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Collective intelligence as collective information processing

Zara Anwarzai [a,b,*], Cody Moser [c], Hannah Dromiack [d,e], Ketika Garg [f], Gabriel Ramos-Fernandez [g,h]

[a] Department of Philosophy at Simon Fraser University, 8888 University Dr W, Burnaby, BC V5A 1S6, Canada
[b] Cognitive Science Program at Simon Fraser University, 8888 University Dr W, Burnaby, BC V5A 1S6, Canada
[c] School of Collective Intelligence, Mohammed VI Polytechnic Institute, Rocade Rabat-Salé, Rabat 10100, Morocco.
[d] Department of Physics, Arizona State University, 1151 S Forest Ave, Tempe, AZ, USA
[e] BEYOND Center for Fundamental Questions in Science, Arizona State University, 1151 S Forest Ave, Tempe, AZ, USA
[f] Department of Humanities and Social Sciences, California Institute of Technology, 1200 E California Blvd, Pasadena, CA 91125, United States
[g] Research Institute on Applied Mathematics and Systems, National Autonomous University of Mexico, University City, Coyocan, 04510 Mexico City, Mexico
[h] Global Research Centre for Diverse Intelligences, University of St Andrews, St Andrews KY16, United Kingdom of Great Britain and Northern Ireland

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ABSTRACT

Collective intelligence research spans multiple disciplines and focuses on a broad range of collective behaviors, including group problem-solving, flocking in social animals, and the formation of social knowledge. It is not apparent what these different forms of collective intelligence have in common, apart from being instances of collective behavior. In this paper, we develop a framework that enables us to better classify different forms of collectively intelligent behavior in relation to one another based on the information processing mechanisms involved. We argue that these behaviors share a common foundation, which we call collective information processing, or CIP. CIP involves two key mechanisms: (1) individual processing of group information and (2) group processing, or group-level sensitivity to the arrangement of individual information. We operationalize the CIP framework to analyze different forms of collective intelligence, both classifying them in relation to one another and in alignment with generalized quantifiable measures of information processing. Our account of collective intelligence as CIP offers a novel framework for identifying and classifying forms of collective intelligence across a wide range of disciplinary contexts. This framework is meant to unify and subsume, rather than simply challenge, existing attempts to define collective intelligence.

1. Introduction

A wide array of conceptual frameworks, mathematical models, and empirical paradigms have been developed to study collective intelligence and, more broadly, collective behavior. But what, if anything, do these analyses, or the phenomena underlying these analyses, have in common? Part of what has long complicated inquiry into collective behavior is the inability to make clear and reliable comparisons between forms of collective behavior which unfold in drastically different contexts, from insect coordination to mass political action. Despite the extensive breadth of collective behavior studies, it is not apparent what binds the widespread phenomena of collective intelligence, from how individuals interact to the way cultures develop and persist over time.

We argue that a multidisciplinary framework and a common vocabulary are needed to revise and identify commonalities within collective intelligence studies. Existing attempts to define collective intelligence have offered frameworks which are neither explicitly for multidisciplinary application nor adequately suited for identifying common mechanisms which give rise to collective intelligent behavior. At present, the lack of any such framework poses deep problems for productive and comparative inquiry in this area: How should we relate insights about collective intelligence to one another, both within and across disciplines? What, for instance, can flocking models tell us about joint action? Is collective problem-solving a form of distributed cognition or is it a separate process? What role does information sharing play in collective knowledge? In this paper, we develop a framework that enables us to better classify different forms of collectively intelligent behavior in relation to one another based on the information processing

* Corresponding author at: Department of Philosophy at Simon Fraser University, 8888 University Dr W, Burnaby, BC V5A 1S6, Canada.
E-mail addresses: zanwarza@sfu.ca (Z. Anwarzai), hdromiac@asu.edu (H. Dromiack), kgarg@caltech.edu (K. Garg), gabriel@aries.iimas.unam.mx (G. Ramos-Fernandez).

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mechanisms involved. We argue that these behaviors share a common foundation, which we call collective information processing, or CIP.

We identify CIP as a form of information processing that involves two key mechanisms: (1) individual processing of group information and (2) group processing, or group-level sensitivity to the arrangement of individual information. Identifying how these information processing mechanisms unfold in particular instances of collective intelligence allows us to compare its different forms. Further, it enables us to better understand the relationship between individual contributions, the structure of interactions between individuals, group-level structure, and group-level outcomes within each form. Using these two information processing mechanisms, we develop the CIP spectrum, from which we can locate, compare, and analyze different forms of collective intelligence in alignment with potentially quantifiable measures of information processing.

In Section 1, we provide an overview of the different disciplinary perspectives on collective intelligence and argue that, across these perspectives, the lack of a unifying framework poses a classificatory problem for comparative inquiry into collective intelligence. In Section 2, we explain what CIP is and how it allows us to better classify and compare forms of collective intelligence. In Section 3, we highlight the main conceptual and empirical benefits of the CIP framework. Conceptually, it offers analytic tools for describing and interpreting the mechanisms involved in within and across instances of CI, and empirically, it has the potential to provide metrics for those dynamics and mechanisms.

2. Section 1. Collective intelligence studies and their classification problem

Collective intelligence (CI) research does not fall under a single research domain; it is an accumulation of separate fields ostensibly converging on a set of shared phenomena. To capture these perspectives, we outline the research areas of inquiry which have contributed to understanding collective intelligence. We then introduce a key problem with this body of work: CI studies lack a classificatory framework or measures to compare across instances of CI. We cannot systematically or quantifiably compare forms of CI, both within and across disciplines. This problem is exacerbated by contentions about the causal mechanisms and agential properties underlying collective intelligent behavior, as well as the ontological structure of CI (e.g., whether a collective or its constitutive parts are fundamental).

2.1. Collective Behavior (CB) and Collective Intelligence (CI) studies

CI studies are situated within the broader domain of collective behavior (CB) research. Across different disciplines, CB research centers on “phenomena in which repeated interactions among many individuals produce patterns at a scale larger than themselves” (Sumpter, 2006). Disciplines such as philosophy and physics have advanced general concepts or methodological tools to study collective behavior (Garnier & Moussaid, 2022; Sulis, 1997). Other disciplines, such as animal behavior and psychology, have focused on uncovering specific mechanisms for collective behavior within specific collective systems. (For a summary of this review, see Table 1. Readers familiar with the widespread disciplinary perspectives on CB are also invited to skip to Section 1.2.) (See Table 2.)

The conceptual foundations of collective behavior have long been debated by philosophers and sociologists. Philosophers have highlighted features of collective action such as intentions, goals, and planning (Bratman, 1992; Gilbert, 1989, 1996, 2000; Tuomela, 1989, 2002, 2005) and have considered whether agency towards these actions resides within individuals or groups. This research includes debates over ideas such as extended minds (Clark & Chalmers, 1998), distributed cognition (Theiner et al., 2010), macrocognition (Huebner, 2013), and group agency and intentionality (Ludwig, 2015; Palermos, 2016; Searle, 1990). Similarly, sociology has debated the relationship between individual agency and group structure, particularly whether social phenomena are explainable primarily by individual behavior and motivations (Weber, 1968), whether social structure determines individual behavior (Durkheim, 1895), or more fruitfully, how both accounts can be integrated (Archer, 1995; Bourdieu, 1990; Elder-Vass, 2012).

Social psychology has also investigated how membership in a collective affects individual behavior – for example, how a collective's goals or structure influence an individual's choices and actions (Stasser &

Table 1
An overview of different disciplinary efforts to study forms of collective behavior and the underlying mechanisms that might give us reason to consider these behaviors as falling under the label of collective intelligence.

Disciplinary perspective	Leading frameworks	Phenomena of interest	Features which might suggest these behaviors are intelligent
Philosophy	Joint action Group vs. individual minds	● Shared intention ● Individual vs. group agency	● Information sharing
Social & Organizational Psychology	Collaborative configurations	● Synergistic interactions ● Coordination	● Information sharing ● Joint processing of information ● Common recall
Political Science & Economics	Optimality models and Social choice theory	● Voting processes	● Reaching consensus ● Arriving at an optimal or correct estimation
Sociology	Social structures and institutions	● Relationship between individual agency and group structure	● Organized societies with institutions that regulate individual behavior and interactions
Cultural Evolution	Cultural knowledge and practices	● Collective knowledge formation, transmission, and innovation ● Group adaptation	● Group adaptation through cultural innovation
Computer Science	Computer interaction	● Efficiency of computational algorithms for distributed tasks	● Efficiency of problem solving
Animal Behavior	Flocking Swarm Intelligence	● Distributed search ● Rules of interaction	● Efficient use of resources ● Predator detection and escape
Population genetics	Fitness landscape models	● Gene flow ● Adaptation	● Avoidance of local adaptive solutions in favor of global ones
Network Neuroscience	Information Theory	● Information aggregation ● Synergy	● Distributed and flexible learning capacities
Physics	Statistical mechanics and Multi-level analysis	● Interaction dynamics ● Non-equilibrium dynamics	● Diffusion ● Collective Motion ● Interaction effects across scales
Complexity Science	Multi-level organized properties	● Organized structures ● Functional properties ● Adaptation capacity	● Self-organization ● Emergence ● Information hierarchies

Table 2
Prominent accounts of collective intelligence and their explicit definitions of collective intelligence, or the phenomena they treat as paradigmatic of collective intelligence.

