

# Turning the Cacophony of the Internet's Tower of Babel into a Coherent General Collective Intelligence

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## ABSTRACT

Increasing the number, diversity, or uniformity of opinions in a group does not necessarily imply that those opinions will converge into a single more "intelligent" one, if an objective definition of the term intelligent exists as it applies to opinions. However, a recently developed approach called human-centric functional modeling provides what might be the first general model for individual or collective intelligence. In the case of the collective intelligence of groups, this model suggests how a cacophony of incoherent opinions in a large group might be combined into coherent collective reasoning by a hypothetical platform called "general collective intelligence" (GCI). When applied to solving group problems, a GCI might be considered a system that leverages collective reasoning to increase the beneficial insights that might be derived from the information available to any group. This GCI model also suggests how the collective reasoning ability (intelligence) might be exponentially increased compared to the intelligence of any individual in a group, potentially resulting in what is predicted to be a collective superintelligence.

## KEYWORDS

general collective intelligence; human-centric functional modeling; functional state space; collective social brain hypothesis

Increasing the number, diversity, or uniformity of opinions in a group does not necessarily imply that those opinions will converge on a more "intelligent" opinion, where "more intelligent" is defined in terms of the increased fitness of the cognitive system to achieve any outcome in general, as represented in the human-centric functional modeling (HCFM) approach defined later in this paper. When attempting to collectively solve a problem within a group of individuals, it is conceivable that in some cases, such as perhaps an attempt to discover specific knowledge within a group of equally qualified participants, diversity in groups might yield better (more intelligent) results. It is also conceivable that in some cases, such as perhaps problems involving general knowledge, a consensus among the entire group might yield better (more intelligent) results and that this consensus might be aided by uniformity in the group. In other cases, such as problems requiring specialist expertise, better results might be obtained by restricting participation to the most highly qualified experts. Additionally, these generalist and specialist problems might be subdivided. The specialist ones perhaps are those best solved by increasing the level of consensus among a greater number of qualified experts and those best solved by increasing the intelligence of the answer regardless of a complete lack of a consensus. As an example, when attempting to collectively solve a problem with a group of one thousand individuals, for problems requiring specialist expertise such as an understanding of general relativity, better results might be obtained by asking the one physicist in a group of nine hundred and ninety-nine farmers. Increasing the number of farmers in the group does not necessarily increase the ability of the group to answer a question in general relativity, just as increasing the number of physicists in a group does not necessarily increase the ability of the group to answer a question about agricultural legislation.

## 1 Literature Review

A critical component of HCFM is representing problems in terms of mathematical constructs called functional state spaces. State spaces have long been used to represent system behavior<sup>[1]</sup>. As useful abstractions for reasoning about the behavior of a given system state, spaces are widely used in the fields of artificial intelligence and game theory. HCFM is a new approach that defines this new type of state space (this "functional state space"), which is meaningful in that none of the states or processes it describes require an understanding of external information because they are represented in terms of the way all human beings innately perceive. Functional state spaces contain networks of functional states and therefore allow network science<sup>[2]</sup> to be applied to problems or solutions defined in terms of such spaces. However, in addition to being networks, functional state spaces are also mathematical spaces, so any system property that can be described in terms of motion through these spaces can be described mathematically in terms of these spaces. The approach of defining conceptual spaces<sup>[3]</sup> has existed for decades and has been useful because it has enabled a method for deducing semantic distance to be defined. However, the approach of defining functional state spaces through HCFM has been used to define a single universal "conceptual space", and because this conceptual space is universal and human-centric (requires no specialized tool or expertise to understand), it can potentially be used to represent all cognitive behavior, and for this reason, it has enabled defining the first functional model for the existence and magnitude of intelligence. Unlike others who have stopped at identifying general problem-solving ability at the group level as being measured by a "general collective intelligence" or "c factor"<sup>[4]</sup>, this approach potentially provides a model for measuring that factor and has also been used to define a model for a general

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collective intelligence platform having the  $c$  factor. To the author's knowledge, all other works that mention "general collective intelligence"<sup>[5]</sup> are referring to this  $c$  factor rather than platforms that explicitly create a  $c$  factor, as is the case here.

