensory modalities affect the information available to interacting entities and the resulting collective behavior. Through numerical simulations, the authors compare combined auditory and visual sensing with scenarios relying on either modality alone. Their results indicate that combining sensory inputs allows entities to interact with more neighbors and acquire more information, facilitating the formation of a single, aligned group under a narrow sensing region. The findings demonstrate how sensing capabilities and information acquisition can influence the emergence of collective patterns.

This contribution provides insight into the relationship between information, local interaction rules, and collective behavior. It also has potential implications for robotic swarms and other distributed systems in which individual agents must coordinate without relying on comprehensive centralized control. More generally, it highlights the importance of investigating how information availability and sensing limitations shape collective decision-making and the behaviors that emerge from interactions among constituent entities.

3. A Synthesis of Contributions

Taken together, the five articles illustrate several complementary dimensions of collective dynamics, decision-making, and self-organization. First, they demonstrate the importance of *interaction and information*. The study of three-dimensional collective motion shows how sensing modalities influence the information available to interacting agents and the collective patterns that emerge. The patent study similarly examines how patterns in the distribution and evolution of technological topics relate to the subsequent recognition of individual patents.

Second, the articles emphasize the relationship between *decision policies and system-level outcomes*. The customer-retention study demonstrates that decision policies must be evaluated in terms of economic value, stability, and interpretability rather than ranking performance alone. The organizational resilience study shows how alternative decision-making structures and crisis-aware AI can influence performance under disruption.

Third, the contributions demonstrate the value of *model-based analysis for complex interventions and changing conditions*. The social care study uses system dynamics to investigate long-term policy scenarios, while the organizational resilience study uses agent-based simulation to compare alternative organizational structures and crisis responses.

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These approaches enable researchers to examine interactions and potential consequences that may be difficult to assess through isolated or static analyses.

Finally, the articles reveal the importance of evaluating outcomes at multiple levels. A policy that benefits an individual entity may not necessarily improve collective performance; a model with strong predictive or causal-ranking results may not yield stable decisions; and a locally effective interaction rule may produce system-level behaviors that depend on the broader configuration of the system. These observations reinforce the need to investigate how local decisions, information structures, organizational arrangements, and environmental conditions interact to shape collective outcomes.

Although the articles address distinct application domains, their combined contributions establish a useful basis for advancing research on complex systems. They demonstrate the value of computational and empirical approaches while highlighting the need to examine the conditions under which observed patterns and model-derived insights remain valid.

4. Conclusions and Future Research Directions

The contributions to this Special Issue advance understanding of collective dynamics, decision-making, and self-organization across organizational, social, biological, and technological contexts. Collectively, they show that system-level outcomes are shaped not only by the characteristics of individual entities but also by the interactions among those entities, the information available to them, the decision policies they employ, and the structures within which they operate. They further demonstrate the value of computational modeling, simulation, causal machine learning, system dynamics, and data-driven analysis for investigating these relationships.

At the same time, the findings point to an enduring challenge: understanding how complex systems behave when conditions depart from those assumed by conventional decision models. Real-world sociotechnical systems frequently operate under ambiguity, uncertainty, emergence, non-ergodicity, and non-monotonicity. These characteristics challenge assumptions about the availability and interpretation of information, the predictability of system behavior, the stability of decision policies, and the transferability of conclusions across contexts. Addressing these challenges should be a central priority for future research.

First, future research should investigate decision-making under ambiguity and uncertainty. Existing approaches can compare alternatives when objectives, available information, and evaluation criteria are sufficiently specified. However, complex systems often involve competing interpretations of events, incomplete knowledge, and changing perceptions of risk. Research should examine how individuals, organizations, and autonomous agents interpret ambiguous signals, revise their beliefs, and adapt their decision policies as new information becomes available. Particular attention should be given to the consequences of disagreement among decision-makers, the distribution of information across system boundaries, and the mechanisms through which local interpretations influence collective action. Such research could clarify when decentralized decision-making supports adaptability and when it amplifies inconsistent or counterproductive responses.

Second, research should examine emergence and the relationship between local interactions and system-level behavior. The contributions on collective motion and organizational resilience demonstrate the importance of interaction rules, sensing capabilities, and organizational structures. Nevertheless, predicting how changes in these elements will influence collective outcomes remains difficult. Future studies should investigate the conditions under which local interactions produce desirable patterns, unintended consequences, or cascading failures. This includes examining the formation and dissolution of coalitions, the propagation of information and behavioral changes, and the emergence of coordination

or fragmentation across organizational and technological networks. Multi-level modeling and simulation, supported where possible by empirical observations, could help establish more robust explanations of how micro-level decisions generate macro-level outcomes.

