

Essay

Collective Intelligence for Disaster Resilience: A Research Agenda

Vittorio Nespeca, Frances Brazier, Tina Comes

Abstract. This essay argues that collective intelligence is essential for disaster resilience. Despite the potential of collective intelligence, the underlying principles and paradigms remain insufficiently addressed in current research. To start addressing this gap, this essay proposes a dedicated research agenda on collective intelligence for disaster resilience. By outlining this agenda, the essay seeks to stimulate further inquiry at the intersection of these fields.

Keywords. *Design for emergence, self-organization, adaptation, AI, distributed computing, modeling and simulation, mixed methods, participatory design, multiscale computing*

The Need for Disaster Resilience

In this increasingly complex and chaotic world, fraught with systemic, compounding risks and crises, disaster resilience is more crucial than ever (Eshghi & Larson, 2008; Rockström et al., 2023). Disaster resilience requires institutions and communities to have the capacity to prepare for, withstand, recover, and learn from shocks and stresses (Adger et al., 2005; Norris et al., 2008; Rockström et al., 2023). In other words, they need to be able to absorb, adapt and transform. Absorption is related to the ability to withstand shocks and quickly recover, returning to the previous state of a system before the shock occurred (Hollnagel et al., 2006; Klein et al., 2003). Adaptation focuses on a system's ability to gradually and incrementally learn from and adjust in response to external shocks and ongoing shifts, reaching a new system state or maintaining the same state despite evolving conditions (Folke et al., 2010; Kates et al., 2012; Wise et al., 2014). Transformation refers to the ability to transition into a new system configuration when the current configuration is no longer viable or difficult to change incrementally (Folke et al., 2010; Kates et al., 2012; Walker et al., 2004).

Building resilience over time also entails accounting for complex interactions across multiple spatial and governance levels (or scales¹). Resilient systems are not isolated; rather, they are embedded within broader socio-ecological, socio-technical, and institutional contexts in which processes at one scale can both influence and be influenced by dynamics at other scales. This perspective aligns with the concept of *panarchy*, with interconnected, adaptive cycles that operate across these scales (Folke et al., 2010; Walker et al., 2004). Within a panarchical system, local-scale dynamics (such as community responses to disturbances) are shaped by higher-level structures, including national policies or global environmental trends, while simultaneously contributing to transformations at those broader scales. As a result, resilience-building efforts must consider cross-level linkages, feedback loops, and potential cascading

¹ “Level” or “scale” are used interchangeably to denote a defined range of analysis within a given dimension (Borgdorff et al., 2013). For example, when governance is the dimension considered, a local scale spans from individual urban dwellers to city-level institutions, while a broader scale extends from the regional to the national level.

effects that can enhance or undermine a system's ability to absorb, adapt and transform over time.

Finally, fostering disaster resilience also includes *temporality*, that is the interplay across multiple scales in time² (Comes, 2016; Copeland et al., 2023; Krishnan et al., 2024; Wise et al., 2014). First, considering temporality is key when short-term crisis response or recovery decisions induce path dependent long-term risks, possibly hampering resilience in the long term (O'Brien et al., 2012). This takes place, for example, when building progressively higher dykes in response to flooding events in floodplains drives an increase in population density in the proximity of the mitigation infrastructure, leading to the unintended build-up of higher level of exposure over time; a potential driver of increased risk (Ding et al., 2023). Second, temporality is equally important when long-term processes and conditions shape short-term absorption capacities and outcomes. Pre-existing socio-economic inequalities, institutional arrangements, and prior investment decisions can significantly influence how effectively actors are able to respond to and recover from sudden disruptions. As such, long-term underinvestment in critical infrastructure or preparedness measures may constrain immediate response options, while sustained investments in risk reduction, capacity building, and adaptive planning can enhance the system's ability to act swiftly and effectively during crises (Maor, 2025; Norris et al., 2008). Third, considering temporality is essential when systems include multiple subsystems characterized by different cycles of renewal and maintenance (Krishnan et al., 2024). Each of these cycles, termed "rhythms," is associated with a different timescale. For instance, within cities, some subsystems such as mobility patterns or public space use may change rapidly, while others, such as transport infrastructure, housing stock, or ecological systems, evolve much more slowly. For a system to be resilient, it is therefore essential to account for the temporal interplay across these rhythms or timescales, as mismatches between them may undermine the system's overall resilience.