## 2 Human-Centric Functional Modeling of Individual or Group Cognition

Human-centric functional modeling<sup>[6]</sup> represents the behavior of any consciously perceptible human system (i.e., the sensory-motor system, the emotional system, the cognitive system, or the consciousness) as moving through a "functional state space". Each functional state space is a graph containing a network of nodes, with each node representing a functional state the system might occupy, where these nodes are connected by edges representing the processes through which the system might transition between functional states. This network of functional states is  $N$ -dimensional in that any network path can be expressed as a combination of  $N$  basic operations. If the meaning of any functional states can be described in terms of processes that connect them to other functional states, and if the meaning of any processes in functional state space can be described in terms of the functional states that connect them to other processes, then any functional state space can provide a complete representation of any meaning and is then a complete semantic representation. This  $N$ -dimensional graph ( $N$  is believed to be four in the case of the conceptual space, so in this case, the network is four-dimensional) is hypothesized to exist in a three-dimensional space in which the distance between any two vertexes (nodes) represents their similarity in terms of the relative number of connections they share with any third vertex (i.e., this distance is a "semantic" distance).

In the case of the human cognitive system, cognition (the execution of reasoning processes) is represented as moving the cognitive system through a hypothetical conceptual space (the functional state space of the cognitive system) in which all functional states are concepts and all reasoning processes with which the cognitive system might transition between concepts can be represented as a path through this conceptual space. In this conceptual space, the distance between concepts is a semantic distance, and any concept spanning a large semantic distance is a general concept that can contain more specific concepts that span a smaller semantic distance. Assuming that computing automates human reasoning, all computing processes can also be uniquely represented as a set of paths through this conceptual space.

HCFM is powerful because it allows complex properties of cognition and other human systems to be understood simply by looking inward (self-reflection) to observe how they function in terms of this well-defined conceptual space. This self-observation is invaluable for cases like cognition, in which no external tools to measure those cognitive functions in the human organism yet exist. Furthermore, if all functional state spaces have the same structure in terms of being  $N$ -dimensional graphs containing networks of functional states connected by transition processes, then functional state spaces differ only in the topology of the specific network they contain, as well as in whether that network is open (unbounded) and whether the  $N$ -dimensional network exists in a three-dimensional physical space or a space of lesser dimensions. If functional state spaces have the same number of network dimensions, are spatially distributed over the same number of physical dimensions, and have the same property of openness, then any property definition that is valid in one functional state space is potentially valid in other functional state

spaces, and because HCFM can potentially be used to model any system that humans can perceive, these definitions can be massively reused to increase problem-solving ability in a wide variety of ways. For example, the definition of general problem-solving ability in the cognitive domain might be reused in a domain defined to describe all functions of blockchain platforms (the blockchain state space) or in a domain defined to describe all identity management functions (the identity management state space).

General collective intelligence (GCI)<sup>[7]</sup> has been defined as a hypothetical platform with the capacity to organize vast groups into a single collective cognition that can not only coherently execute collective reasoning to achieve general problem-solving ability (intelligence at the group level or "collective intelligence") but also potentially do so with superintelligence. Having the general problem-solving ability, a "general collective intelligence" has the potential to be applied toward solving any problem in general. When it is applied to solving group problems, GCI might be considered a system that leverages collective reasoning to increase the beneficial insights that might be derived from the information available to any group. This GCI model also suggests how that reasoning might be exponentially increased compared to the intelligence of any individual in the group to potentially achieve this predicted superintelligence.