Third, non-ergodicity warrants greater attention in the evaluation of decision policies and system performance. When system behavior changes over time or depends on its evolving history, aggregate averages may conceal important differences among trajectories, operating conditions, and affected entities. A policy that performs well on average may produce unacceptable outcomes in particular circumstances or may become ineffective as the system evolves. Future research should therefore distinguish between population-level averages and trajectory-dependent outcomes, evaluate the persistence of policy effects over time, and examine how learning, adaptation, and historical dependencies influence subsequent behavior. Repeated-run validation, longitudinal analysis, and scenario-based evaluation can contribute to this effort, provided that the selected methods are appropriate to the underlying system and its temporal dynamics.

Fourth, future research should address non-monotonicity and the possibility that interventions produce unexpected or changing effects. In complex systems, increasing resources, strengthening control, introducing additional information, or optimizing an individual performance measure does not necessarily improve overall system outcomes. Interventions can create feedback effects, shift incentives, alter interaction patterns, or generate new constraints. Research should investigate these relationships explicitly rather than assuming that improvements in individual components translate directly into improvements in the whole. This priority is particularly relevant to AI-supported decision-making, organizational restructuring, preventive public policy, and resilience engineering. Studies should examine trade-offs among efficiency, stability, adaptability, fairness, and recovery, while identifying the conditions under which an intervention produces benefits, diminishing returns, or adverse consequences.

Fifth, future research should integrate self-organization with governance and resilience. Self-organized systems can adapt to changing conditions through local coordination, but the absence of comprehensive centralized control does not automatically guarantee effective collective outcomes. Future studies should investigate how decentralized decision-making can be combined with appropriate governance mechanisms, information sharing, accountability, and constraints on harmful behavior. Research should also distinguish between resilience as the ability to maintain performance during disruption and resilience as the capacity to adapt or transform when existing operating arrangements are no longer viable. This distinction is important for critical infrastructures and other sociotechnical systems whose continued operation depends on coordination across organizational, technological, and institutional boundaries.

Sixth, the integration of AI with collective decision-making requires further investigation. The organizational resilience study demonstrates the potential of crisis-aware learning, while the customer-retention study highlights the importance of policy stability and interpretability. Future research should bring these concerns together by examining how AI-supported policies behave when data distributions shift, causal relationships change, and operating conditions differ from those represented in training or simulation. Researchers should evaluate not only predictive accuracy or immediate performance but also decision stability, transparency, robustness, and the consequences of interactions between human and artificial agents. The objective should be to establish when AI enhances collective adaptability and when its use introduces additional sources of uncertainty or systemic vulnerability.

Finally, future research should strengthen empirical validation and cross-domain comparison. The diversity of applications represented in this Special Issue offers opportunities to identify common mechanisms across biological collectives, organizations, public services,

manufacturing systems, and technological innovation. However, similarities in observed patterns should not be taken as evidence that the same mechanisms operate identically across domains. Future studies should test whether findings obtained through simulation or analysis of particular datasets hold under alternative assumptions, different operating conditions, and real-world interventions. Comparative research could help distinguish general principles of collective dynamics from domain-specific relationships and clarify the limits within which particular models and decision strategies remain applicable.

These priorities suggest the need for research frameworks that connect individual decision policies, interactions among constituent entities, system-level outcomes, and the changing environments in which complex systems operate. Such frameworks should combine theoretical explanation with empirical evidence and should evaluate not only whether a strategy performs well under specified conditions but also how robustly it performs when those conditions change. Particular emphasis should be placed on the relationships among ambiguity, uncertainty, emergence, non-ergodicity, and non-monotonicity, since these characteristics can interact and compound the difficulties of prediction, coordination, and control.

Ultimately, advancing the study of collective dynamics, decision-making, and self-organization requires moving beyond the assumption that complex systems can be understood or managed solely by optimizing their individual components. Their behavior depends on interactions, feedback, adaptation, and the conditions under which local decisions become collective outcomes. The research presented in this Special Issue provides a foundation for examining these relationships across diverse application domains. Future work should build on this foundation to develop and validate approaches that explain emergent behavior, support defensible decision-making, and strengthen the adaptability and resilience of complex sociotechnical systems operating in environments characterized by ambiguity, uncertainty, emergence, non-ergodicity, and non-monotonicity.

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