The Role of Collective Intelligence

Collective intelligence (CI) refers to the ability of a system composed of multiple individuals (actors) to act collectively in ways that appear intelligent (Malone et al., 2009; Malone & Bernstein, 2015; Woolley et al., 2010). Such intelligence, in its most general sense, entails a system's ability to solve a wide variety of complex problems in a broad range of environments or to adapt to a changing environment (Galesic et al., 2023; Malone, 2018).

To determine whether CI emerges within a system, two conditions must be met: (a) the system comprises multiple heterogeneous actors whose activities are at least partially interconnected, with dependencies among them (Malone & Crowston, 1994); and (b) the system is designed to address one or more specific challenges in pursuit of defined goals (Malone & Bernstein, 2015). From this perspective, CI is observer-dependent and relies on performance indicators to assess how effectively the system addresses these challenges.

When studying disaster resilience, the systems under observation comprise a diverse set of heterogeneous actors and groups, including governmental organizations operating at multiple levels of governance (local, regional, national, and supranational, such as the EU), non-governmental organizations (NGOs), private sector organizations, and informal entities such as local communities. Activities undertaken by these groups—and more specifically, by their individual members, hereafter referred to as "actors"—are often highly interconnected. For

² When considering time as a dimension, a scale may for instance span seconds to hours, months to years, or even years to decades. The interplay across such time scales consists of the interaction across phenomena that may take place at one scale but can also have implications at different time scales.

instance, in disaster response contexts, actors may compete for limited resources such as customs capacity, slots in airports and seaports, or humanitarian funding to support operations. Further, these actors also need to collectively distribute response efforts across disaster-affected areas in a way that is proportional to local needs (Whittaker et al., 2015)

To be resilient to disasters, systems must address complex challenges arising from disruptive environmental changes, whether sudden or gradually unfolding (Boin & Hart, 2001). Such disturbances require a system not only to absorb shocks but also to adapt and, when necessary, transform into a new system state.

A system characterized by collective intelligence draws from a number of collective capabilities of a group, including sensing, remembering and learning (Malone, 2018; Mulgan, 2018, 2023).

- Sensing (or observing) refers to the timely detection and interpretation of relevant changes in the environment.
- Remembering involves preserving information and knowledge and transferring it from where it is available to where it is needed for coordination and decision making.
- Learning is the ability to recognize and internalize effective practices (such as identifying which actors are most effective in specific roles) and adapt accordingly.

These collective capabilities of CI can enhance resilience, as discussed in the following section.

Synergies Between Collective Intelligence and Disaster Resilience

The collective capabilities associated with collective intelligence have been found to support specific resilience capacities. For instance, in disaster contexts, collective sensing entails detecting and interpreting relevant environmental changes that may constitute potential disastrous events in a timely manner. This sensing capability is crucial for resilience because it enables actors to *absorb* shocks by activating a timely and effective response in the short term, as well as to enact *adaptation* or *transformation* when needed in the long term (Burnard & Bhamra, 2011; Comfort, 2007; Galesic et al., 2023; Rockström et al., 2023; Walker et al., 2004).

Collective *learning* supports the *absorption*, *adaptation* and *transformation* capacities of resilience by recognizing and retaining lessons learned from past crises, and preparing communities to respond to future ones (Azad et al., 2022; Haraldseid-Driftland et al., 2022). *Learning* can also take place during crises, supporting adaptation as well as absorption (Comes et al., 2020; Comfort, 2007). For instance, collective learning enables distributed selection of actors who are effective in fostering inter-group information exchange, improving the groups' ability to retrieve external information required for *sensing* critical changes in their environments (Nespeca, 2025, pp. 119-148).