Author(s)	Definition (or examples) of collective intelligence
Weschsler (1971)	CI arises in groups that as a unit have a greater amount of knowledge at its disposal, and where individuals tend to influence each other's thinking.
Sulis (1997)	CI lacks internal hierarchical organization, and yet exhibits adaptive systemic behavior.
Lévy (1997)	CI is a form of distributed processing enhanced and coordinated in real-time, resulting in the effective mobilization of skills.
Wolpert and Tumer (1999)	CI lacks centralized control, and yet functions to address system-wide tasks.
Malone and Bernstein (2015, 2022)	CI describes a group in ways which appear intelligent, e.g., distributed prediction or wisdom of crowds
Bettencourt (2009)	CI describes the degree to which information is aggregated within a group in complementary rather than redundant ways, e.g., synergistic interactions.
Trigo and Coelho (2010); Tindale and Winget (2019); Kao et al. (2024)	CI describes the mechanisms which give rise to collective decision making.
Krause et al. (2010)	CI describes either the way individuals share information with one another or a group's ability to address problems, e.g., swarm intelligence.

Dietz-Uhler, 2001). On the other hand, organizational psychology focuses on the outcomes of collective behavior, studying how groups of different sizes perform compared to individuals (Steiner, 1966). These fields also explore what types of collaboration configurations lead to better performance (Centola, 2022; Lazer & Friedman, 2007; Simon, 1978) and the types of information sharing occurring within groups (Barkoczi & Galesic, 2016; Galesic et al., 2023; Garg et al., 2022; Smaldino et al., 2024). Psychologists studying coordination take a more mechanistic approach and employ tasks where pairs or groups of individuals work together. Multiple studies have investigated coordination dynamics such as movement coupling (Riley et al., 2011), synchrony in facial expressions (Chikersal et al., 2017), nonverbal synchrony (Tomprou et al., 2021), neural synchrony (Reinero et al., 2021) and dynamic turn-taking (Moeller et al., 2023).

In fields like political science and economics, collective behavior has been studied through macro-level phenomena such as voting, segregation, financial markets, 'wisdom of crowds' or 'madness of mobs' (Landenmore, 2012; Lo, 2015; Surowiecki, 2005). These fields conceptualize these phenomena as arising from the aggregation of individual decisions, the influence between individuals in their decision-making, and the way information flows in the collective (Feddersen & Pesendorfer, 1997; Schelling, 1978). When considering longer time scales, similar concepts underlie questions in cultural evolution. For instance, how learning, teaching, imitating others, and innovation of existing practices, can lead groups (or societies at large) to acquire, maintain, or change their cultural practices and accumulate knowledge over generations (Sterelny, 2012).

In computer science, collective behavior concepts are behind the use of networked computers to process information, and the ensuing computational advantages of distributed search (Hopfield, 1982; Minsky, 1988; Vesterstrom & Thomsen, 2004). Similarly, principles of collective behavior like particle swarms have been used to improve optimization algorithms in applied settings such as developments and robotics and space search problems (Bongard, 2009; Wang et al., 2018). The study of collective knowledge in online distributed systems such as Wikipedia (DeDeo, 2014), or crowdsourcing solutions to innovation or business problems (Bahrami et al., 2010), has shown the practical applications of distributed information processing as the basis of collective intelligence at society-wide scales. More recently, the design of collective intelligence platforms, specifically aimed at achieving optimal collaboration from multiple actors in solving complex problems, has gained traction (Suran et al., 2020).

Animal collective behavior research emphasizes coordination in flocks, swarms, or insect colonies and how it arises from the accumulated decisions of individuals (Conradt & List, 2009; Gordon, 2016; Hein et al., 2015; Warren et al., 2024). Modeling approaches from statistical physics have been instrumental in demonstrating how simple rules of local interactions can give rise to coordinated behavior at the collective level (Sulis, 1997; Wolpert & Tumer, 1999). At a longer timescale, say that of an individual's lifetime, collective behavior also implies that individuals learn to adjust to each other's behavior (Flack et al., 2013), which results in individuals learning more about the group's behavior as a whole (Collet et al., 2023). At even longer timescales, collective solution searching occurs in population genetics. Adaptation models have shown that one advantage of limited gene flow between diverse subpopulations is that the local optima in a fitness landscape can be avoided, allowing the population as a whole to find a global optimum (Falandays et al., 2023; Kauffman & Levin, 1987; Wright, 1932).Some neuroscientists describe coordination and synchronization between neurons or between parts of the brain as collective intelligence. This introduces a picture of collective intelligence which might unfold at a much smaller scale than the systems under interest in other disciplines. Against the modular model of neural processing, there is support for a coordination-based model of cognition on which neural responses are generated when multiple brain regions work together in synchronized ways (Bressler & Kelso, 2016). Collective dynamics of neurons such as coordinated spiking activity in neuronal ensembles have also been argued to underlie information transfer and computation in cortical networks (Truccolo et al., 2010.

Physics focuses on the fundamental constituents of matter and has a longstanding history of inquiry into the motion and behavior of collective living systems. Due to this perspective, many of the most widely used models for collective behaviors have been outlined; early examples include mathematical models replicating the motion dynamics of flocking, herding, and schooling (Reynolds, 1987; Vicsek et al., 1995). While minimalistic models such as these fail to answer questions concerning the intelligence, agency, or internal decision-making of the individuals within a group, they have spurred forward advances in characterizing such phenomena in other ways. Molecular dynamics and solid-state physics have demonstrated that the macroscale behaviors of collectives of molecules or atoms cannot be explained

simply by their microscopic constituents and that multiple scales of organization are necessary (Weinan, 2011). To that end, physicists have endeavored to create mathematical frameworks to bridge scales of organization and account for multi-level interactions in such systems.

Finally, complexity science offers a fruitful, multi-level perspective on collective intelligence, wherein intelligent, adaptive behavior arises at different scales, from cells to tissues to organisms, and from the individual to the group (Feibleman, 1954; McMillen & Levin, 2024; Miller & Page, 2009; Moussaid et al., 2009; Novikoff, 1945). Processes like self-organization, coordination, or emergence are thought to underlie group behaviors that seem intelligent and adaptive but do not result from centralized control by any individual or task-specific structural demands (Holland, 1992, 2006).

2.2. Classifying collective intelligences

Across and within these disciplinary perspectives, various accounts of collective *intelligence* have been proposed (see Shweta et al., 2020 for an overview). Weschsler (1971) proposed that CI occurred when a group of individuals working together acquired or made use of perceptions or insights not experienced or available to them when working or cogitating alone, allowing the group to arrive at solutions that could not have been arrived at by individual pursuit. Lévy (1997) defines CI as a form of universally distributed intelligence – constantly enhanced, coordinated in real time, and resulting in the effective mobilization of skills. Sulis (1997) and Wolpert & Tumer, 1999identify CI as a feature of a decentralized system which nonetheless exhibits adaptive, organized system-wide behavior. Malone and Bernstein (2015) use CI to describe instances of collective behavior that appear intelligent. Bettencourt (2009) defines CI as a complementary (rather than redundant) information sharing process within groups.

There are some commonalities between these accounts, which seem to pick out features which are consistently involved in collective intelligence: they involve some degree of information sharing, or require complex forms of behavior because of cognitive or organizational demands, or result in outcomes which are potentially indicative of cognitively or psychologically sophisticated processes. However, there are also significant discrepancies in the accounts given about the kinds of phenomena involved in collective intelligence. For instance, is information sharing between group members necessary for group-level outcomes to be considered intelligent? What should matter more for the evaluation of the group as collectively intelligent: group member *interactions* or group-level *outcomes*? These discrepancies raise questions about what binds the diverse forms of collectives studied within this area: it is unclear how forms of CI should be classified in relation to one another (see Reznick, 2020 on the value of unifying diverse phenomena under a single explanatory framework). We refer to this as the *classification problem* about collective intelligence.

This classification problem poses two interconnected issues. The first is about the lack of suitable measures to compare instances of CI. How do the forms of behavior which fall under CI studies (e.g., distributed search, distributed cognition, wisdom of crowds, swarm intelligence) relate to each other? What makes them similar or dissimilar, and by what other measures should we quantitatively or qualitatively compare them? To the extent that classificatory measures for assessing CI have been developed (some explicit and some implicit within accounts of CI), they fall short of enabling both quantitative and qualitative cross-disciplinary comparisons.

