



When the Value of Cooperating Scales: Collective Intelligence, Information Processing, and the Leadership Meta-Capability

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Specialty section:

This article was submitted to
Social Networks,
a section of the journal
Frontiers in Human Dynamics

Received: 22 October 2020

Accepted: 04 January 2021

Published: 17 February 2021

Citation:

Hazy JK (2021) When the Value of Cooperating Scales: Collective Intelligence, Information Processing, and the Leadership Meta-Capability. *Front. Hum. Dyn.* 3:620399. doi: 10.3389/fhumd.2021.620399

This article explores the nexus where purposeful individual-driven collective action, what is called organizational leadership, interacts with collective intelligence and agency. Based on recent numerical models from complex network theory and empirical studies of collective dynamics in social biology, it describes how intelligent collective agency forms around three order parameters: expectancy alignment, instrumentality inside the collective, and a subjective belief by individual agents in the generalized trustworthiness of other members of a collective. When the value of one or more of these scaling metrics becomes dynamically stable, fractal structures in the collective provide useful information to individuals that informs their choices during interactions including leadership activities. The theory contributes fifteen testable assertions that if supported empirically suggest fruitful ways that new information technology applications could enhance organizational effectiveness.

Keywords: complexity leadership, complex networks, goal alignment, organizational leadership, criticality

INTRODUCTION

This article proposes a new conceptual model of emergent collective intelligent agency (CIA). As I will define in the next sections, it argues that collective agency (CA) is enabled by collective intelligence (CI) and actualized through specific interactions, defined later as ‘leading events.’ These interactions enable and sustain a shared subjective representation of dynamically stable coarse-grain properties which define the collective as an organization. These properties like for example a weekly payroll cycle, can be recognized by members as a reason for participation in the organization. The conceptual model described herein builds on three related numerical models that simulate phase transitions and decision making in complex networks. Taken together these contributions further elaborate the particulars of leadership as a requisite mechanism for human organizing.

To explore these ideas, the article considers three questions that are relevant to collective agency. Each of these questions requires a collective response in the form of coordinated purposeful action. Each also highlights a distinct aspect of emergent agency that is often associated with organizational leadership (Hazy, 2008). The questions are: What do ‘we’ as a collective want to do? How do ‘we’ as a collective organize to do it? Finally, as an individual, with whom do ‘I’ cooperate, or stated differently, who is included in ‘we’? All of these questions involve the sensing, recognition, and interpretation of information about changing dynamic states of the members of the collective. Consequently, the model describes the local decision states of

individuals as they interact as members of a collective, and how their choices synchronize into a dynamically stable organizational system with predictable properties.

By exploring these three questions, this article contributes to the CI field by specifying requisite conditions that imply collective agency (CA) in the sense that, when the choice dynamics are considered objectively, no one individual decides the answers to any of these questions. The collective decides in concert through the aggregation of individual choices. Practically speaking, ‘we’ form ‘organizations’ through a shared representation of commonly understood ‘organizational properties’ such as sales or profits, and then decide the answers in the form of organizational and departmental objectives and key results. But ‘we’ do these things not as individuals, but as nodes in an influence network. Importantly, each collective choice may (or may not) be supported by CI or even be informed by local events that are distributed and recognized as signals across the physical, temporal, and social environment. The sensing of events occurs within individuals as they interact whether the agents are human, artificial or hybrid. By including individual and collective human agency in CI conversations, the approach described herein suggests specific ways that information and communication technologies (ICT) can be developed to augment CI in ways that increase local efficacy when sensing and interpreting the local situation to better inform purposeful collective decision making and action.

To summarize the argument that follows, I begin by describing the decision making model (DMM) on complex networks (Turalaska et al., 2009) and the Selfish Algorithm (SA) model (Mahmoodi et al., 2020). This model describes how the DMM influences local choices by specifying the conditions and mechanisms that enable the global synchronization of choice and action. These two models relate to collective learning by assuming the principle of complexity matching which describes how new information enters a complex network as changes to the ordering of internal structure when a subset of nodes in the collective interact with external nodes that are part of a more complex network in the ecosystem (Turalaska et al., 2009; West, 2016).

Next, I show how the CIA model builds on these models and the influence process structural learning (IPSL) model (Hazy, 2012) to illustrate how complex networks and the collectives they actualize might learn, decide, and take purposeful action as a distinct organization with well-defined properties. More specifically, I suggest that the collective may learn in a manner analogous to deep learning in artificial neural networks (Bossmmaier, 2000). This is followed by a discussion of distinct classes of observable information which have been shown empirically to be encoded in social networks of non-human social animals (Tunstrøm et al., 2013; Koorehdavoudi and Bogdan, 2016; Xue and Bogdan, 2017; Balaban et al., 2018), and how this information can be made available to individual agents to inform their decisions and actions.

Lastly, I describe the CIA model and show how individuals can observe, interpret, and locally use information that is signaled by coarse-grain social structures of various kinds as these can be observed by individuals from their unique local positions. This might be reflected in an ordered subjective structure (Jøsang, 2016) that is socially constructed through dialog and conversation (Fairhurst, 2017) as perceptions and beliefs about differences in

the status, reputation or political power are negotiated along multiple dimensions. For example, the observed scale could be associated with past success, personal history, family or clan, common goals, or some other socially constructed ordering criteria. However, social structure could also be observed objectively as physical structures such as metrics describing multi-fractal structures, emergence, or self-organization. However, the CIA assumes that in either case, advanced technology could be developed to decode ‘information’ embedded in the ordering scale for agents using the algorithms associated with probability density functions of values that are associated with order parameters (Cheng et al., 2020). These could include, for example, metrics of free energy, multifractal structure, emergence and self-organization (Boettcher and Burnson, 2015; Koorehdavoudi and Bogdan, 2016; Balaban et al., 2018). The model assumes that this information could be interpreted as system-level properties which in turn can be used by agents during individual-level interactions to improve their decision making. These information processing conditions suggest opportunities for future ICT research and development.