Yet, acquiring knowledge does not help when such knowledge is forgotten before it is needed. Disaster response systems are, in fact, prone to collectively 'forgetting' knowledge acquired through past experiences. For instance, this phenomenon is observed in areas surrounding dykes, where population density in the years following a flood may surpass pre-flood level (Ding et al., 2023). This trend is driven by the construction of higher dykes after a flood, which increases the time interval before a next flood occurs. As a result, both populations and institutions have time to gradually but significantly lose the memory of past flood consequences, thereby enabling the resettlement of inhabitants in greater numbers in close proximity to the dyke (Di Baldassarre et al., 2015). Collective forgetting also occurs in

humanitarian response organizations due to high staff turnover and the challenges of transferring knowledge between those leaving and those entering the field (Caballero-Anthony et al., 2021; Caroline Martins & Meyer, 2012; Ramalingam, 2006). Smarter strategies for collective *remembering*, such as awareness raising campaigns, exit interviews, and storing and making information accessible through the use of large language models (LLMs) (Burton et al., 2024; Ramalingam, 2006), are thus crucial to help retain acquired knowledge and support all resilience capacities.

These examples highlight promising synergies between fostering collective intelligence and enhancing resilience.

A Research Agenda on Collective Intelligence for Disaster Resilience

While earlier studies provide examples of synergies between collective intelligence and disaster resilience, current scholarship focuses mostly on crisis management (see, e.g., Palen et al., 2010; Starbird, 2013; Starbird & Palen, 2011; Vieweg et al., 2008; Vivacqua & Borges, 2012), particularly with respect to the short-term absorption capacity of resilience. However, the dynamics between collective intelligence and long-term resilience, especially concerning the capacities for adaptation and transformation, and their interplay with absorption, remain largely unexplored. Accordingly, this essay presents a research agenda—originally introduced by Nespeca (2025) and further developed through contributions from all the authors of this essay—that focuses on how collective intelligence can support resilience (CI4RE).

This CI4RE agenda includes four cross-cutting themes, namely *Collective Intelligence for Coordinated Self-organization*, *Hybrid intelligence*, *Mixed Agent-Based Modeling Methods*, and *Participatory Modeling and Sensemaking*. Each of these themes is presented in the following sections.

Collective Intelligence for Coordinated Self-Organization

A system's collective intelligence hinges on its ability to *coordinate* resources, including information and knowledge, and direct them towards specific problems (Heylighen, 2013; Woolley et al., 2015). The need to coordinate resources is rooted in dependencies among the activities of different actors and groups within a considered system (Argote, 1982; Malone & Crowston, 1994). As previously discussed in relation to the role of collective intelligence, examples of such dependencies during disasters include competition over access to limited resources such as funding or transportation infrastructure. In such situations, coordination involves managing dependencies among the activities of different actors and groups operating in disaster response (Comfort, 2007; Malone & Crowston, 1994). The conceptualization of collective intelligence as emerging from coordination under conditions of distributed action and resource interdependence, as well as its relationship with disaster resilience, are summarized in Figure 1 and elaborated upon in the following paragraphs.

Due to the volatility of crisis environments, all involved actors continually need to adapt their activities to the changing situation. Actors often adapt autonomously. This occurs both in contexts where no central control authority exists, such as humanitarian response operations, and in contexts where centralized organizational structures are formally in place, yet autonomous adaptation still emerges in practice (Haynes et al., 2020; Wolbers et al., 2018). As a result, adaptation processes tend to become decentralized, often giving rise to the

spontaneous emergence of new organizational patterns³ such as the formation of new groups or changes in organizational structures and roles (Altay & Labonte, 2014; Dynes & Aguirre, 1979; Haynes et al., 2020; Whittaker et al., 2015). This process, by which the operational patterns emerge, is known as self-organization (Anzola et al., 2017; Comfort, 1994; Kauffman, 1993).