Some accounts of CI assume an *outcomes*-based approach for comparative inquiries. Using this kind of approach, we can compare forms of CI based on behavioral output. Riedl et al. (2021) offer an example of this kind of classificatory metric through their attempt to quantify collective intelligence as a factor defined by a "group's ability to perform a wide variety of tasks," which can be used to compare collectives which are more or less intelligent. McMillen and Levin (2024) similarly highlight how analogous transformations can occur across biological systems at different scales (e.g., the interplay between individual movement and collective movement in cell migration is analogous to the movement occurring within swarms of insects). Classifying collective intelligence using this dimension suggests that the primary feature of collective intelligence is the capacity for a group to achieve particular end-states.

Other accounts of CI assume a *mental states*-based approach to comparison. This kind of approach compares CI on the basis of the mental states of the members of the collective or those attributed to the collective itself. On some such approaches, what matters for intelligence is whether individuals *intentionally* act collectively (e.g., in service of some shared goal) or not.[1] Comparisons using this metric might suggest that, because intentional collective action is more cognitively demanding on individual agents, it is a more complex, and hence, more intelligent behavior compared to unintentional or emergent collective action (see, e.g., discussion from Knoblich et al., 2011 on the additional demands of planned over emergent coordination).Both the outcomes- and mental states-based approaches offer relatively narrow metrics for identifying intelligence, which creates a problem for cross-disciplinary, cross-contextual inquiry. Comparing forms of CI on the basis of collective intentionality might work well in certain investigations of human action. However, intentionality might not yield fair or fruitful comparisons for other forms of cross-species or nonhuman species interaction. Intentionality has no uncontroversial analogue in nonhuman species, which complicates any effort to compare forms of animal interaction from birds flocking to ants navigating on that basis and to assess whether these interactions constitute CI. Similarly, assessing CI by looking at behavioral outcomes might be useful when comparing similar groups with similar tasks (e.g., two groups of college students solving similar sets of puzzles). However, it would be unlikely to yield any fruitful comparison regarding more diverse cases (e.g., one group of college students solving a set of puzzles and one group of artificial agents engaged in a navigation task). A more robust metric of comparison, one which allows us to understand whether (or why) the many forms of collective behavior studied across disciplines constitute collective intelligence, and one which allows us to make cross-species, cross contextual comparisons, is needed.

The second issue posed by the classification problem relates to major points of contention in contemporary CI studies about types of causation (top-down or bottom-up, emergent or not) and forms of agency (group, joint, or individual) involved in collective behaviors. Disputes about causation often focus on whether CI involves bottom-up, top-down, or emergent causation (Gordon & Levinthal, 2023; Theiner et al., 2010), while disputes about agency often focus on whether CI involves individual or group agency (List & Pettit, 2011; Ludwig, 2015; Searle, 1990). On some accounts, we might describe CI in terms of individual causal contributions and the cognitive states of the individuals involved. In other words, a group-level outcome (e.g., a group successfully puts together a puzzle) can be fully explained by each individual's contribution (e.g., one individual found border pieces, another organized middle pieces by color, etc.). Other accounts might describe collective intelligence in terms of the group-level cognitive and causal contributions, rather than at the individual-level. In explaining how a group successfully put together a puzzle, for instance, one might appeal to states or attitudes which they think are irreducible to individuals' contributions, such as a sense of group cohesion. Further accounts might describe collective intelligence in terms of the ways group-level processes determine individual contributions. On this view, a group's dynamics may enable and constrain individual thought and action, as in the case of a division of labor which specifies each individuals' task and area of specialization.[2]

These debates complicate our efforts to classify instances of CI because either side of each debate implies an entirely different picture of the nature of CI. Comparing these accounts depends on the relevant causal and cognitive processes for understanding collective intelligence. When it comes to causal attributions, we must determine: Is a group behavior caused by the parts, the structure of relations between the parts, or by some top-down mechanism which exists over and above the parts? Are these different causal sources compatible or not? When it comes to attributions of a certain kind of agency, there are questions about how agents (individuals within a group versus group agents) enact certain cognitive processes and psychological capacities, from planning to problem solving to changes in mood. For example, is a team as a whole planning and strategizing, or are individual members planning and communicating their plans to others? Does a pair of football teammates get around defenders, or are their coordinated but wholly distinct individual behaviors what make this possible? Does a whole team's morale get boosted or just that of the individuals? Disagreement

[1] See Goldstone & Gureckis, 2009 for an overview of this distinction.

[2] These competing approaches come from the debates over "methodological individualism" in the social sciences or the debates over "reductive ontological individualism" in Philosophy (see, e.g., Weber 1922; Schmitt, 2003; Epstein, 2015; Guala, 2022 for overviews).

about the kind of agency or causation involved in CI can be traced to fundamental disagreements about the ontological nature of CI and its underlying parts and mechanisms. Our account of CIP in the next section aims to provide a better framework for thinking through these disputes.

2.3. Section 2. Collective information processing

In this section, we make the case that our Collective Information Processing (CIP) framework identifies the important mechanisms which consistently underlie the phenomena labeled as CI. In Section 2.1 we explain the two different information processing mechanisms which comprise CIP. In 2.2, we develop a classificatory account of CIP on the basis of these mechanisms. In Section 2.3, we offer important clarification around how CIP fits into existing debates about collective behavior, including those on how to distinguish individuals from groups and those about the nature of agency and causation within collective behaviors.

2.4. Collective information processing as collective intelligence

Significant differences exist between the information processing involved in isolated, individual behavior and that which is involved in collective behavior. In collective behavior, individuals might process information *about* the group or individuals may process information aimed at bringing about a specific group outcome. In some cases, a combination of these different forms of group-related information processing may occur. Similarly, different forms of collective behavior might require certain kinds of group-related information processing but not others. For instance, working as a ship crew member will require individuals to process highly specialized information about their own tasks, those of other crew members, and those of the group. Navigating a crowded mall, by contrast, does not require individuals to know much, if anything, about others' specific aims or actions. Similarly, voting in an election tends not to necessarily require knowledge of the activities of the group as a whole, whereas developing an investment strategy requires knowledge of the broader stock market.

To capture these differences, we propose two specific information processing mechanisms that are fundamental across forms of collective intelligent behaviors: (1) *individuals processing group information* – that is, individuals processing information that is about (or otherwise relevant to) others in a group or a group's outcome, and (2) *groups processing individual information* – that is, the means by which information processing is distributed across a group. When a collective behavior involves any degree of both (1) and (2), we refer to this as Collective Information Processing, or CIP.[3]

This follows Wimsatt's (1986, 1997) use of 'aggregativity' for identifying features of emergence in the real-world. At the first level, we can ask to what extent individual-level information processing is the result of individual components processing information from and about others. On the second level, we can ask to what extent group-level outcomes are the result of the sensitivity of groups to the structural arrangement of their components. This allows us to clarify that group-level processes do not imply individual-level processes (and vice versa), and that different dynamical processes unfold across distinct levels.

With ***individual processing of group information*** (IP), we refer to individuals processing information which is from others, about others, or which is directed at group-level outcomes. A wide range of information processing tasks require this kind of mechanism, including behaviors wherein an individual must process information about others' intentions or mental states, interpret others' present or future actions, others' roles or contributions to a shared task, others' knowledge or store of information, or attend to how their behavior relates to group-level progress, outcomes, or goals. What is relevant here is not the cognitive or psychological processes underlying individual processing, but rather, the idea that individual processing from others is *directed at* group-related aims or processes.

In cases where IP is high (that is, where a behavior requires a great deal of IP, or involves multiple forms of IP), there will be greater (e.g., computational, cognitive) demands on individuals and, typically, a distinctiveness of individual processing where each individual has a specialized role they play in service of some collective goal.[4]

With ***group processing of individual information*** (GP), we refer to cases in which information originating at the level of individuals can only be processed, interpreted, or acted upon through structured interactions among group members. In such cases, informational outcomes are sensitive to the organization of the group, including patterns of interaction, role differentiation, and the distribution of contributions, and are not reducible to the sum of individual processing. Group processing of individual information occurs in a wide range of tasks, especially where group dynamics are sensitive to the knowledge or contributions of individuals in a group or in cases where group members adjust their behavior according to their interactions with other members as they collectively progress toward some goal. This conception aligns with Wimsatt's (1986, 1997) analysis of non-aggregative systems, in which system behavior is sensitive to components' arrangement and organization rather than merely their individual properties, asking if groups were rearranged, removed, duplicated, or rewired, their information processing dynamics would change in a qualitative manner.

GP is high in cases where any of the following types of patterns occur: task-relevant information might be widely distributed across individuals in the group, group structure may partially or fully determine individual contributions, and the distribution of information across the group may bear equally on individual contributions, pairwise interactions, and group-level outcomes. GP is thus meant to capture both how individuals are situated in relation to one another within some network or unifying structure, how their information is pooled, and how individuals' place in a network bears on the nature of their information pooling and exchange.