The central contributions of this article are the assertions that suggest that information relevant to individuals is embedded in three distinct scaling structures which interact along distinct degrees of freedom. Further, it conjectures that information about each of these types can be quantified in relation to a different order parameter: alignment of agent attention vis-a-vis the ecosystem, instrumental momentum among the agents within the organization who are associated with that organization’s properties, and the level of trustworthiness of others that is assumed by agents within the organization. This parameter is related to commitment to long term membership in ‘us’. The CIA model assumes that each agent observes, decodes and uses information along each of these degrees of freedom to inform the evolving and interdependent decision states of interacting agents as events unfold. Exposing these information processing conditions in human organizations suggests opportunities for future ICT research and development.

ANALYTIC AND NUMERICAL MODELS OF COLLECTIVE AND INDIVIDUAL CHOICE

To begin, I briefly describe the conceptual thinking behind the DMM, SA, and IPSL models. All of these are analytic and numerical models rather than empirical models and are based on physical phenomena such as dynamic phase transitions and complex network theory. The DMM, takes a collective perspective and examines situations where nodes in complex networks synchronize individual states, and under conditions of self-organizing criticality, modify those states in synchronized phase transitions. In practice, observing these dynamics could help agents determine what to do, how to do it, and with whom to cooperate. Of particular interest are situations where networks interact with one another and transfer information from the more complex network to the less complex one (Turalaska et al., 2009), a phenomenon called complexity matching.

In contrast, the SA uses the DMM as a substrate but focuses on the choice conditions, and thus localized decision making, at each individual node. It can be used to explore how observable collective dynamics are mechanistically enacted at the individual level as information is transported to individual nodes to influence the local choices made by agents to cooperate or defect at each interacting pair of nodes (Mahmoodi et al., 2020).

Finally, IPSL uses feedforward information transport and back propagation neural network learning algorithms to reward success by changing the collective's internal influence structure by assigning higher levels of relative status, reputation or political power to successful agents. In this context, 'success' is purportedly defined in the context of a shared representation of an organization's properties, and therefore this ordering of network structure stores information about the organization's position relative to the ecosystem within the organization's social and political influence structure. Observing this could help agents determine with whom to interact. To provide background for the argument to follow, each of these models is described in a bit more conceptual detail in the next three subsections.

Synchronizing the Choice to Cooperate or Defect as a Collective Outcome

The DMM builds on percolation theory and is based on a complex network structure wherein each node exists in one of two binary states and thus notionally reflects an agent's last independent binary choice to either cooperate or defect along a given degree of freedom (Turalska et al., 2009). To determine the interacting states of individual nodes, the model exploits conditions of structural and dynamic complexity across interacting networks—such as the internal networks of firms and boundary-crossing network connections from firms to their markets. The principle of complexity matching suggests that when nodes of a network interact with nodes in an external but more complex network, the first network may have access to new information which could change its internal structure, effectively matching its complexity (West, 2016).

The CIA model assumes that as new information enters a complex network, agent choices to cooperate or defect may change along with its internal network structure. This article argues that synchronization of choice and action can be shown to occur in networks of human agents when the presence and nature of scaling structures in the collective (Boettcher and Burnson, 2015) can be observed by agents and when this occurs, observations of these structures and the choices they inform, can enable organizational leadership because they provide the agents valuable information about the organization's position in the ecosystem.

Next, I describe the SA model which shows how information might be transported to and used at the specific locations in the network where it is useful as individuals take their local decisions to cooperate or defect when interacting with others over time.

TABLE 1 | Payoff matrix for the Selfish Algorithm.

		Player <i>j</i>	
		C	D
Player <i>i</i>	C	(1, 1)	(0, 1 + T_c)
	D	(1 + T_c , 0)	(0, 0)

How Scaling Structures Influence Local Choice and Action

The SA (Mahmoodi et al., 2020) is based upon the DMM but focuses on local node or agent choice conditions and how these might vary according to local information conditions. For modeling purposes, these impacts are summarized for each agent as changes to the payoff matrix of a generalized Prisoner's Dilemma Game (PDG) that is biased by a cumulative tendency to cooperate based on the two prior events. In the SA model agents learn if continuing cooperation pays off from recent interactions.

More specifically, the SA models interactions in a PDG that is played by pairs of agents in a population at each time step. As shown in **Table 1**, the SA defines its payoff matrix in the context of a parameter, $0 < T_c < 1$, which reflects the incremental benefit from 'cheating' over cooperating when others are cooperating. Thus to sustain a cooperating regime, within a population the level of T_c benefit of cheating must be overcome by a subjectively learned belief that there is consistent value from ongoing cooperation. This is why this is called the Selfish Algorithm Learning (SAL) model.

However, as I argue in a later section, beyond learning from local interaction, information about the collective and its ecosystem can be observed by agents. Furthermore, this information may impact an agent's subjective belief about its payoff matrix since the states of collective structures could impact the probability (Jøsang, 2016) that there are ongoing benefits to continuing cooperation that would impact its perceived PDG payoff matrices. First, however, it is useful to explore the bigger picture.

Influence Process Structural Learning

Using numerical modeling that emulates a simple neural network, Hazy (2012) demonstrated that collective learning, what he called influence process structural learning (IPSL), can occur in organizations even in cases where decisions about resource allocation are made by agents with no direct visibility into the opportunity or threat conditions in the environment. In this model, local choices involve processing information that is conceptually—although not explicitly—related to two of the order parameters identified, namely: First, *expectancy alignment* (EA) with respect to opportunities and threats in the ecosystem as identified by some agents might be observed as shared goals or objectives. Second, *instrumental momentum* (IM) that is already operationally efficient in the system can be used to (probabilistically) predict results. Belief in the efficacy of these instrumental capabilities increases the subjective probability

(Jøsang, 2016) that the payoff assigned to the choice to cooperate will continue to be viable.