HCFM assumes that all collective reasoning processes can be expressed as paths through the collective conceptual space, and all processes with which a group might cooperate to scale the outcomes of that reasoning can be expressed as paths through the cooperation state space of the participants<sup>[8]</sup>. All possible attributes of collective cognition are then potentially categorized by the properties relevant to these reasoning and cooperation processes. A representation of some properties of collective cognition in HCFM is shown in Fig. 1. In Fig. 1, some subsets of the graph of the collective conceptual space are received as input to a collective reasoning process, and some (potentially new) subsets of the graph of conceptual space are produced as output. In conceptual space, some of the properties of a given set of input or output concepts or a given set of collective reasoning processes might be used to distinguish different problem-solving domains. In the same way, in the cooperation state space, some of the properties of a given set of input or output activities or a given set of cooperation processes by which the outcomes of reasoning might be scaled, might in turn be used to distinguish different cooperation domains. The properties of cooperation processes in cooperation state space include the participants in cooperation as well as the demographics and other properties of the participants. Both types of processes (reasoning and cooperation) are characterized by their fitness to achieve a given outcome.

In HCFM, collective intelligence (CI) is represented as having a narrow problem-solving ability at the group level, as opposed to GCI, which is represented as having a general problem-solving ability at the group level. A narrow problem-solving ability can only solve a narrow range of problems in the collective conceptual space, while a general problem-solving ability can potentially solve any problem in general that can be defined within the collective conceptual space.

Using as an example, the case in which one expert in a thousand participants has a valid opinion and the correct answer is not represented by the consensus (low signal-to-noise ratio in the input data), or the case in which a thousand participants have a high ability to reach a useful consensus regarding some general knowledge question (high signal-to-noise in the input data), some of the categories of narrow problems for which CI methods have

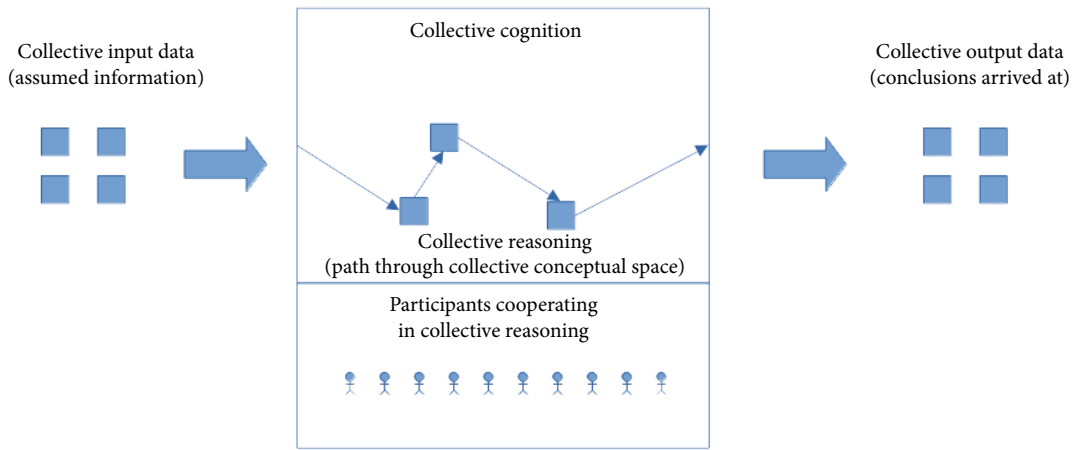


Fig. 1 Model of the properties of collective cognition in HCFM. A GCI is a model of a collective cognition.