At its core, our proposal is that the collective behaviors which get labeled as collective intelligence involve these two mechanisms (IP and GP) and thus can be analyzed along these two dimensions. The concepts of IP and GP are thus applicable in two distinct but not inconsistent ways: first, in evaluation of a collective behavior as a potential instance of CI (i.e., determining whether *any* form of both IP and GP are present in a system), and second, in evaluation of the kind of CI a system manifests (i.e., determining *which* forms of IP and GP are present and how they shape phenomena at distinct levels within the system). In each instance of collective intelligence, precisely how (and to what extent) the behavior recruits each mechanism may vary. This variation is also context-dependent, as demonstrated by cases where the efficiency of any

[3] Allow two points of clarification around both the terms "collective" and "information processing". A collective exists when interactions between individuals are accounted for. A collective C(I,S) of size $n > 1$ would thus be defined by the set of individual agents, $I = \{i1, i2, \ldots, in\}$ and by S, the structured set of interactions among the individual agents in I (e.g. $S \subseteq I \times I$ in the case of a matrix of pairwise interactions). An example of a collective is a flock: sets of individuals bound (even if only temporarily) by the structure of interactions dictated by nearest neighbor interactions. We take information processing as the process whereby a system uses acquired information to adjust its state.

[4] While IP is sometimes used to refer to information processing in general, or Information Processing theories more specifically, we use the acronym here specifically to discuss individual information processing which is *about* the group. There is, of course, individual information processing which may not be about the group. For example, when a ship crew member thinks about their own exhaustion while engaged in some group task, they are individually processing information which is only about them and their bodily or mental states. Individuals may also have goals which are neither purely individualistic nor task-relevant vis-à-vis some specific collective behavior. This kind of processing is not central to the present discussion.

individual's contribution is dependent on the group-level resource availability and distribution, task demands, and collaborator abilities (Almaatouq et al., 2021a, 2021b; Mieczkowski et al., 2025). In focusing on these two mechanisms and their differing relevance to particular forms of CI, we lay the groundwork for a robust classificatory framework of CI.

2.5. Decomposing collective intelligences through CIP

The information processing mechanisms (IP and GP) involved in CIP allow us to decompose instances of collective behavior to identify important features for robust analysis of collective intelligence. With this, we can consider systems where IP is low while GP is high, and vice versa (as well as systems in which processing towards both ends is high or low). This decomposition allows us to understand CIP in both mechanistic and outcome-relevant terms, where different information-related processes lead to an update of the system as a whole.

Given that, in each particular instance, more or less information processing will occur at each of these levels, we conceptualize CIP as a multidimensional, continuous spectrum through which we can locate and compare instances of CI based on the degree of IP and GP involved in that behavior (Figure 1). (See Fig. 2.)

On the basis of this four-part spectrum, we propose the following descriptive categories of CI:

2.5.1. Low Individual Processing, High Group Processing (Structural Intelligences)

Systems with low individual-level processing and high-group level processing include, for example, minimal models of contagion, voter systems, and simple information diffusion. In these systems, local updating rules and the behavior of individual units tend to be simply defined and predictable based on inputs, e.g., in the case of contagion

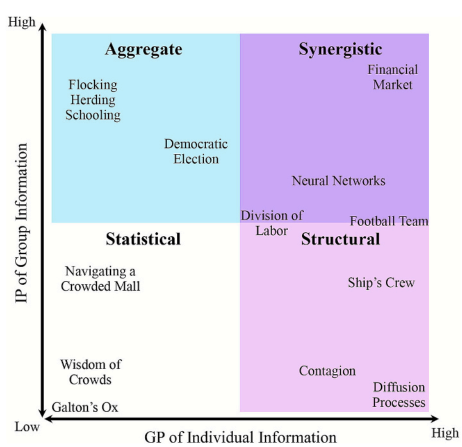

Fig. 1. The Collective Information Processing (CIP) spectrum classifies collective intelligent behaviors based on the degree of Individual Processing of Group Information (IP) and Group Processing of Individual Information (GP) involved. The CIP spectrum includes four categories of CI: Statistical (low IP and low GP; shown in white), Aggregative (high IP and low GP; shown in blue), Structural (low IP and high GP, shown in pink), and Synergistic (high IP and high GP; shown in purple). The boundaries between these categories are not rigid. Many collective intelligent behaviors will fall between categories. Particular instances of a form of collective intelligence may even fall into different categories, depending on the details of that instance. For example, a football team which adheres to a predefined strategy, where individuals do not deviate from their predetermined role, is better categorized as structural intelligence, whereas a football team which plays with some combination of predefined formation and real-time adaptation on the field may require higher IP and thus is better categorized as synergistic intelligence. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

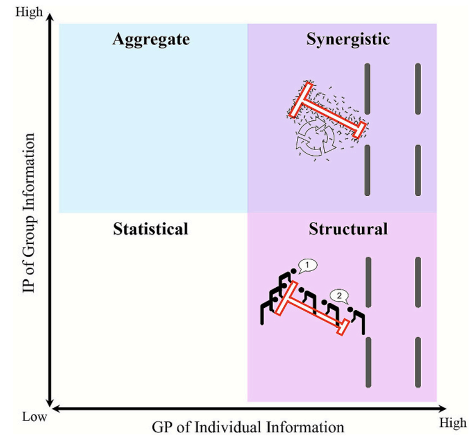

Fig. 2. CIP in Collective Problem-Solving. Large groups of ants (top) and communicating human groups (bottom) successfully solve the piano-movers puzzle in different ways. Each group is tasked with moving an appropriately scaled T-shaped load through a series of openings between sets of gray walls. Part of the task difficulty is that, in some cases, the load must be moved and turned away from the exit to solve the problem. Within groups of ants, this counterintuitive element renders pheromone communication unhelpful. Some groups of humans were able to plan ahead, discuss and assign the most experienced leader ahead of moving the load. Ants by contrast relied on the turnover between individuals that pulled the load in the direction of the exit and those that simply pulled in the direction of others at different times. Communicating humans plan ahead, assign leadership, and coordinate action through explicit role structure with simple individual decision-making rules, relying on a structural form of intelligence, suggesting that GP was more task-relevant than IP. Ants relied on an emergent, short-term memory that was updated due to the turnover of follower and directional movers, which allowed them to move the load persistently along the edges of the enclosure, finding the exit or turning the load appropriately. Because of the feedback between collective outcome and individual knowledge, the ants used both IP and GP, or acted more synergistically, to solve the task. Note that this figure is based on Dreyer et al., 2025 and only compares the two groups whose successful performance is central to their own analysis. As such, we do not include collective behaviors from this study which might be characterized as aggregate or statistical intelligences.

models, one can predict that any individual unit will update to some state based on simple interactions with its nearest neighbors (Andres et al., 2025; Cencetti et al., 2023). On the other hand, despite these simple local rules, the structural, group-level arrangement of these interactions tends to have a stronger influence on the system's overall behavior. While it is difficult to understand the state of the whole system based on observations of its individual components, predictions of system-level behavior are possible by observing its group structure (Dodds & Watts, 2004; Watts, 2002). In these cases, systems have low sensitivity to the rules and behavior of individual components, and much of the causality in the system can be attributed to the structure or form of interaction between all of its parts.

As an example, consider a ship's crew (Hutchins, 1995), where the system's state, i.e., the ship's movement, depends on the commands of a select few high-ranking individuals, with fewer interactions between crew members to achieve the final state. Within CIP, this collective behavior would fall into low IP (though with a non-uniform distribution of processing among individuals) and high GP because individual states are not enough to predict the ship's state, which is highly dependent on the particular collaboration arrangement of the crew. CIP in this case provides both a means to identify global trends within this collective and an avenue to understanding lower-order operations such as individual variation.

2.5.2. High individual processing, low group processing (Aggregative Intelligences)

In some systems, a group is less sensitive to its structural arrangements but extremely sensitive to individual behaviors and updating rules. Taking Wimsatt's term, we define such systems where the behavior of the whole can be accounted for by its parts as *aggregative*. In aggregative systems, individuals actively process information about the other individuals around them, with novel information providing novel behavioral affordances on the local level. We can think about these individual-level computations not only as local, but as being *about the group*. Causal determinacy within these systems occurs in the local computations of the units; this is in contrast to collectives with high GP and low IP, where the causal determinacy resides in the organizational structure of the collective. Wimsatt (1997) distinguishes between aggregative systems whose group-level properties could be attributed to the sum of their constituent parts and those with stronger emergence beyond the sum of their parts. Individuals take an active role in processing local information about their group dynamics, with the emerging collective behavior considered as a sum property of individual contributions. Features of the collective behavior can be thought of as present in the local computations of particular components.

Systems such as bird flocks, herding animals, and fish schools – those which require swarm computation – tend to fall within this category. Successful macro-scale replication of the motion coordination as seen in flocking, herding, and schooling has been achieved using minimalist physics-based models that operationalize inter-individual interactions in terms of repulsion, attraction, and alignment (Couzin et al., 2011; Couzin & Krause, 2003; Salahshour & Couzin, 2025; Vicsek et al., 1995). Such approaches do not inform any underlying reasons for such motion. According to our framework, these systems show high individual processing, as each individual considers the positions and velocities of its nearest neighbors to dictate its state. However, the whole school (i.e., group) shows low processing, as the end state of the group is less sensitive to the particular arrangement of the different individuals.