IPSL suggests that resource allocation decisions taken near the executive or high status level of the network—treated as the output layer in ISPL—increase the perceived status of those who received the funding. These choices then change resource flows through the organization which alters the internal network influence structure. This process effectively acts as back propagation reinforcement signals in middle management structures—the hidden layer of the network—that stores information about the prior success of particular agents by increasing their status, reputation or ‘power’ thus changing the structural dynamics of the system.

Prior IPSL work is delimited, however. Artificial neural networks often have three levels (Bossomaier, 2000): input layer, hidden layer and output layer. The neural network model of IPSL likewise assumes a predetermined three-tiered organizational structure. More specifically, IPSL assumes a decision making process similar to the garbage can metaphor (Cohen et al., 1972) with three tiers: executives/officers in the “output layer” with decision-making authority, middle management serves as a “hidden layer,” and finally individual contributors comprise the “input layer”. Unresolved is the question of whether emergent structures, such a multifractal patterns, can organically develop ISPL.

In the next section, I argue that IPSL can emerge when bits of information about relative status or reputation are correlated with the AE and IM parameters identified herein and when the collective is supported by a climate of organizational efficacy that biases individuals’ choices toward cooperation through subjective belief, i.e., the *generalized trustworthiness* (Cheng et al., 2020), that ongoing cooperation with organizational norms and with other members will provide continuing benefit to the individual. These assertions are discussed next.

ORDER PARAMETERS: ALIGNMENT, MOMENTUM, AND GENERALIZED TRUSTWORTHINESS

This section builds on the DMM, SA, and IPSL models to synthesize a new model of CIA that is enacted by the informed decisions of individual agents through a class of interactions called ‘leading events’ that together support a leadership meta-capability (Hazy, 2008; Hazy, 2013) in organizations. The CIA model describes how individual choices that are made locally can be informed by the inferred levels of three order parameters that address the questions of what, how, and with whom, and roughly align with Vroom’s (1964) three elements of Expectancy Theory. These are: expectancy alignment (EA) of individuals toward organizational objectives, instrumental momentum (IM) associated with organizational capabilities that when activated can achieve key results, and a shared valence to cooperate with like-others which is a measure of the level of belief by agents of the generalized trustworthiness (GT) of the organization and other agents within it.

The values of these order parameters, if observable and recognized by individuals in a social network, reflect subjective categories (Jøsang, 2016) of potentially valuable scaling information that can be used by individuals to inform, and thus influence, their choices as they act locally to maximize their individual benefit as members of the organization. As described by the DMM, under appropriate conditions, these choices can be synchronized with local neighbors. Depending on the circumstances, dynamic processes might reinforce expectancy alignment (EA) about what to do regarding promising opportunities or threats, or sustain and build instrumental momentum (IM) with respect to how to do what needs to be done. Finally, I argue that the level of generalized trustworthiness (GT) within an organization helps individuals decide with whom to do what needs to be done. In this context, GT mediates the direct effects of EA and IM on organizational performance and outcomes.

This section begins with a brief discussion of empirical studies that describe order parameters which characterize observable social dynamics in animal groups.

Order Parameters in Social Biology

Research in social biology has suggested the existence two observable dynamic patterns among social animals that signal the presence of social cognition (Couzin, 2007; Tunstrøm et al., 2013; Koorehdavoudi and Bogdan, 2016). These order parameters reflect discernible and persistent ordering in a collective that stores information in structural dynamics that if observed can be useful to members.

Firstly, *alignment* is observed as collective migration patterns that guide members’ motion to align with one another as they traverse the physical ecosystem (Koorehdavoudi and Bogdan, 2016). Secondly, *momentum* is observed as swirling patterns in schools of fish and flocking birds distribute information to members about the broader topology of seascapes and landscapes respectively and the presence of food or predators relevant to the collective (Tunstrøm et al., 2013; Koorehdavoudi and Bogdan, 2016). Notably, information of these two types is not stored in the memory of individuals. It is stored in the structural dynamics of a collective. When individuals recognize and interpret this information, they can use it for individual and collective benefit.

Different relevant values of these two order parameters have been consistently identified in studies and characterize four distinct dynamic states. First, correlated parallel *alignment* among group members (called a “highly parallel group”) can be observed against the background ecosystem. Second, angular momentum with members circulating in concert around a relatively empty core (called “milling”) is reflective of a recognizable dynamic patterns in the internal relationships within the school, herd, or more generally, any collective (Couzin et al., 2002; Koorehdavoudi and Bogdan, 2016). Implicit in these studies is the additional assumption that a third order parameter, one that reflects clear cohesion or bonding (called “swarming”) that is independent of alignment or momentum, defines individuals as being members (or not) of the collective ‘us’. This is observable as a trait known as

homophily (Kossinets and Watts, 2019) which, I will argue in a later section, is closely related to a bias to trust that like-others will cooperate with organizational norms. When all three order parameters coexist at moderate levels, the collective is a “dynamic parallel group”.

Expectancy Alignment in Relation to Opportunities in the Ecosystem

Research on ordered collectives in nonhuman animals has identified the highly parallel group as a common dynamic state. This is characterized as a high level of alignment of individual agents along one or more degrees of freedom, for example, a heightened sensitivity to risk (Sosna et al., 2019). The strength of this dynamic state is reflected as an order parameter across the orientation of attention of individual agents along particular degrees-of-freedom in a defined population such that the probability density function (PDF) of agent alignment states reflects recognizable polarization against the ecosystem background (Couzin et al., 2002; Tunström et al., 2013; Koorehdavoudi and Bogdan, 2016). When non-random alignment is observed, the collective is effectively using its structure to store information bits about where individual agents should focus their attention. These bits can be recognized, interpreted, and if relevant, used by agents (Couzin, 2007) as they interact with partners to maximize their payoffs at each time step.