been developed and in which CI methods have shown effectiveness might be characterized or differentiated by the signal-to-noise ratio in the input information. The makeup of the participants in the collective reasoning process according to the cognitive biases identified by the “collective social brain hypothesis”<sup>[9]</sup> might also define categories that most frequently characterize or differentiate CI methods. The collective social brain hypothesis states that the vast majority of individuals (anecdotally 999 999 in one million or 99.9999%) fall into either one half of the collective social brain or the other and cannot inhabit both sides. In the case of any topic that causes individuals in the different halves of the collective social brain to come to different conclusions, individuals will find arguments logical when those arguments meet their innate predispositions toward one cognitive bias or the other, rather than there being any objective standard for “correctness”. Thus, when designing a collective intelligence solution to increase a group’s ability to choose the correct answer, the collective social

brain is predicted to determine whether an answer is deemed to be “correct” and is predicted to do so according to the half of the collective social brain that the researcher running the CI experiment resides in. Some of the outcomes predicted to be deemed more or less correct depending on the half of the collective social brain that the researcher resides in are summarized in Table 1. These predictions have been informally validated through thousands of anecdotal observations but not formally validated through a large-scale study.

General problem-solving ability includes the ability to switch between different problem domains. Wherever CI researchers do not explicitly identify that CI problems might be best solved by switching to whichever side of the collective social brain is most fit, they might implicitly assume that one bias is always correct, which is predicted to be an error. In general, CI researchers must explicitly understand the need to switch between probably several additional CI problem sectors to avoid implicitly making the

Table 1 Some outcomes deemed positive or negative according to the different halves of the collective social brain.

Researcher’s bias	Outcome deemed positive	Outcome deemed negative
Predisposition toward Type I reasoning on issues concerning social protection (researcher is in the right half of the collective social brain)	<b>High diversity of vulnerable identities:</b> Defined as an equal or higher proportion of participants in desirable tasks, where those participants identify with a group that considers itself to be vulnerable. Vulnerability must be agreed upon by consensus in that other groups in this half of the collective social brain must agree that any other group is indeed vulnerable for them to be considered so.	<b>Low diversity of vulnerable identities:</b> Defined as less than an equal proportion of participants from vulnerable groups.
	<b>Absence of misinformation or conspiracies:</b> Defined as the blocking of information and reasoning deemed by this half to be misinformation and baseless conspiracy theories, respectively.	<b>Presence of misinformation or conspiracies:</b> Defined as the presence of information and reasoning deemed by this half to be misinformation and baseless conspiracy theories, respectively.
Predisposition toward Type II reasoning on issues concerning social protection (researcher is in the left half of the collective social brain)	<b>Prevent victim blaming:</b> Prevent those who identify with a vulnerable group from being blamed for consequences they should have been protected from.	<b>Allow victim blaming:</b> Fail to prevent those who identify with a vulnerable group from being blamed for consequences they should have been protected from.
	<b>Prevent entitlement:</b> Prevent those who permit themselves to use identity-based reasoning from being entitled to rights and being allowed to avoid responsibility for consequences.	<b>Allow entitlement:</b> Allow those who permit themselves to use identity-based reasoning to be entitled to rights and to be protected from being blamed for consequences.
	<b>High openness:</b> Open to exploring the implications of any reasoning, even on topics deemed to be sensitive, and even with the reasoning that others might consider conspiratorial. Open to great intellectual diversity.	<b>Low openness:</b> Not open to exploring the implications of any reasoning on topics deemed to be sensitive, where labels, such as “conspiracy thinking”, are used to censor reasoning. Not open to intellectual diversity.

incorrect assumption that all problems fall into the same sector and therefore the same CI approach is always optimal. Properties defining the eight sectors assumed to be the most important in collective reasoning are depicted in Fig. 2. Many research articles on the subject of collective intelligence<sup>[10-17]</sup> were reviewed to assess anecdotally and informally whether these articles might be classified according to whether the researchers implicitly make assumptions that assign their CI approach to one or more of these sectors. This assessment was used to determine whether these properties meaningfully differentiate the possible CI scenarios that CI methods might be applied to. The scenarios predicted to drive most research in CI concern information correctness (the level of signal, the level of noise, and signal-to-noise ratio). The properties predicted to drive most research in CI concern whether the researchers reside on the right or left half of the collective social brain, which is predicted to determine what they deem to be correct. If these properties do account for the way CI research is defined in most cases, then most research papers should fall into the eight sectors depicted in Fig. 2 as the most important properties of collective reasoning in HCFM. Anecdotally, the results in the very few papers reviewed appeared to fall into these sectors. This assumption remains to be proven more formally with a much larger sample size.