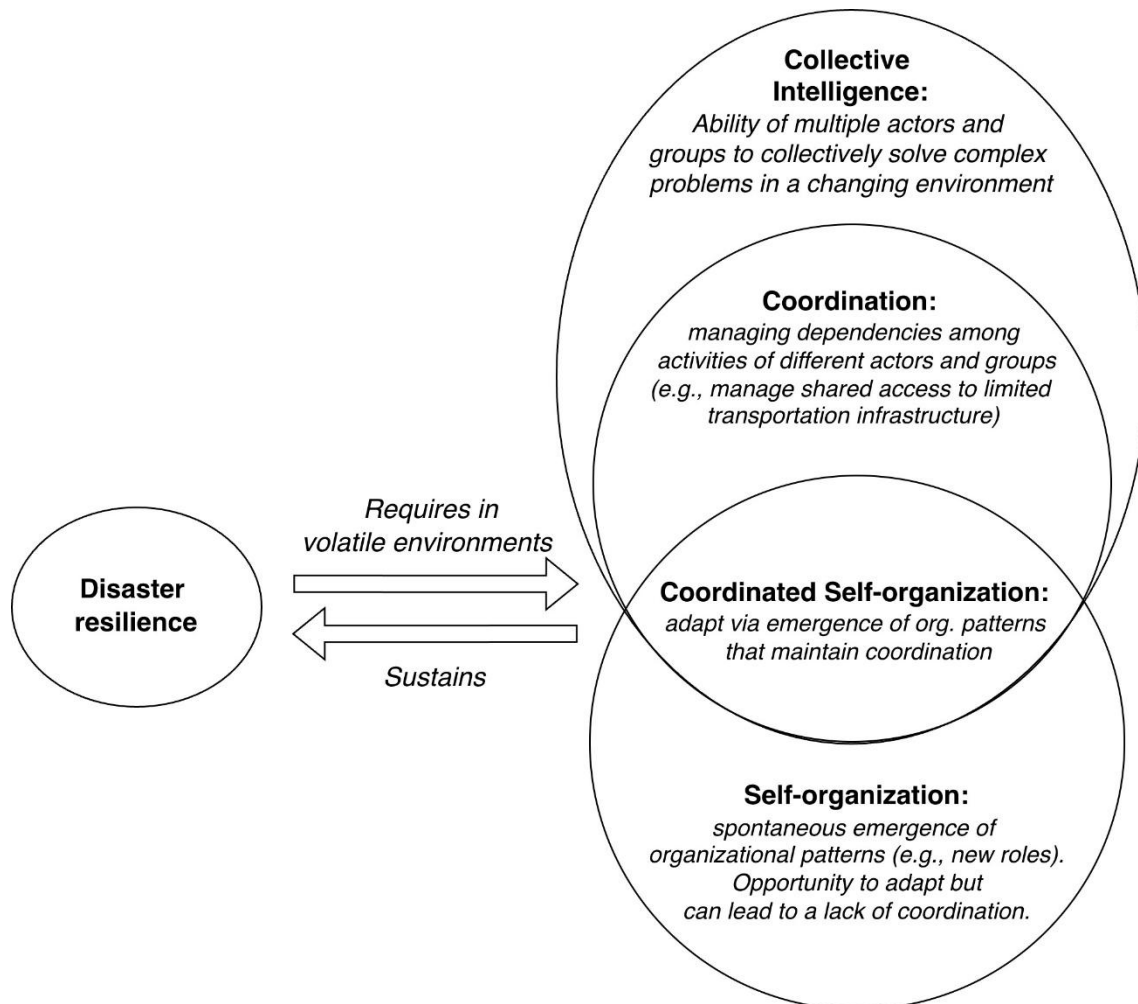


Figure 1. Overview of key concepts and their relationships based on Nespeca (2025, p. 2)

While self-organization can enhance a system's ability to adapt to a volatile environment in a decentralized and flexible manner, it also poses coordination challenges. More specifically, self-organization can lead to the emergence of fragmented pockets of coordination (or 'coordination-information bubbles') that grow increasingly stable and difficult to bridge over time (Comes et al., 2020). This fragmentation can enhance coordination in routine disaster operations (Wolbers et al., 2018). However, it poses significant challenges in non-routine operations, where mutual adjustments between actors and groups are essential, as is typically the case during disaster response (Turoff et al., 2004). In such contexts, fragmentation