In these situations, individuals can recognize opportunity or threat potential by interpreting the ‘bits’ of information that are embedded in structure and reflect an ‘average’ alignment of a subset of others. This information may be valuable as an indicator of potential payoff from cooperating vs. defecting in the PDG payoff matrix for a given time step. However, there are complications. In the case of human systems, EA might be associated with a shared goal or objective in the ecosystem—a promising market or valuable commodity for example—and information about this opportunity may be encoded in language or symbols such that the information is only available to agents who are able to decode it. An example of a class of human organizations which primarily organize around EA are Venture Capital and other Private equity Limited Partnerships. These firms typically form around individual General Partners with a history of successfully identifying investment opportunities and developing them for profit. Others recognize these alignments and benefit from associating with winning deals led by high reputation others. Since general partners make allocation decisions about investments, this process approximates IPSL.

Thus, it is reasonable to assert that there are identifiable conditions in collectives where the following assertion holds:

Assertion 1: An observable level of collective Expectancy Alignment (EA) reflects order in a collective that may impact the local payoff matrices for individual choices.

This information, when it is predictive and is recognized and processed by individual agents, perhaps with the support of ICT systems, can impact the expected value of various payoffs in their

TABLE 2 | Payoff matrix including the respective continuing individual benefits β_i and β_j of EA.

		Player <i>j</i>	
		C	D
Player <i>i</i>	C	$(1 + \beta_i EA, 1 + \beta_j EA)$	$(0, 1 + T_c)$
	D	$(1 + T_c, 0)$	$(0, 0)$

individual decision matrices as agents independently decide whether to cooperate or defect in their iterative interactions. When agent *i* has the capability $0 < \beta_i < 1$ to observe $0 < EA < 1$, the benefits of continuing cooperation would impact the agent’s payoff matrix as shown in **Table 2**.

Assertion 2: For a given agent with capability β_i , information about the PDF of EA in a collective is subjectively predictive of continuing benefit from cooperating for individual agents when the normalized expectancy alignment, EA, of a defined subset of other agents is synchronized over a period of time.

Furthermore, information about EA may be stored in a nested hierarchy (Ferrigno et al., 2020) or involve a multifractal scaling dynamics (Balaban et al., 2018) that can be difficult to decode. By observing the stable value of the EA parameter of different subsets at different structural levels of the nested hierarchy, information about collective alignment can be processed and transported from one individual agent to others and from one nested hierarchy to another by iterative information processing operations. This implies a third assertion.

Assertion 3: Information about agent-states may be stored in a nested hierarchy which may be accessed and interpreted by each agent by recursively applying information processing operations on data observed across the network and up and down the hierarchy.

Instrumental Momentum Within the Collective

Research on ordered collectives in nonhuman animals has identified angular momentum in the changing positional relationships among agents as reflecting an order parameter among social animals. This reflects ‘how’ ‘we’ in the collective move and act. This order reflects recognizable periodic cycles, or “milling”, when measured as circulation dynamics that are internal to the collective (Couzin et al., 2002; Tunström et al., 2013). Ordered momentum stores information bits about the collective’s internal dynamic structure which can be accessed and used by agents at each time step as they make their individual choices and select interaction partners to maximize payoffs in the PDG.

In these situations, bits of information about the relative levels of instrumental momentum (stored energy, resources, or political power) associated with how things get done. This may be valuable when deciding with whom to pair or “connect” to maximize one’s

TABLE 3 | Payoff matrix including the respective continuing benefits α_i and α_j of IM.

		Player j	
		C	D
Player i	C	$(1 + \alpha_iIM, 1 + \alpha_jIM)$	$(0, 1 + T_c)$
	D	$(1 + T_c, 0)$	$(0, 0)$

payoff in the PDG matrix. However, there are complications. In the case of human systems, instrumental momentum might be potentials associated with knowledge, skills, or positional leverage, and information about stored free energy (Koorehdavoudi and Bogdan, 2016) may be encoded in language or symbols such that it is only available to agents who are able to decode it. An example of this might be a government bureaucracy where knowing how to get things done is arguably the principle determinant of individual success. Therefore, it is reasonable to assert that there are identifiable conditions in collectives where the following assertions hold:

Assertion 4: An observable level of collective Instrumental Momentum (IM) reflects internal order in a collective that may impact the payoff matrices for individual choices.

The observed value of this order parameter for various components of the network stores bits of information about the nature of instrumental momentum available for leverage at various points in the collective. This information, when it is predictive and is recognized and processed by individual agents, can influence the expected value of various payoffs in their decision matrices as they decide with whom to interact and whether or not to cooperate when interacting with others at each time step. When agent i has the capability $0 < \alpha_i < 1$ to observe $0 < IM < 1$, the benefits of continuing cooperation would impact an agent’s payoff matrix as shown in **Table 3**.

Assertion 5: For a given agent with capability α_i , information about the PDF of agent IM states is subjectively predictive of continuing success when the PDF of the dynamic IM states of various subsets of members is stable for a period of time.

Furthermore, information about IM may be embedded in a nested hierarchical structure. By observing the value of the IM parameter at different levels of the nested hierarchy, information about collective instrumental momentum can be processed and transported from one individual agent to others and from one nested hierarchy to another by iterative operations up and down the hierarchy.