### 3 Orchestrating Coherent Collective Reasoning

How would the orchestration of collective reasoning work in collective cognition? Any attempt to obtain thousands of people over the Internet to comment on any problem generally results in chaos. Opinions on sensitive issues can be deeply polarized. Even if we assume this polarization can be explained by the collective social brain hypothesis, no tools are available that use this hypothesis to resolve the divide and allow individuals to derive benefit from viewpoints originating from the other half of the collective social brain. Thus, in any unstructured forum that is open to any comments from people of different viewpoints, judging from the responses they evoke, many of the comments will appear too biased, too stupid, and too uninformed (ignorant of the facts) to be useful to people on the other side of any given polarizing divide. Many of the remaining comments might be too repetitive to be useful. On the other hand, popular platforms that provide more structured attempts to coordinate the crowdsourcing of opinions or information (such as Wikipedia or YouTube) are closed to many purposes. These platforms cannot be asked just any question and cannot be used to solve problems in certain sectors. The most common issue that prevents platforms from discovering solutions in different sectors is the same problem that confronts any centrally managed platform. Namely, even within the purposes for which the platform is

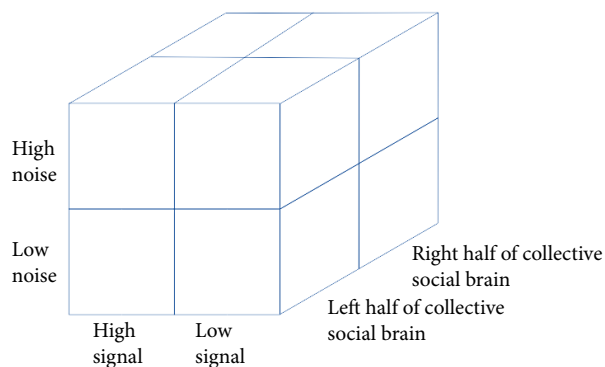


Fig. 2 Most important properties of collective reasoning in HCFM.

intended to be used, if the collective social brain hypothesis is correct, then using such platforms for any purpose or to reach any conclusion that goes against the bias of the group that runs it might be nearly impossible. If (as per the hypothesis) this bias is generally only visible in others whose bias differs from our own, then processes that self-select platform administrators with the same cognitive biases as the founders or current executives of the company owning the platform are likely to create an echo chamber of people who share the same views in critical areas. Worse still, if only biases that run counter to our own are visible to us, then the walls imprisoning groups in any such echo chamber are not only impenetrable but also invisible.

Assuming that a platform with intelligence (general problem-solving ability) at the group level could be created to allow group reasoning to be targeted at answering any question in any sector, what new or different problems would this platform solve? The answer begins with considering that intelligence solves different problems at the individual and group levels. At the individual level, in HCFM, intelligence (general problem-solving ability) is represented as the ability of the cognitive system to solve any problem, in general, that might exist within the cognitive domain, within the resolution of concepts and reasoning that the cognition can navigate. In other words, the property of intelligence is represented as solving the general problem of increasing fitness to achieve all of the cognitive system's functions to accomplish optimization of outcomes for some individual ("individual optimization"). At the group level, intelligence solves the general problem of optimizing outcomes for a group ("collective optimization"). Solving group (collective optimization) problems beyond some level of complexity (beyond some resolution of concepts and reasoning in conceptual space and/or spanning a larger region of conceptual space than can reliably be navigated) is predicted to require GCI. The reason is that in HCFM, each individual or intelligent agent with general problem-solving ability in the cognitive domain is considered capable of solving non-computable problems using Type I processes and computable problems using Type II processes. In software used by intelligent agents, Type I and Type II processes might be implemented using pattern recognition algorithms such as AI and procedural programs, respectively. General problem-solving ability also requires a metric for the fitness of any solution. Without a way to switch between Type I and Type II approaches depending on which is optimal, and without a means to switch between any problem sectors that fall underneath reasoning type, groups or system groups designed as problem-solving tools might restrict themselves to either type of approach, which means that solutions requiring the other approach remain undiscoverable.