2.5.3. Low individual processing, low group processing (Statistical Intelligences)

On one side of the spectrum, some systems have both low IP and low GP; in extreme cases, agents would have little to no influence on one another, either because they lack a shared communication system or given the limitations of the structural arrangement of their parts. While it may seem as if this would not yield any productive group dynamics, a portion of the collective intelligence literature has found that such systems still yield interesting outcomes (Da & Huang, 2020; Galton, 1907). In particular, in the case of the Wisdom of Crowds and Galton's ox situations, wherein *no collective information processing is taking place*, averaging the aggregate components of the system yields results showing that statistical aggregates of information tend to be more accurate than non statistical aggregates. It is important to note that much of the wisdom of crowds literature works to examine deviations from such idealistic Galton's ox arrangements in the real world, asking how shared expertise, memory, and social influence – even the most minimal of coordinating mechanisms – greatly affect the ability of groups to make more accurate decisions, even in cases of statistical intelligences such as voter models (Atanasov et al., 2017; Goldstein et al., 2014; Surowiecki, 2005).

2.5.4. High individual processing, high group processing (Synergistic Intelligences)

Finally, systems that require high IP and are highly dependent on the structural arrangement of the group's parts are *synergistic*. Such systems, composed of contributions of individual components, cannot be seen as an additive product of individual contributions, such as in aggregate or statistical systems, but as a synergistic total of their different contributions. Individual contributions are non-linear, complementary, or otherwise rendered meaningful or causally effective by virtue of the group's structure. In such systems, however, component contributions are not just determined by structure – they also lead to changes in structure, which causes downstream changes to future individual contributions. This circularity makes ascriptions of causal determinacy between the system and its parts difficult. While the state of the system can be deduced neither from an assessment of its independent components nor directly from its overall structure, a certain coarse-graining of the system allows the assessment of causality: local interactions lead to higher-order neighborhood interactions which lead to global outcomes. Minimal examples of such systems can be modelled via Ising models, models of collective problem-solving, and structured models of biological populations on fitness landscapes are some simple examples. Real-world examples include financial markets (which exhibit both structurally local herding behavior and global trends), neural networks operating at the level of brain regions, the behavior of formal organizations, and scientific collaborations.

2.6. How CIP addresses points of contention within CI studies

The viability of CIP as a reliable analytic framework depends in part on its usefulness for addressing points of contention which have in part contributed to the lack of systematic, productive analysis across CI studies. We consider two important points which CIP serves to clarify: (1) concerns about parsing out individuals from groups, and (2) contentions about attributions of agency and causation to groups or group-level phenomena.

2.6.1. Using CIP to parse out individuals from groups

There are longstanding difficulties which come with any effort to parse out individuals from groups or collectives. Some have argued that, for some systems, the distinction between groups, components, subcomponents cannot be made in a principled, non-circular fashion. For example, in trying to delineate what counts as an individual cognitive system, there is debate about what counts as the smallest appropriate unit of cognitive activity: is it one area of or system within the brain (e.g., the olfactory system), the entire brain, the whole organism (e.g., a human), or the organism within their environmental context? Whereas some extended mind theorists will argue that the organism *and* their environment *together* constitute a cognitive system (e.g., Clark & Chalmers, 1998), others have argued that the organism and environment are *coupled* but *distinct* systems (e.g., Adams & Aizawa, 2001). Part of distinguishing individual processing from group processing requires us to make a clear distinction between individual and interacting systems.

We propose that such distinctions can be grounded in patterns of *mutual adjustment*, wherein individuals can be identified by closed loops of feedback as interacting components in a larger system (Polanyi, 1962). Such causal partitionings within a given system may be inherently multi-scale, such that at one level we may identify feedback loops that stabilize between individuals (e.g., dyadic interactions between neurons in a brain), while at another we may identify higher-order loops accounting for multi-unit causality in a system (e.g. interactions between groups of neurons in a neural region) (Hofstadter, 1979). Such partitions are not arbitrary, but reflect the architecture of information transfer within a system, which itself has been related to topics including emergent causality in complex systems (Klein et al., 2021). Accordingly, the identification of “individuals” within a system will likely be scale-dependent, with ontological units emerging relative to the causal partitioning applied to the system (Bruineberg et al., 2022; Hoel et al., 2013; Krakauer et al., 2020).

Granting that a distinction between individuals and groups can be made, it's also important to highlight the important differences between IP and GP as information processing mechanisms. For IP (but not necessarily GP), we can consider this mechanism in at least three separate ways. Defined by Langton (1990) and Lazer and Friedman (2007), processing of information within individual units can be thought of as those processes relevant to information storage, transmission, and modification. Scaling up this behavior to between-component interactions, these processes allow for additional behaviors which can only be described minimally on a dyadic level: information transfer (or diffusion) and recombination (or modification of partner information). While other breakdowns of unit-level information processing, such as those relevant to the copying, erasure, and imparting of causal alterations of information exist (Mediano et al., 2021), these can generally be subsumed under broader functions of "modification."

To distinguish genuine group-level processing from mere aggregations of individual interactions, Wimsatt (1986) identifies four features of collective, emergent systems. These conditions concern whether a system's property or behavior persists under 1) the rearrangement, 2) addition, or subtraction of parts, 3) whether it survives decomposition and reaggregation, and 4) whether it arises linearly without cooperative or inhibitory interactions among parts. Such features point to emergence as forms of higher-order causality in a system where its properties or behaviors cannot be reduced to, or predicted from, the simple summation of individual contributions. Instead, in systems which exhibit such forms of information processing, appeals to causality must be made to the structuring of the collective in terms of its group-level features and not its individual components (Smaldino, 2014). For a collective behavior to be considered CI it must involve some degree of both IP and GP, which requires at a minimum some apparent information processing component of the behavior.

2.6.2. *Ontological reducibility and causal irreducibility in CIP systems*

CIP provides initial clarification on CI as a property attributed to groups and explained by reference to groups (and not individual members of groups), and which can only be examined or referred to in relation to the collectives in which individuals are situated. Following Smaldino (2014), we hold that group-level properties, *stricto sensu,* do not belong to any single individual. As such, we understand CIP as a form of information processing which can only be explicated by an examination of local interactions as part of a whole.

Capturing local interactions in their context is why we distinguish between individual information processing and group information processing. There is, however, extensive philosophical debate about the nature and feasibility of group minds and group agency which raises reasonable skepticism about the claim that groups (as independent entities) process information (see, e.g., Gilbert, 1989, 2000; Bratman, 1999, 2007; Tuomela, 1989, 2005; Theiner et al., 2010; List & Pettit, 2011; Schweikard, 2011; Ludwig, 2015; Overgaard & Salice, 2021). These debates raise two doubts about whether groups can process information, first on the basis of intentionality and second on the basis of agency. Importantly, our claim that groups process information hinges only on a particular *structure* and *nature* of information processing (e.g., whether multiple individuals are needed for the information to be processed, the structure which enables information pooling, the types of networks which yield efficient processing). On our view, whether groups process information does not hinge on the specific nature of the information being processed (e.g., whether the information is a representation of some perceptual experience of the world), the specific cognitive capacities which tend to accompany individual information processing in humans (e.g., representing, sensation), or the character of the information *processor* (e.g., an agent, a cognitive being, a psychological being). In focusing on the structure and nature of information processing (rather than the information itself, or the processors themselves), we sidestep concerns about whether group intentionality is necessary for group-level information processing.

We do, however, see our framework as offering a helpful intervention into the debate over attributions over group agency (and the related debates on causation) within analyses of collective intelligence. Debates about the nature of agency and causation within CI are arguably at an impasse, which has effectively stalled progress on inquiry into the nature of CI. Rooting our analysis of CI in the mechanistic structure of its particular instances, however, better equips us to identify the form of agency or causation involved in each instance. As such, we can sidestep some of the major points of contention while enabling productive comparative inquiry.

Across cases of CI, we think that the CIP framework gives us good reason to take what we call an *ontologically reducible, causally irreducible* approach to studying CI. By *ontologically reducible*, we mean that the individual level compositions of collectives are necessary for determining processual outcomes. In other words, the system as a whole is conceived of as being made up of simpler agents (e.g., a flock is made up of individual birds, a voter model is made up of individual voters), and the system-wide behavior cannot be understood without scaling down to the level of the component agents or parts. We cannot study the kinds of systems we are interested in without studying both the parts, their contributions to the collective behavior, and the interactions between those parts. This is so, regardless of the causal relationship between the parts and or the whole of a system. We thus take individual agents to be the most fundamental parts of any system engaged in some collective intelligent behavior.