Assertion 6: Information about the PDF of agent IM states may be stored in a nested hierarchy. This information may be observed and processed by agents by recursively applying information processing operations up and down the hierarchy at each time step to inform their payoff matrices for various actions prior to choosing to cooperate with a given individual.

Boundaries From Belief in Generalized Trustworthiness Delimit an Organization

Research on ordered collectives has identified patterns of collective order which are classified into various types of dynamic cooperation according to the order parameters discussed in this article. These include: ‘swarming’, a type of cohesion or valence that is characterized by proximity or shared social identity (Turalska et al., 2009); dynamic order or ‘milling’ (high momentum); the highly parallel group (high alignment); and finally dynamic order that includes moderate parallel alignment along with high momentum among agents (Couzin et al., 2002; Tunström et al., 2013; Koorehdavoudi and Bogdan, 2016). All of these are dependent on each agent identifying a categorization by other agents with whom that agent associates and believes are trustworthy in matters related to the collective. This constitutes the collective’s socially constructed ‘boundary’. An example of this in the human case might be clan, church, or other affinity groups where trusting that others believe as you do engenders a deep sense of belonging.

In human collectives, bits of membership information that serve to classify individuals in workgroups, departments, projects, or organizations are also often structured in nested hierarchies. Each level of hierarchy may be relevant to agents in different contexts as they seek to determine with whom to work and how to work with them along various degrees of freedom.

However, there are complications. First, in the more complicated case of human systems, the potential that a given agent may believe in (Jøsang, 2016) generalized trustworthiness of specific other agents might be related to the personality characteristics, personal history, situational context, social and emotional intelligence, or political skills of the deciding agent. Further, relevant information may be encoded in emotional queues, language, or symbols that are only available to agents who are able to decode them (Fairhurst, 2017). Finally, in human systems, the order parameter, GT, might involve a nested hierarchical structure. In these cases, it is important to be able to recognize and exclude those individuals who are not included in the relevant subset of the organization. This is because, as a possible example of homophily, the GT characteristic is assumed to be inherited only by members of an organization or the relevant subset. Others who do not cooperate with the broader group would be excluded and are similar to what have been called ‘zealots’ in the literature (Mahmoodi et al., 2018). In each of these cases, however, one would expect that there are identifiable conditions in collectives where the following assertions hold:

Assertion 7: The PDF of agent states in a defined subset of the population that reflects a synchronized tendency for agents to believe in the Generalized Trustworthiness (GT) of others in their group reflects information as order in a collective. This information can influence agents’ payoff matrices in favor of cooperating during interactions. These GT effects mediate the effects of EA or IM.

The observed value of this order parameter stores information about which finite set of other individuals in the collective are

TABLE 4 | Payoff matrix including the respective continuing benefits γ_i and γ_j of GT.

		Player j	
		C	D
Player i	C	$(1 + \gamma_i GT, 1 + \gamma_j GT)$	$(0, 1 + T_c)$
	D	$(1 + T_c, 0)$	$(0, 0)$

likely to cooperate with others in the set in various components of the network along various degrees of freedom. When this information is predictive and is recognized and processed by individual agents as a category of trustworthy agents, this incremental knowledge can impact the expected value of various payoffs in an observing agent’s decision matrices as each individual decides whether or not to cooperate or defect in their interactions at each time step. When agent i has the capability $0 < \gamma_i < 1$ to observe $0 < GT < 1$ for a given category of agents, the benefits of continuing cooperation would impact that agent’s payoff matrix as shown in **Table 4**.

Assertion 8: For a given agent with capability γ_i , information about GT is predictive for agents when the agent-states of members in the agent’s local neighborhood are synchronized and dynamically stable over a time period.

Furthermore, information about varying levels of GT may be embedded in a nested hierarchy structure. By observing the value of the GT parameter at different levels of a categorical representation of a the nested hierarchy, information about consistent variations in the beliefs of others about collective trustworthiness can be processed and transported from one individual agent to others and from one nested hierarchy to another.

Assertion 9: The information about the GT states of subsets of other agents may be stored in a nested hierarchy which may be processed by other agents by defining and applying information processing operations up and down the hierarchy.

INFORMATION PROCESSING TECHNOLOGY IN COLLECTIVES

This section describes a more formal representation for social information processing in complex social networks that could be used to develop a technology-augmented social-information processing architecture to support dynamic organizing. To begin, I suggest that an individual’s abstract perception of a ‘collective’ can be represented mathematically as a formal Category (for example, a directed network) wherein the agents or groups of agents are objects with directed mapping relationships among them, and such that both the identity map (each agent maps to itself as the agent) and the associative property (compositions of mapping relationships) are defined in the collective (Mac Lane, 1978; Spivak, 2014).

Significantly, under these definitions, this simple representation provides at least one “bit” of relevant information that can be quickly accessed and used by an observer: Namely, any given individual is either included or not included as an agent-object in the categorical representation of the collective. Among other things, this property defines the collective’s boundary for a given representation.

Similarly, when using the categorical representation, it is also trivial to show that since by definition, collective intelligence cannot be in the members either individually or in their aggregate, it must reside, that is information must be stored and processed, in the interaction relationships among member-objects. This implies a proposition which defines collective intelligence:

Proposition 1: Collective intelligence in the categorical representation can be described in the context of a complex network of relationships that represents the collective as a mathematical category.

Furthermore, I define as an ‘organization’ as a collective category such that its member-objects share a representation of coarse grain properties that benefit the collective or its members. This implies a second proposition:

Proposition 2: Collective agency can be described as a functor that maps a collective category to a category of coarse-grained properties that are defined for an organization.