³ A pattern is a regularity that can be observed in reality, e.g., the flocking of birds. Patterns can emerge through interactions among different parts of a system (Grimm et al., 2005). The flocking behavior of birds, for example, can spontaneously arise from interactions among individual birds (Reynolds, 1987). Organizational patterns are ways of performing and dividing tasks among actors. While such division is typically the result of top-down decision making regarding hierarchical structures, mandated roles, and standardized procedures (Galbraith, 2014), organizational patterns can also emerge through interactions among actors. This can lead for instance to the emergence of new groups (Backstrom et al., 2006), informal leaders (Foti & Hauenstein, 2007), or roles (Levina & Vaast, 2005).

disrupts communication between groups, impairs collective sense-making, and prevents the development of a ‘common operating picture,’ which is vital for effective coordination and collective intelligence (Bharosa et al., 2010; Comes et al., 2020; Comfort, 2007). This lack of coordination, in turn, undermines collective intelligence and resilience.

To support collective intelligence and resilience in volatile environments, it is imperative for actors and their groups to self-organize in a way that maintains effective coordination. Actors need to align their activities through a process defined as *Coordinated Self-Organization or CSO* (Nespeca, 2025; Nespeca et al., 2020). A system characterized by coordinated self-organization can restructure and adjust its organizational patterns through an emergent, decentralized process, allowing it to adapt to changing environmental demands and the evolving needs of its actors and groups, while managing the dependencies among their activities. In other words, CSO is a system’s ability to adapt via self-organization while sustaining coordination.

Achieving coordinated self-organization, however, remains a challenge. This research theme therefore examines how CI can support CSO by enhancing the capacity of systems composed of governmental agencies, NGOs, and communities to collectively: (a) detect and make sense of environmental changes, (b) learn and adapt, and (c) retain and transfer relevant knowledge to where it is needed, thereby fostering absorption, adaptation and transformation. It relies on the methods developed in the themes *Mixed Agent-Based Modeling Methods* and *Participatory Modeling & Sensemaking* described later in this essay.

Hybrid Intelligence

Information systems and technologies such as social media, crowdsourcing platforms, and AI (including LLMs) already shape and hold significant potential to foster the collective intelligence of co-evolving, hybrid human-machine systems in volatile environments (Comfort, 1994; Vivacqua & Borges, 2012; Ramchurn et al., 2016; Tessler et al., 2024; Tsvetkova et al., 2024; Vaccaro et al., 2024).

At the same time, these technologies have introduced novel challenges that threaten collective intelligence and resilience, including the spread of misinformation, knowledge homogenization, polarization and radicalization, as well as the unintended introduction of hidden biases in AI-supported decision making (Burton et al., 2024; Chen et al., 2023; Wang et al., 2019).

Research is needed on designing coordination mechanisms that combine information systems, AI agents, and human groups to enable smarter sensing, remembering, and learning, while addressing the challenges introduced by these technologies. The goal is to foster absorption, adaptation, and transformation within disaster response systems. For instance, this theme focuses on collective sensing in volatile environments. This includes detecting misinformation and identifying high-quality information to be shared with those who need it. It also includes using LLMs as tools for collective learning and remembering, with a focus on avoiding knowledge homogenization and bias (Burton et al., 2024).

Further, contemporary perspectives in Human-Centered AI emphasize the importance of maintaining humans “in the loop,” thereby fostering synergies between human and artificial intelligence rather than fully delegating tasks to AI systems. However, these approaches remain largely grounded in an optimization-centric paradigm that assumes objectives to be predefined and stable. This assumption does not hold in complex and volatile crisis environments, where *objectives cannot be specified a priori* but instead emerge through ongoing processes of sensemaking, understood as the collective interpretation and construction of meaning in ambiguous and evolving situations that enables adaptive action (Weick, 1995). Further, human-centered AI primarily focuses on augmenting individual

intelligence, often overlooking that sensemaking is inherently a collective process that emerges through interactions among multiple individuals. In such contexts, increasing effectiveness of AI in achieving predefined individual outcomes risks narrowing collective sensemaking and reducing the capacity to interpret unexpected events as they occur, thereby potentially impairing collective intelligence and resilience.