By *causally irreducible*, we mean that, to understand the most relevant causal processes within the whole system, we have to look at more than just individual interactions. This is because causal power is minimally a group-level property of a collective's structural arrangements. These causal powers cannot be reduced only to the contributions of individuals within the group. Instead, in these cases, outcomes should be viewed as determined by the ways individuals process information and the feedback between individual processing and the structural arrangement of individuals within a group (Juarrero, 2013; Witherington, 2011). Critically, a collective's sensitivity to its group-level structure informs us *to what extent* outcomes are set by group-level features, setting a gradient between different kinds of systems: some are aggregative and determined by individual-level computations and where outcomes in the system can be thought to be additive characteristics of individual-level interactions; others are more emergent, in that causal outcomes are facilitated by the group's structure and neither an aggregated feature nor fully reducible to individual-level states (Wimsatt, 1986, 1997). Sometimes, group-level outcomes are relatively insensitive to the structural arrangement of a group. Perhaps in these cases, what matters more are individual contributions (Steiner, 1966) or the way information is processed between individuals (Garg et al., 2025). In this way, CIP may help to distinguish to what extent system-level outcomes are caused primarily by individuals versus the group in a collective behavior.

The ontologically reducible, causally irreducible approach thus helps to elucidate: (i) the relationship between a group and its components and their contributions; (ii) the relationship between components' interactions and information processing; and (iii) the effect of these factors on group-level outcomes. Understanding how these factors are differently relevant to specific forms of CI is critical to making accurate and precise attributions about the causally potent processes and kinds of agents involved. This clarification, together with the descriptive categorization that CIP provides, sets us up to better understand both the mechanisms and relevant dynamics involved in a wide range of cases of CI.

2.7. *Section 3. CIP in Action*

CIP offers a novel, context-independent set of measures by which we can compare and contrast cases of CI, with potential for multidisciplinary usage. In this section, we consider conceptual and empirical implications of the CIP framework. In 3.1, we put CIP in action, using it to better analyze an existing case study in collective problem-solving. In 3.2, we put forward a proposal for the future formalization of the CIP framework. Finally, in 3.3, we consider how the CIP framework, both as a theoretical and formalized framework, can lend both conceptual clarity and empirical rigor to future inquiry into CI.

2.8. *An example of collective problem solving using CIP*

To illustrate the different contributions of individual and group processing to collective intelligence, we use a study examining the problem-solving strategies used by groups of ants and humans (Dreyer et al., 2025). Groups of ants and groups of humans were each given an identical task (scaled appropriately to the average physical size of the individuals in the group). Each group was tasked with the piano-movers puzzle, where a subject must move an oddly shaped load across a tight and obstructed environment. Different combinations of two conditions were applied: groups could be small or large, and group members could have the possibility to communicate or not. Performance was measured in terms of path length or state transitions until the load was finally out of the chamber. Small groups of ants and non-communicating human groups of any size performed poorly. These groups often pulled the load toward the direction of the exit without placing it in the correct position (which often requires moving the load away from the exit in order to turn it). Large groups of ants and groups of humans who could communicate performed more efficiently. Dreyer et al.'s analysis highlights two different qualitative mechanisms to explain increased efficiency in these groups. Humans who could communicate were able to plan ahead, choose a leader who was most capable or experienced, and follow that leader's instructions in order to pull or push the load according to their position. Large groups of ants, however, were able to solve the task via the emergence of persistent movement which resisted perturbations, e.g., carrying the load in a consistent manner that followed the walls of the environment.Across all groups, what Dreyer and colleagues find is that there are two interconnected factors that bear on the efficiency of cooperative problem solving: organizational scale and cognitive abilities. While cross-species comparisons on only one of these dimensions (e.g., comparing small groups of humans to small groups of ants) do not yield fruitful analyses, the authors argue that cross-species comparisons which consider the interplay of these factors (e.g., comparing the scalability of cognitive ability across group sizes in ants versus humans) better explain the dynamics underlying performance differences and similarities across groups.

Using CIP, we can add to the analysis offered by Dreyer and colleagues. Here, we treat group processing as present when problem-solving performance is sensitive to the arrangement, turnover, and interaction of individual contributions, rather than to individual processing in isolation. In the cases of the small groups of ants and non-communicating humans, we can interpret these collectives as exhibiting low group information processing, with the direction of movement determined by the additive aggregation of individual movement tendencies. We can also interpret the group as highly sensitive to individual-level information. The collective effect is thus simply the aggregation of each individual's direction of movement.

CIP also helps us elucidate the differences between the two efficient groups – which are best characterized in terms of structural and synergistic intelligence, respectively. In other words, the communicating human groups relied on a high level of group processing, while individual contributions varied and were simply limited to their position in the collective arrangement. Humans in this case were thus using structural intelligence to solve the task. Performance in these groups is therefore sensitive to the rearrangement of roles and communication pathways, even when individual abilities are held constant, with individuals primarily executing simple, role-defined action rules rather than engaging in extensive independent planning. Ants, on the other hand, found their way out much like a blind-folded person might do so by sliding their hand along a wall. The emergence of persistent movement, which often must occur away from the direction of the exit, requires a constant turnover of ants who remember where the exit is and those that are simply following the current direction of movement. The turnover is the result of ants going back and forth to and from their nest (located at the end of the last chamber, where they are trying to take the object to), thus updating the information about the relative location of the object with respect to the nest. The large group of ants is therefore sensitive both to local information available to individual ants, but also to the pattern of circulation and turnover of individual information generated by ongoing group-level movement. Given this feedback between individual and group-level information, we characterize the behavior of large groups of ants as synergistically intelligent, exhibiting capacities dependent on interaction dynamics and cannot be recovered by summing individual strategies.

In the case of the small groups of ants or the humans without communication, we can reduce the explanation of group behavior to the sum total of each individual's contribution. However, in the case of the large groups of ants or the humans with communication, we need to understand how each group is processing information about individuals in order to explain group performance. Our explanation, in the latter two cases, cannot reduce group behavior to individual-level behavior. In the communicating human groups, we must consider how they divide their tasks and reach decisions, while in the large group of ants we must consider the constant turnover between knowledgeable and follower ants and the transmission of behavior across interaction pathways, from which a short-term, group-level analogue of memory storage arises.

CIP offers several important additions to the type of analysis we see from Dreyer and colleagues. First, CIP gives us an interpretive framework which compares the two groups *on the same terms* (e.g., IP and GP). The current analysis explains similar degrees of efficiency in terms of drastically different mechanisms (large groups of ants have emergent processing, whereas the communicating humans have a capacity to plan). Identifying points of similarity in both cases of collective problem-solving is critical for understanding the nature of the phenomenon.

Second, CIP helps us better explain the relationship between group-level properties (group size, structure) and performance – a relationship which seems important for Dreyer et al.'s analysis. The authors identify structural changes which occur when we compare small and large groups of each species individually. In ants, though ant interactions themselves are scalable across group sizes, there is a structural shift which leads the group to establish feedback mechanisms which serve the role of short-term memory storage. Even with individual turnover, a large enough group will at any given point retain enough members who understand enough about the task at hand. In humans, neither their interactions nor their group structure are scalable across group sizes. As groups grow, Dreyer et al. point out, they introduce new forms of organization, such as hierarchy or divisions of labor. CIP helps us understand that, what is important in these cases is not group size *per se*, but rather, the relationship between group size and the structural arrangement of the group. Some group size increases will impact how members of a network interact, and others will not. It is noteworthy that only ants improved in large groups compared to small ones, while human groups that could communicate performed at the level of single human solving the task, further suggesting that the way in which human groups solved the task relied mostly on the structural arrangement between knowledgeable and follower individuals. In thinking about group *processing* as the relevant factor (e.g., whether and how information is processed on the basis of the group's structural arrangement), we can better understand the specific mechanisms which give rise to different group performances.

Third, CIP gives analytic tools which are potentially formalizable. Our goal here is not merely to offer another qualitative mechanism, similar to the mechanisms already identified by Dreyer et al., by which we can understand and interpret each group's behavior in this case. Instead, an important part of the CIP framework is that it identifies qualitative mechanisms within collective behaviors which are potentially measurable through a formalized framework of IP and GP. We explore this point in the following section.

2.9. CIP in a formalized framework

Using CIP to analyze the Dreyer et al. (2025) comparative case study in group problem-solving demonstrates how, as a descriptive framework, CIP already has value as an interpretive analytic tool. It allows us to identify and describe the mechanisms involved in any given instance of CI, compare different forms of CI on the basis of the information processing demands individuals and groups are faced with, and better consider the agential and causal processes involved in CI by appeal to information processing (rather than the cognitive or psychological features of the agents or systems). A formalized model of CIP (e.g., in the form of a mathematical framework) is necessary, however, for making this descriptive framework falsifiable or at least more general and amenable to a more thorough exploration of its consequences. While a full-fledged model falls outside the scope of the current proposal, existing mathematical frameworks provide us with an adequate basis for envisioning how CIP could be measured.