In addition to solutions remaining undiscoverable if they require the opposite reasoning type to which the group has confined itself, complex group problems might require GCI because the group is too large. To understand this requirement, define " $N$  independent participant problems" as those problems involving interactions between  $N$  independent intelligent entities, and being intelligent is represented in HCFM as each entity having its own independent general problem-solving ability and metric of fitness for solutions. Type II logic fails when  $N$  is too large and  $N$  participant problems become intractably complex and not computable. However, in a group with  $N$  participants having the general problem-solving ability and a metric of fitness at the group level, those problems can be considered " $N$  participant group problems", thus, a virtual collective entity has been created that has Type I and Type II collective reasoning. Because Type I and Type II reasoning can solve uncomputable problems and

problems where computing is required, respectively, by having both types, some combination of Type I and Type II processes can always be used to discover some solutions, and that metric of fitness can always be used to discover which of those solutions is collectively optimal.

If the well-being of a system comprising a group of individual entities is defined as its fitness to execute all its functions, and if all functions of a collective system in a given domain of its behavior can be represented by paths in its functional state space corresponding to that domain, then if the fitness of the system to execute each path can be determined, that collective well-being can be calculated. Defining how to measure relative “fitness” in solving a problem, defining how that fitness can be aggregated over all group members to define the “collective fitness to execute all functions” (collective well-being), and defining how general problem-solving ability can be modeled as navigating the collective conceptual space while maintaining a pattern of stability in this collective fitness space, are problems for which simple solutions have already been approximated in software platform design. The concepts of such platforms have been defined for achieving collective outcomes in agriculture, education, and other areas<sup>[18]</sup>.

According to the reasoning in this paper, GCI can always be used to discover solutions in the collective conceptual space and to optimize those solutions, and therefore GCI can always be used to solve collective optimization problems beyond the level of complexity manageable by an individual but within the level of complexity manageable by GCI. Thus, a collective reasoning process might involve  $M$  reasoning steps in which each of  $N$  people executes one or more of those steps. It might not be possible to compute all of the possible combinations of individual reasoning to determine which combination of those processes is collectively optimal, but it is reliably achievable to discover an arbitrarily large number of collective reasoning processes and determine which of those processes are collectively optimal. When applied to problems such as the sustainable development goals (SDGs), applying this GCI-based collective reasoning to allow the discovery of better and more impactful solutions is predicted to radically increase the impact on the SDGs to the point that the SDGs become sustainably self-funding and to the point that impact might not just be limited to what can be accomplished with the available funding but also might reliably be increased to the degree that it is required globally regardless of funding<sup>[19]</sup>. Applying GCI toward increasing societal impact in the general case is the subject of ongoing research.

In GCI, a single human can devise this collective reasoning process that targets a given outcome at an abstract level. Other individuals can devise parts of this reasoning process at successively more detailed levels (abstract reasoning is elaborated in detail, as shown in Fig. 3). The reasoning constructed this way might be far more detailed and explore knowledge domains well

outside what a single human is capable of.