Accordingly, a new paradigm for AI design, referred to as *Sensemaking AI*, is required to examine how AI can support the collective, networked interpretation of evolving situations, enable the construction of shared understanding in uncertain and rapidly changing environments, and facilitate adaptive responses (Comes, 2026). This includes ensuring that systems can recognize when optimization diverges from the original purpose and take timely action to redirect sensemaking trajectories before they become overly rigid (Comes et al., 2020) for example by dynamically adjusting objectives, roles, and tasks. It also entails moving beyond a model of control based on a “human-in-the-loop” approach to forms of self-regulation that emerge from interactions among actors, organizations, and AI agents within the system.

This research theme builds upon the methods outlined in the following sections on *Mixed Agent-Based Modeling Methods* and *Participatory Modeling & Sensemaking*.

Mixed Agent-Based Modeling Methods

Collective intelligence and its contribution to disaster resilience can be fostered through both distributed, self-organized mechanisms and more traditional, centralized hierarchical arrangements—formalized as organizational structures (Malone et al., 2009). In multi-actor systems where actors operate at least partly autonomously, without fully hierarchical arrangements, it is often the interplay between centralized and distributed forms of organization that shapes collective intelligence. In such contexts, collective intelligence emerges from interactions across multiple levels of analysis, including micro-level individual behaviors, meso-level organizational characteristics such as formal structures and informal networks, and macro-level factors such as features of the decision environment (e.g., complexity, uncertainty, and urgency) and inter-organizational information sharing and collaboration practices (Bharosa et al., 2010; Joseph & Gaba, 2020; Marrone, 2010).

Modeling and simulation can support the study of the interplay between centralized and decentralized ways of organizing from a collective intelligence and resilience perspective (Altay & Pal, 2013; Comfort et al., 2004; Fiala, 2005; Watts et al., 2019; Zagorecki et al., 2009). While several modeling paradigms can be used to study CI4RE, Agent-Based Modeling (ABM) is one such approach, given its ability to capture and investigate the implications of complex interactions across multiple levels of analysis and their impact on system's behavior for a given phenomenon of interest (Epstein, 1999; Shnerb et al., 2000; Bonabeau, 2002; Antosz et al., 2022).

Yet, while ABM provides a useful means to study CI4RE, its application has often focused on conceptual and theoretical explorations (Altay & Pal, 2013; Comfort et al., 2004; Zagorecki et al., 2009). Although these studies offer valuable theoretical directions for future research or illustration of key principles, they require empirical grounding for practical application (Edmonds et al., 2019). ABM has also been used in combination with empirical approaches, including surveys, interviews and laboratory experiments, which provide a stronger basis for investigating key phenomena (Wijermans et al., 2022). However, research in crisis management and resilience often relies on insights derived from one or more case studies to

infer key principles and mechanisms⁴ (Comfort, 2019; Wolbers et al., 2021). Yet, despite recognition of its potential to be combined with case study research (Castellani et al., 2019; Tubaro & Casilli, 2010), and advances in this area (Ghorbani et al., 2015; Nespeca et al., 2023; Schüter et al., 2025), integrating ABM with multiple case studies remains a challenge.

As such, further research is required that explores how combining ABM with case study research can advance CI4RE research. First, research in this theme focuses on developing formal approaches to *theorize through ABM*, enabling the systematic formalization and inspection of our understanding of phenomena as well as the formulation of propositions that guide case study design. Second, it delves into *using ABM to integrate, assess, and compare findings across (quantitative and qualitative) methods and cases*. Together, these two approaches offer promising synergy between ABM and empirical, case study research by supporting theory-driven case study research design and enabling mixed-method integration to enhance construct, internal, and external validity in multiple case study research.