Several information theoretic frameworks have attempted to address the challenge of parsing causality within nested systems. Employing information theory as a framework for neuroscience, for example, allows researchers to decompose how information is distributed across a system and identify functional roles of both synergistic and redundant information in neural processing, as in the case of visual processing (Nigam & Schwiedrzik, 2024). The application of information theory to neuroscience raises questions about parallels between brains and other collective systems that process information synergistically, often characterized as more intelligent than redundant systems, where all components supply the same system-level information (Bettencourt, 2009; Garg et al., 2025; Hinsz et al., 1997; Kemp et al., 2023; Luppi et al., 2024).

In particular, partial information decomposition (PID) is an information-theoretic framework that has proved particularly useful for understanding systems with multiple interactions between components and collective, organized behavior (Mediano et al., 2022). In this framework, the organized behavior of the system can be treated as a target variable and the contributions of each component as source variables. The latter are in turn decomposed into different information atoms: *unique information*, contained within some component variables but not in others; *redundant information*, which is contained within components; and *synergistic information*, which is contained only in the interaction between components. To illustrate, consider the organized behavior of a crowd, such as its direction of movement, as a target variable. Individual trajectories (the source variables) may provide each of the information atoms about the crowd. Trajectories providing unique contributions are those where a single person's direction reveals information about a crowd otherwise not captured by other trajectories (as in Jadhav et al., 2024). Redundant contributions occur when measuring an increasing number of individual trajectories provides no new information about a crowd's movement. Synergistic interactions occur when the direction of movement of a crowd cannot be predicted without accounting for particular interactions between individuals.

Such formal frameworks can be extended to understand how different components serve to predict the future system behavior. Formalisms such as integrated information decomposition (ΦID) expand the concepts of PID's three information atoms to 16 information atoms, enabling us to view a system's organized behavior at time (t) as the source variable, and the system's organized behavior at time ($t + 1$) as the target variable (Mediano et al., 2021). This framework uses information theoretic metrics to understand the interplay between two co-evolving elements of a system in time. In CIP, these two elements are the individuals' states and the group state. Mediano et al. (2021, p. 5) define six information dynamics representing how information is transformed between the past and the future, two of which are especially relevant: *upward causation* (involved in “collective properties that are defined by individuals”) and *downward causation* (involved in “collective properties that define individual futures”; Fig. 3A). Their importance lies in the presence of synergistic information within them. When elements interact in such a way as to have synergistic information (upward causation), this alters the state of the system as a whole, making its future state a result of these interactions. When synergistic information creates unique or redundant information in a future state, these alter the future state of the elements (downward causation). These dynamics allow for quantitative connections to the CIP conceptual framework.

The ant collectives in the piano-movers task illustrate how information-theoretic decompositions can operationalize CIP. If the future direction of the group's motion is treated as a target variable and individual actions as source variables, the case of movement exhibits all three relevant information atoms: (i) some ants provide unique information when task-relevant organization biases movement, (ii) many ants redundantly reinforce the current direction by aligning with ongoing motion, and (iii) the persistent wall-following behavior that enables successful reorientation cannot be predicted from any individual or from additive combinations of actions, but only from group interaction and turnover, yielding synergistic information. These dynamics involve both upward causation, whereby interactions among ants generate a collective state: a particular proportion of knowledgeable and follower ants that at a given time pull the object in the right direction; and downward causation, whereby the identity of knowledgeable and follower ants is continuously updated by turnover, thus constraining individual behavior and placing the ant collective in the synergistic regime of the CIP spectrum.

In contrast, communicating human groups solving the same task rely primarily on structural organization. Through planning and communication, interactions generate synergistic information that is subsequently transduced into roles and communication pathways, such that future behavior is governed by downward causation. Individual contributions are therefore unique across roles and redundant within roles, with task performance highly sensitive to the rearrangement of this structure. Causal influence here is dominated by downward causation, with group-level structure determining individual behavior even when individuals follow relatively simple, role-specific algorithms. As a result, human performance is highly sensitive to the rearrangement of roles and communication pathways but less dependent on interaction-generated synergy, placing these groups in the structural regime of the CIP spectrum.

Placement on the CIP spectrum is determined by which information dynamics define a collective system's causal structure (Fig. 3B). When a system predominately integrates information by upward causation dynamics, the system corresponds to a high degree of IP (but not GP), identifying as aggregate intelligence. Inversely, when information is predominately integrated via downward causation dynamics, the system involves a high degree of GP (but not IP), placing it as structural intelligence. Synergistic intelligences involve both high degrees of IP and GP, and therefore would integrate information utilizing a significant degree of both upward and downward causation dynamics. Statistical intelligences involve relatively little IP and GP and therefore would not be meaningfully impacted by either information dynamic and instead would integrate information via copy, erasure, and storage dynamics. Each qualitative dynamic presented within ΦID can be quantitatively measured via any functional form of time-dependent mutual information, (see Mediano et al., 2021 for proofs).

2.10. CIP for revised theoretical and empirical inquiry into CI

CIP as a potentially formalizable analytic framework promises important benefits for future conceptual and empirical investigations into CI.

Notably, CIP provides a mechanistic and multi-scale definition of CI, which also serves to unify existing many accounts of CI. CIP is mechanistic insofar as it anchors CI to a set of information processing mechanisms. As we argue in 1.2, both outcomes- and mental-states-based definitions are ill-suited for classificatory and comparative analysis of CI. With the CIP spectrum, however, we can point to a two-axis continuum of information processing to determine where a specific form of collective behavior falls, thereby better identifying the mechanisms which generate such behaviors. For instance, the wisdom of crowds phenomenon in its most minimal form, has no meaningful group-related information processing done between individuals within the group.

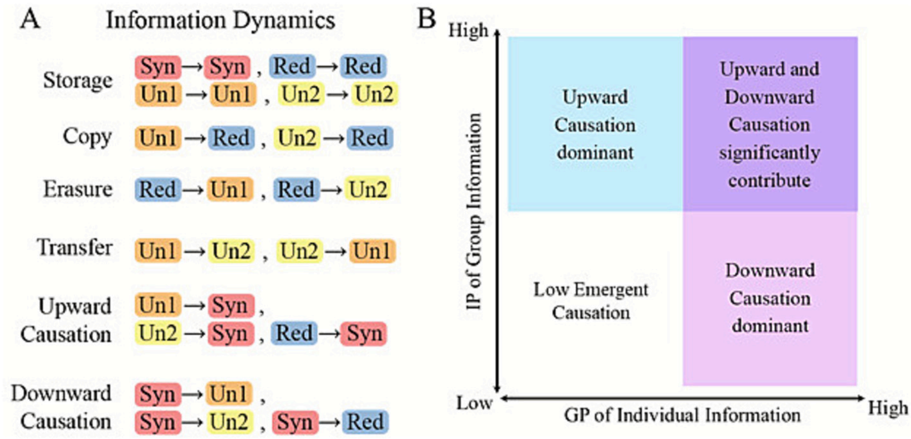

Fig. 3. CIP Spectrum Formalized using Integrated Information Decomposition (ΦID). Labels: Unique Information (Un), Redundant information (Red), Synergistic information (Syn). A: Information dynamics for a system at times t and $t+1$, as presented in Mediano et al., 2021, corresponding to information atoms for distinct phenomena. Storage: information remains in a given element. Copy: information duplication; Erasure: deletion of redundant information; Transfer: information moving from one element to another. B: CIP spectrum outlining which information integration dynamics are dominant within each CIP category. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Instead, the processing lies outside the group, usually with an external observer. However, many real-world collective systems apply different forms of wisdom of crowds strategies that do demonstrate collective intelligence and can be classified through CIP based on where information processing occurs. Numerous accounts from human decision-making show that people make more accurate choices when information is aggregated and paired with deliberation (Navajas et al., 2018), sharing of confidence (Bahrami et al., 2010), and identification of experts (Bahrami et al., 2010; Koriat, 2012). Within CIP, these are examples of high IP. On the other hand, there are examples of wisdom of crowds which are both high IP and GP, for example, when there is feedback between individuals and the group that can help tune network structure (Almaatouq et al., 2020) or adjust individual heuristics based on the group (Berger et al., 2025). Thus, CIP can help disentangle the underlying mechanisms of similar phenomena and better classify instances of collective intelligence.

A mechanistic definition has the added benefit of allowing us to distinguish which information processing mechanisms are required by different group formations engaged in the same task. For instance, take the piano movers puzzle presented by Dreyer et al. (2025). In the same task, the group of communicating humans (marked by structural intelligence) seemed to rely more on group-level plans and strategies, while groups of ants (marked by synergistic intelligence) seemed to rely more on the turnover of individuals with constantly updated spatial memory. Importantly, different group formations achieved similar outcomes (e.g., the non-communicating humans did as well as most ants). By contrast, an overemphasis on the similarity of outcomes can lead us to overlook the significance of the differences in how each group achieves the same or similar outcomes.CIP as a definition of CI enables a multi-scale approach through which we can test and analyze different aspects of CI. CIP is multi-scale insofar as it considers the different organizational and causal scales which are present within a system to analyze that system's behavior (Feibleman, 1954; Fotiadis et al., 2023; Novikoff, 1945; Weinan, 2011). Organizationally, CIP provides tools for identifying the causal attribution of system states and the means by which a causal partitioning of any given system can be obtained. This is important for addressing questions about where the key causal mechanisms of a collective behavior arise: within the individuals (or lower-level components) or within the collective (higher-level group). Further, our approach doesn't weigh the relevance of causal contributions in terms of their direct effect on the group-level outcomes, but rather, assesses their relevance by looking at their role in a system. Collective behaviors generally do not unfold at only one level, so we take this feature of our account to be a distinctive benefit.