The Conceptual Implications of CIA: Organizational Leadership Defined

When one assumes propositions 1 and 2, CI exists when structures and dynamics of complex networks within the collective gather and store bits of information about the ecosystem that are relevant to its members. This information can be recognized by agents as objects and relationships in the category, decoded, and interpreted by individuals or in groups through dialog (Fairhurst, 2017) to guide their decisions and actions. Individuals in the collective can then use this information to increase the probability of collective success and individual success. When this information is framed abstractly and represented in formal structures, it can be stored and processed in information and communications technology (ICT) systems (Spivak, 2014).

Collective intelligent agency (CIA) attracts agents to participate as members of the collective when it benefits them by allowing them to leverage cooperation that scales in the context of shared representations of coarse-grain properties. These points of leverage include: clarifying what to do by, for example, setting objectives, EA; clarifying how to achieve key results, by for example, leveraging organizational capabilities as an organization, IM; and clarifying with whom to cooperate by setting a tone for trust and community, GT. The attraction that draws agents to participate in these dynamics arises because the

expected value of the payoffs to the agent by continually cooperating with collective activities increases their relative payoff in each time step. This implies some assertions:

Assertion 10: Collectives vary in their level of EA and thus in their ability to identify and set objectives which align expectations of individual agents with high value opportunities in the ecosystem and thus would be perceived to increase the expected payoffs to members for continuous synchronized cooperation. Furthermore, these differences would be expected to be dynamically stable over time.

Assertion 11: Collectives vary in their level of IM and thus in their ability to achieve key results and outcomes over time and thus to increase realized payoffs to cooperating members. Furthermore, these differences would be expected to be dynamically stable over time.

Assertion 12: Collectives vary in their level of perceived generalized trustworthiness (GT) across their nested hierarchies and thus the expected payoffs to cooperating members. Furthermore these differences would be expected to be stable over time.

High levels of EA to set objectives grounded in real opportunities, IM to actualize key results and outcomes efficiently, and GT to engender a valence toward cooperating, when combined with purposeful individual actions that drive the emergence of efficacious organizational properties, signal the presence of an active leadership meta-capability in a collective. For the purposes of this article, I define organizational leadership as the orchestration of leading events which leverage cooperation that scales in each of these areas to achieve coarse-grain properties that define the collective as an organization.

Advanced ICT systems could support, augment, and advance this process by helping individuals find, identify, and align their goals and objectives with situations of “opportunity” in the ecosystem or by leveraging operating momentum in the form of dynamic and operating capabilities (Helfat et al., 2006) to increase the probability that key results and outcomes will be achieved. This would tend to increase the predicted local payoffs in each agent’s decision matrices by increasing each individual’s capacity to recognize and interpret relevant information. More specifically, advanced ICT systems could improve the organizations EA, IM and GT as well as agents’ α , β and γ capability levels.

The Practical Implications of CIA: Leading Events Defined

This section discusses how expectancy alignment (EA), instrumental momentum (IM), and generalized trustworthiness (GT) may interact during leading events in the context of organizations and the leadership meta-capability as well as how emerging intelligent technologies may be developed to augment and better inform these interactions. The earlier section of this article, **Order Parameters: Alignment, Momentum, and Generalized Trustworthiness**, shows how each of the three scaling structures that enable CIA might be

TABLE 5 | Payoff matrix including the respective continuing benefits R from leadership L.

		Player j	
		C	D
Player i	C	$(1 + R_L, 1 + R_L)$	$(0, 1 + T_c)$
	D	$(1 + T_c, 0)$	$(0, 0)$

integrated into the selfish algorithm (SA) model to describe how each agent uses this information to decide what to do, how to do it, and with whom to interact when deciding whether to cooperate or defect at each time step in the prisoner’s dilemma game.

Because the values of α , β and γ relate to the probabilistic subjective belief (Jøsang, 2016) that individuals have about the trustworthiness of social data about others, Collective Intelligent Agency is defined to be present when Assertions 10, 11, and 12 are satisfied, and because GT allows agents to identify trustworthy others, the following assertions are also observed:

Assertion 13: The level of perceived GT in a collective mediates the effects of EA and IM in achieving CIA.

The GT, EA and IM mechanisms create potential for purposeful individual-level leadership activity that can occur during local interactions. This involves individuals enacting ‘leading events’ that organize activities across levels of scale by increasing the values of the α , β or γ parameters so that other agents are able to recognize and therefore better leverage EA, IM and GT in ways that operationalize the leadership meta-capability in the organization (Hazy 2008, 2013).

Assertion 14: By influencing the values of α , β and γ of other agents, some individual agents can enact leading events that leverage the scaling mechanisms of EA, IM and GT to further their own individual or collective interests.

Given that Generalized Trustworthiness (GT) mediates the effects of EA or IM through each agent’s payoff matrices to favor continuing cooperation, and given that α , β , and γ reflect each individual’s capability to decode this information, the incremental value of cooperation, R_L , could be operationalized for each agent through leading events as shown in **Table 5**. The previously described relationships can be formalized with $0 < R_L < 2$ as follows:

$$R_L = \gamma GT (\beta EA + \alpha IM) \tag{1}$$

Thus, I offer a final assertion:

Assertion 15: Leading events can be used to optimize organizational outcomes for each agent in the organization by maximizing its R_L in the context of an organization’s leadership meta-capability according to **Table 5**.

The effects of Generalized Trustworthiness (GT) mediates the effects of EA or IM through each agents’ payoff matrices to favor continuing cooperation in all three areas.