Participatory Modeling & Sensemaking

The development and use of one or more conceptual and computational models is an essential feature of collective intelligence, illustrating the way a group (e.g., the government) makes sense of and learns from a crisis (Hernantes et al., 2013; Mulgan, 2018, 2023; Page, 2018; Stephens et al., 2020; Turoff et al., 2013). This theme focuses on fostering the collective intelligence of groups of decision-makers, domain experts, and scientists when making sense of, responding to, and learning from crises (Christianson & Barton, 2020; Faraj & Xiao, 2006; Maitlis & Sonenshein, 2010; Weick, 1988). It does so by developing and implementing problem structuring techniques involving the participatory development and use of conceptual and computational models and evaluating their impacts on decision making and sensemaking (Rouwette et al., 2009; Stephens et al., 2020).

While participatory modeling is typically limited in terms of group size—usually, up to 15 participants (Vennix, 1996)—recent developments in AI and group deliberation tools show promise in up-scaling these techniques (Burton et al., 2024; Tessler et al., 2024), which will be further explored in combination with the use of conceptual and computational models in this theme. Given that fostering resilience requires the interplay of multiple temporal and governance-related scales—which, as outlined in the first section of this essay, is linked to temporality and panarchy—the conceptual and computational models adopted to support resilience should be capable of capturing these different scales. One single model is often not sufficient to consider the complex interplay among such different scales. The use of multi-models, i.e., combinations of interacting models, is a promising approach to address this challenge (Filatova et al., 2025; Nespeca et al., 2024). Yet, the participatory techniques necessary to design multi-models capturing multiple scales in collaboration with groups are currently lacking and require further research.

Conclusion

As this world struggles to cope with increasingly threatening, pervasive, frequent, and compounding disasters and crises, the quest to enhance disaster resilience becomes paramount. This essay has discussed how harnessing the capabilities of multiple actors and

⁴ The choice of case study research is supported by the fact that the absorption, adaptation and transformation dynamics associated with resilience are often strongly shaped by their context (e.g., characteristics of the decisional environment) and cannot easily be analytically separated from it (Yin, 2014).

groups to self-organize, coordinate, and act in a collectively intelligent manner is a promising avenue for building disaster resilience. By fostering the collective ability of governments, NGOs, and communities to sense, learn, and remember critical information and knowledge, systems can absorb, adapt, and transform in response to shocks, improving their resilience and better addressing both the challenges of today and those of tomorrow. This research agenda indicates a path forward for research that can support communities, organizations and governments striving to build a more resilient future.

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About the Authors

Vittorio Nespeca is a postdoctoral researcher at Leiden University whose work focuses on collective intelligence for disaster resilience. He combines computational modeling with case studies to investigate emergent, self-organized mechanisms that enable multi-actor systems to collectively recognize and address problems in dynamic environments. His research explores how ICT and AI can be designed to collaborate with human groups to strengthen these mechanisms. Ultimately, his goal is to understand how collective intelligence can be harnessed to improve a system's capacity to absorb shocks, adapt to changing conditions, and transform, thereby advancing disaster resilience.

Author Email: vittorionespeca@gmail.com
ORCID iD: <https://orcid.org/0000-0002-1691-0143>

Frances Brazier is Emerita Professor of Engineering Systems Foundations at Delft University of Technology. Her research and areas of expertise include participatory systems, distributed systems, multi-agent systems, autonomic computing, and socio-technical system design. She has made significant contributions to the development of Internet and digital society research in

the Netherlands, including her involvement in the establishment of NLnet, one of Europe's earliest Internet service providers. Brazier has supervised numerous PhD candidates and authored more than 400 academic publications in the fields of artificial intelligence, distributed systems, and socio-technical systems engineering.

ORCID iD: <https://orcid.org/0000-0002-7827-2351>

Tina Comes is a Full Professor of Decision Theory & ICT at TU Delft (Netherlands) and Director of the DLR Institute for Terrestrial Infrastructure Protection (Germany). She is a member of the Norwegian Academy of Technological Sciences and Academia Europaea. Additionally, she leads the EU Commission's scientific advice on AI in crisis management, contributing her expertise in digital technologies and decision theory. Her research focuses on scenario-based decision support for managing complexity and uncertainty, near real-time analysis, and supply chain risk management for designing agile networks. She also specializes in information and communication technologies, critical infrastructure, and smart cities.

ORCID iD: <https://orcid.org/0000-0002-8721-8314>

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