Several quantitative approaches, including dynamic causal models (Friston et al., 2003; Manicka & Levin, 2022), information decomposition (Mediano et al., 2021), information integration (Mediano et al., 2022), and coarse-graining (Klein et al., 2021), have been developed to analyze causality in complex collective phenomena. As we outline in 3.2, some of these information-theory based approaches could be used to quantitatively measure CIP in various systems. These frameworks enable both individual-level and group-level attributions (Yuan et al., 2024), providing tools to examine how computationally equivalent systems achieve collective intelligence through their internal dynamics. Through classifying and identifying the causal mechanisms, CIP can aid in studying the interplay between individual-level and group-level processes, and how each level is sensitive to the other.

Finally, when compared to other frameworks introduced to study CI, CIP is distinctively unifying in that it offers a definition which aims to subsume, rather than challenge, other discussions of CI. Collective behavior and collective intelligence in the current literature are defined by accounts which are sometimes quite broad (Atlee, 2003; Lévy, 1997; Malone & Bernstein, 2015; Por, 2024) and other times system-specific and overly narrow (Smith, 1994). CIP helps us understand what, mechanistically and hence conceptually, these different accounts have in common, even where there are vast differences in the organizational structures or observable outputs of the behaviors which are paradigmatic to these accounts. With CIP, we can explain why processes as diverse as swarm intelligence and divisions of labor are both collective intelligence, as well as specify their differences and similarities in terms of the underlying information processing mechanisms.[5] By identifying the causal-mechanistic phenomena which bind certain collective systems into a readily identifiable space, our analysis can go beyond conventional coarse-graining and provide a shared language with which to frame these systems. This enables informed empirical design for investigations into CI by drawing focus on the level at which systems prioritize processing information and the interactions between such levels.

3. Conclusion

Increased interest in collective behavior is symptomatic of parallel shifts across different disciplines to reconsider overly individualistic treatments of thought, action, behavior, and causation. However, as interest in collective behavior grows, and as the breadth of application of the term ‘collective intelligence’ widens, a unifying framework for understanding the nature of collective intelligence and its underlying mechanisms is urgently needed to ensure work in this area is productive and directed at some shared phenomenon. We have advanced Collective Information Processing as the phenomenon underlying many of the collective behaviors under inquiry in this area. We have detailed the two key information processing mechanisms involved in CIP and outlined how they help advance CI inquiry by classifying forms of CI and offering a fine-grained framework for analyses of causation and agency within instances of CI. In advancing this framework, we have attempted to contribute to the kind of comparative inquiry needed to tell a sufficiently broad yet fruitful story about collective intelligent behavior.

Understanding what enables groups to act together in a way that does not misrepresent or reduce a group's unique ability to affect certain outcomes, the contributions of individuals, the importance of individuals' structural relations to the group, or the importance of individuals' interactions with other members of the group requires is essential for capturing the full picture of collective behavior. As a theoretical framework which offers potentially quantifiable metrics, CIP is an important first step towards that goal. A critical next step, then, is proper formalization of CIP to both further assess its utility and to enable productive empirical inquiry into collective intelligence. Taking these steps is critical for understanding the mechanisms which underlie and give rise to certain distinctive forms of collective behavior. If anything binds the vastly different phenomena which have, across many disciplines, fallen under the label of collective intelligence, researchers invested in this area ought to find out what precisely that is.

CRediT authorship contribution statement

Zara Anwarzai: Writing – review & editing, Writing – original draft, Project administration, Investigation, Conceptualization. **Cody Moser:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Hannah Dromiack:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Ketika Garg:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Gabriel Ramos-Fernandez:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

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Data availability

No data was used for the research described in the article.

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[5] Though CIP is a unifying framework, it also introduces a distinction between CI and collective behavior (CB). Not all behaviors which are labeled as CI meet the criterion of involving CIP. For instance, wisdom of crowds has conventionally been used to describe both statistical properties of systems and strategic mechanisms utilized by systems (usually via the statistical properties; see Almaatouq et al., 2020). Therefore, not every instance of Wisdom of Crowds is considered CI: if there is no information being processed at either level of the system, then CIP is not present. To clarify the distinction, if one were to look at how many brunettes are in a population, this is a statistic of the system, it does not in turn influence the system. In such cases, the phenomenon is fully manufactured by an outside observer (e.g., the aggregation of a group's responses to a problem is not something any member of the group does, nor do they have knowledge of this aggregation). But if a group decided to use the average opinion to determine their group state, then it is a strategic mechanism to process information, and therefore, this system has CIP present. The distinction between CI and CB serves to elucidate the scope of relevant inquiry into CI.

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Glossary

Aggregative Intelligence: A form of collective intelligence characterized by high IP and low GP, in which individuals actively process information about others, but group-level outcomes remain largely additive and insensitive to the group's structural arrangement.
Aggregativity: A property of systems in which group-level outcomes can be explained as the additive result of individual contributions and as largely insensitive to the rearrangement, removal, or duplication of components.
Causal Irreducibility: The view that system-level processes exert causal influence that cannot be fully captured by decomposing the system into individual-level interactions.
Classification Problem: The problem of systematically comparing and relating different forms of collective intelligence across contexts and disciplines, given the absence of shared criteria for identifying common mechanisms, causal structures, or information-processing demands.
Collective: A system composed of multiple individuals together with interactions among them, where those interactions are relevant to explaining system-level behavior.
Collective Behavior (CB): Patterns or dynamics that arise from interactions among multiple individuals, producing outcomes at a scale larger than any single individual, regardless of whether those interactions, outcomes, or their underlying mechanisms are considered intelligent.
Collective Information Processing (CIP): A framework for analyzing collective intelligence that characterizes collective behavior in terms of two information-processing mechanisms: individual processing of group information (IP) and group processing of individual information (GP). A system exhibits CIP when both mechanisms contribute, to some degree, to collective outcomes.
Collective Intelligence (CI): Collective behaviors which arise from the information processing mechanisms involved in CIP.
Downward Causation: Causal influence from group-level states or structures to individual behavior, such that the organization or dynamics of the collective constrain, enable, or shape individual-level information processing and behavior.
Group-Level Outcome: A system state, behavior, or performance measure that is defined at the level of the collective and cannot be attributed to or evaluated by any single individual's behavior alone.
Group-level Processing (GP): Information processing that depends on structured interactions among individuals, such that informational outcomes are sensitive to the arrangement, interaction patterns, or turnover of individual contributions and cannot be reconstructed from individuals processing the same information in isolation.
Individual Processing (IP): Information processing performed by individuals that is directed at, derived from, or relevant to other group members or to group-level outcomes, such as processing others' intentions, roles, knowledge, or the collective's progress toward a goal.
Information Processing: The use of acquired information by a system to update its state, behavior, or internal organization, including processes of storage, transmission, modification, and integration.
Mutual Adjustment: A process in which individuals continuously modify their behavior in response to one another through feedback loops, such that they can be identified as interacting components within a larger system rather than as independent agents.
Ontological Reducibility: The view that collective systems are composed of individual components, such that an analysis of individual units within a system, and interactions between those units, is necessary for determining the system's processes and outcomes.
Redundant Information: Information about a target variable that is shared across multiple components, such that observing additional components provides no new information beyond what is already available.
Statistical Intelligence: A form of collective intelligence characterized by low IP and low GP, in which group-level accuracy or performance arises from statistical aggregation (e.g., averaging or sampling effects) rather than from information processing.
Structural Arrangement: The structure of relationships, roles, or interactions among individuals in a collective that constrains how information flows and is processed and which collective outcomes may be sensitive to.
Structural Intelligence: A form of collective intelligence characterized by low IP and high GP, in which collective performance depends primarily on the organization, roles, or interaction structure of the group, rather than on rich individual-level processing.
Synergistic Information: Information about a target variable that arises only from the joint state or interaction of multiple components and cannot be obtained from any component in isolation.
Synergistic Intelligence: A form of collective intelligence characterized by high IP and high GP, in which collective outcomes depend on non-additive, interaction-dependent contributions and feedback between individual processing and group-level dynamics.
Unique Information: Information about a target variable that is provided by one component (or source variable) and not by any other component in the system.
Upward Causation: Causal influence from individual-level states or interactions to group-level outcomes, particularly when interactions between individuals generate collective properties that are not present in individuals alone.