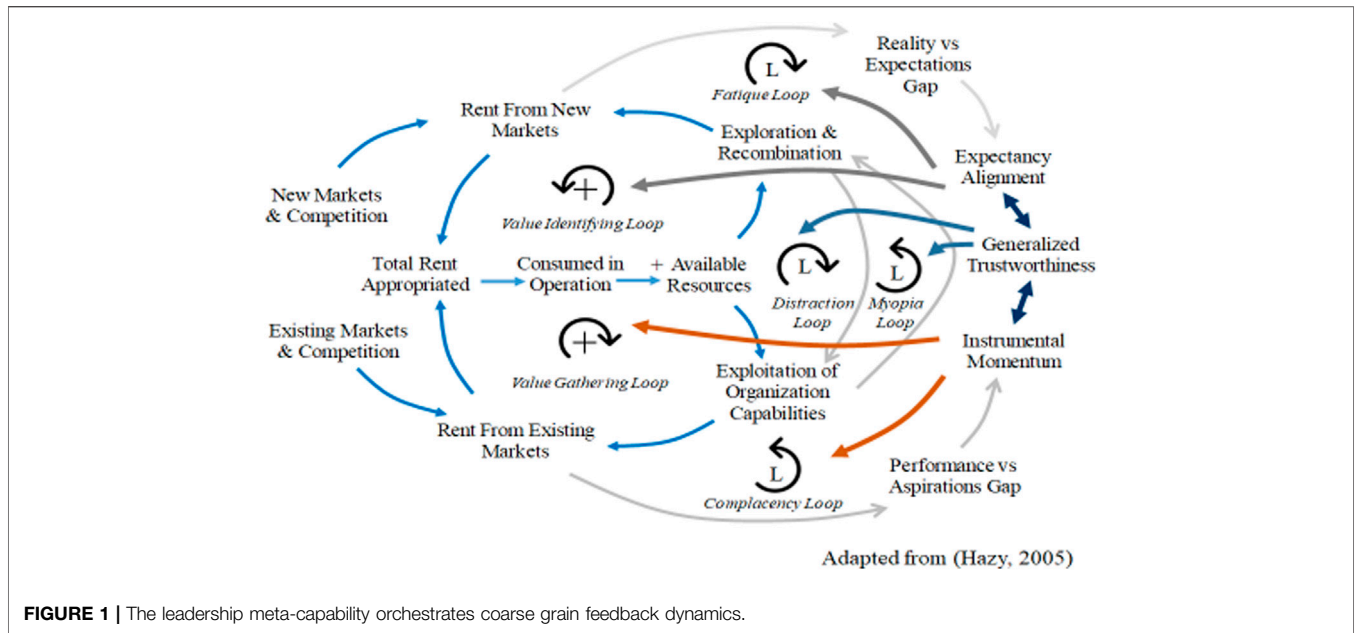


FIGURE 1 | The leadership meta-capability orchestrates coarse grain feedback dynamics.

To summarize, in this article I argue that EA and IM are operationalized by processing information associated with setting goals and objectives as reflected in the order parameter Expectancy Alignment (EA), and by achieving key results and outcomes as reflected in the order parameter Instrumental Momentum (IM). Furthermore, these effects are enabled and amplified by clear definitions of the category of members and the nature of relationships among them that together cultivate a climate with high levels of generalized trustworthiness (GT). All of these relationships could potentially be augmented and facilitated through advanced ICT systems. Some possibilities for future ICT research and development are discussed next.

DISCUSSION AND IMPLICATIONS FOR FUTURE RESEARCH

This section broadens the lens to the coarse-grain level of resolution to consider the questions of what, how, and with whom, but this time from the perspective of the organization. It is through scaling dynamics that leading events enact organizational properties when the uncertainties of complexity are most consequential (Koorehdavoudi and Bogdan, 2016). It is, therefore, at this nexus where advanced technology is best positioned to improve the accuracy, clarity and usefulness of information that is associated with scaling in social networks to support choices made by individual agents, each in its own local contexts.

Practically speaking, by defining better objectives and more effectively delivering key results (Doerr, 2018), next generation IT systems could enable purposeful CIA by making explicit the key points of dynamic leverage identified in the leadership meta-capability model shown on the right side of **Figure 1** (Hazy, 2008). By clarifying, accelerating or moderating information transfer—for example, by developing what might be called an “assisted flight simulator”—these

systems would be particularly useful for managing resilience and transformation as organizations approach and respond to phase transitions and unpredictable renewal events.

Making Sense of Interaction Resonance

When the scaling dynamics described in prior sections are considered from the point-of-view of an individual who is trying to make sense of his or her broader social environment, the interpretive conundrum faced by agents is that current information signals that may be relevant to future states can only be inferred by observing persistent coarse-grain patterns in the decision-states of other agents as these were observed during prior time steps. These perceptions associated with relevant instances of EA, IM and GT in the past are reinforced and sustained as structural attractors (Hazy, 2019) that are supported by individuals as coarse-grain properties of the organization. This occurs through a class of individual choices and action that I am calling ‘leading events’.

On the margin, however, resonance dynamics may sustain beliefs about probabilistic predictability (Jøsang, 2016), even perhaps beyond the point where their effects are actually helpful. This is because the information being used for decisions is historic and does not take into account the inherently unpredictable occurrence of renewal events or phase transitions when structures suddenly change (Turalska et al., 2009; Koorehdavoudi and Bogdan, 2016). The primary practical challenge for individual agents at the micro or fine-grain level who are seeking to enact leading events, therefore, is that although one might reasonably conclude that what was true yesterday will likely (although not certainly) be true today, this heuristic only holds until it doesn't, and exactly when that might occur is unpredictable.

In contrast, for individuals who are engaging at the macro or coarse-grain-level, the primary practical challenge arises when the socially-constructed simplified conditions of stability in the social network structure no longer match the complexity conditions in the

ecosystem. This mismatch signals the potential for an immanent phase transition in the organization's complex networks or those of its markets. These uncertain conditions of impending transformation create conflicts between organizational realities and individuals who continue to believe that old ways are still working. Research that explores how new IT systems can support individual agents as they engage these challenges before, during, and after renewal events is needed.

In contrast to current systems that focus on organization level dashboards as a means to monitor and control individuals and their choices, this future research would develop ICT systems that use technology to gather data about dynamic CIA structures and process these data in ways that simulate and test possible scenarios to improve the quality of the local choices made by individuals in the organization (Hazy, 2013).

The Levels of EA and IM are Inversely Related to the Relative Benefits of Defection

Objective setting is an important aspect of organizational success (cf. Doerr, 2018). It would seem plausible that a focal agent who is able to recognize when there is a high level of EA among a subcategory of agents in a collective could also be informed about the probability that current alignment is indeed focused on an opportunity or threat that suggests a higher potential payoff for cooperation. This confidence would arise because, in addition to its own direct observations, the focal agent would be able to leverage the information about potential opportunities that are embedded in ambient social structures (Sosna et al., 2019).

Likewise, when a focal agent is able to recognize high levels of IM among agents that are associated with operating capabilities, there is reduced risk associated with achieving key results and thus an increased expected value for the payoff from continuing cooperation. This is because the focal agent who cooperates would, on a going forward basis, be able to leverage information and instrumentality already available in the organization within its dynamic 'ordering' activities and organizational capabilities. This is also a promising area of ICT research and development.

The availability of additional indirect information suggests an opportunity for ICT that more accurately informs individuals about the nature of opportunities and threats in the ecosystem based upon changing structures, for example using multifractal metrics (Xue and Bogdan, 2017; Balaban et al., 2018) or quantification of emergence or criticality conditions in various components of the social network (Koorehdavoudi and Bogdan, 2016). Data embedded in distributed relationships, physical resources, and even socially constructed objectives and operating plans could be observed, quantified and interpreted by ICT systems, for example, by implementing methods for analyzing multifractal structure (Balaban et al., 2018) embedded in distributed relationships, and then using this analysis to simulate probable organizational outcomes in near real-time (Hazy, 2013).

Generalized Trustworthiness Creates Valence Toward Cooperation

When a focal agent is able to recognize the category of agents for whom there is a high level of GT among the agents, there is

increased relative payoff associated with continuing to cooperate. This is because agents who remain as 'us' are able to continuously leverage information and instrumentality that is available to them due to 'ordered' alignment of objectives toward opportunities and 'ordered' instrumental structures that facilitate the achievement of key results in the organization (Hazy, 2013).

New ICT systems could elaborate and clarify the value of this indirect information about variations in GT associated with different departments and workgroups as well as how these differences interact with variations in EA around objectives and IM available to achieve key results. In contrast with current support systems that focus on transactional organization level functions, future research should target ICT systems that inform and improve the quality of relationships within and across organizations and then forecast the implications of these differences with respect to objectives and key results and use these data to simulate probable outcomes (Hazy, 2013).

Individual Agency and the Leadership Meta-Capability

This article contributes to the conversation by presenting models that show how changing human social networks and resource flows in the ecosystem can, by transporting information, trigger locally enacted interaction dynamics among human and synthetic agents at the micro level that can have manifestations at the organization or macro level. These interactions can include local leading events that, due to their exploitation of scale crossing regularities that occur during self-organizing criticality dynamics (Koorehdavoudi and Bogdan, 2016; Xue and Bogdan, 2017) impact the outcomes of organization-level properties. Taken together, the orchestration of the various types of local activities constitute the class of interactions that enact the purposeful leadership meta-capabilities in organizations.

In their turn, changes to coarse-grain properties generate further signals that, when interpreted by locally situated agents, impact local interactions and decisions by changing the payoff matrices of key actors who might engage in leading events. This iterative process of reinforcing feedback continues as long as conditions support it, and as long as the system remains stable. However, if these feedback dynamics are not monitored and controlled with targeted balancing feedback, pre-existing stability can be disrupted with unintended consequences, even for example, cascading failures across large scale interdependent networks (Duan et al., 2019). In short, new information processing technology and systems that simulate potential outcomes could be used to improve the quality and efficacy of these all too human leadership meta-capability processes (Hazy, 2013).

CONCLUDING THOUGHTS

In this article I argue that three distinct but interacting complex networks coexist in human collectives. The complexity dynamics of these social networks underlie information processing mechanisms that can emerge as CAI during complex organizing in human organizations. Taken together, by systematically influencing local

agent choices according to a shared representation of an organization's coarse grain properties, these three conceptually distinct and independently recognizable pillars of scaling social structure are posited to support most, if not all, dynamically stable intelligent organizational forms.

The model of collective intelligence and agency (CIA) proposed herein makes a unique contribution by showing how information associated with scaling universalities can provide scale-crossing feedback to agents. This information, if it is relevant for making sense of the environment at a particular level of scale, can be useful to individuals as they make their choices about what to do at that level of scale, when and how to cooperate and organize with others to do it, and with whom they should work to frame their objectives and organize activities to achieve key results.

Further research is needed to quantify the constructs and formalize the relationships described herein, empirically test the fifteen assertions that flow from the analysis, and verify that the CIA model has practical value. In anticipation of future research

that offers empirical support, the article suggests a roadmap for ICT research and systems development.

Next generation systems that are proposed would continually gather data about the details of interactions in the firm's complex social networks, process that data with machine learning and artificial intelligence algorithms, and then continuously perform simulations and scenario analysis to assess the potential implication of these data at various levels of scale over time (Hazy, 2013).

The results of this analysis would inform each individual's choices as they occur locally in and across workgroups and up and down all levels of scale. When the value of cooperating scales, individuals are drawn to participate in organizations and would almost certainly become more effective at setting appropriate objectives and achieving key results.

AUTHOR CONTRIBUTIONS

The entire work is by JH.

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Conflict of Interest: The author declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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