By using an algorithm that organizes a group to select the collective reasoning components that are the fittest to achieve the targeted outcomes, vastly more complex logic might be constructed, where this complexity is limited only by the cognitive capacity of GCI. Just as we might restrict our attention to the set of real numbers between one and two, while at the same time, this set does not seem restricted because it contains an infinite set of numbers, existing platforms such as Wikipedia can be used to organize groups to achieve an infinite set of collective reasoning outcomes but are also restricted. If the functionality in these platforms can be represented by a set of paths through the collective conceptual space, where each path segment, in turn, represents some functional component of the platform, then these paths will exclude some regions of the collective conceptual space. However, GCI can potentially follow any path whatsoever through the collective conceptual space. If the collective conceptual space can model any possible reasoning and any possible concept representing any possible outcome, then GCI can potentially organize groups to achieve any collecting reasoning outcome.

#### 4 Using Rather Than Eliminating Bias

As mentioned, the “collective social brain hypothesis” provides a simple functional model of bias that is potentially universal in describing the underlying source of most, if not all, polarizing biases in groups. According to this hypothesis, the underlying cause of bias and hence the polarization of opinions in any group are that reasoning in human groups results from the interplay between two halves of a “collective social brain”, and each individual is predisposed to belonging to one half or the other. One-half compels individuals to prioritize rights using Type I (intuitive reasoning) for issues in which the individual identifies as part of a vulnerable group. The other half compels individuals to prioritize responsibility using Type II (rational methodical reasoning) for issues in which the individual assumes responsibility for the protection of themselves and/or others. Although the belief that intelligent individuals are convinced by the most reasonable arguments might seem logical, according to this hypothesis, the reality is that each human has a strong predisposition to find either Type I or Type II arguments reasonable for issues that concern social protection. Furthermore, if people are not consciously aware of these predispositions (which anecdotally is over 99% of the population today), the predispositions themselves are hypothesized to arise from genetic factors and low-level behavioral conditioning that are completely outside the domain of reasoning. However, while individuals of each predisposition appear to the other group to have unuseful biases, both of these predispositions are necessary for solving different problems. As mentioned, Type I reasoning solves

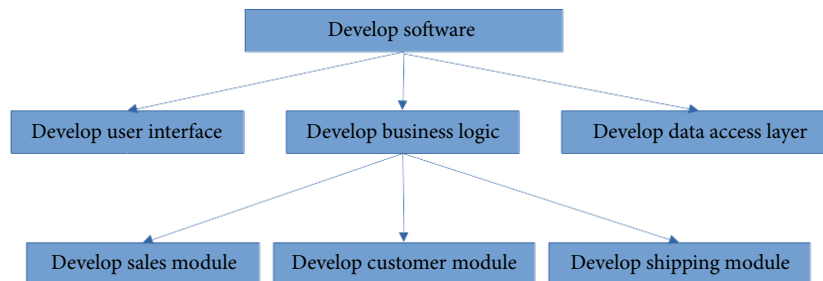


Fig. 3 Abstract reasoning elaborated in detail.

uncomputable problems by detecting patterns of solutions observed in the past. One of those solution patterns is reasoning according to what everyone else thinks (“group think”). Type I reasoning is great at forming consensus, but it completely fails in cases where solutions are so disruptive that they have not been observed before. Anecdotally, Type I reasoning is also not reliably capable of opposing the group consensus on issues in which the group identifies itself as vulnerable. However, Type I reasoning is necessary when Type II reasoning cannot be used to “compute” the answer. This case might be pertinent where no such reasoning exists, where reasoning exists but does not adequately account for all relevant factors, where the facts required to execute that reasoning are not available, or where the reasoning is outside the capacity of the individual to execute. The same applies to Type I collective reasoning, which must be used by groups in the absence of Type II collective reasoning. The general problem-solving ability at the individual level requires the ability to switch between these reasoning types, an ability that all individuals have at the individual level regardless of their predisposition toward one reasoning type or the other. This switching occurs unconsciously but, like breathing, can also be controlled consciously. General problem-solving ability at the group level also requires groups to be able to switch between these reasoning types. The “collective social brain hypothesis” posits that small groups with tight social bonds have processes outside the domain of reasoning that give them an innate ability to switch between these reasoning types in small group sizes but that GCI is required to have this ability to switch in large group sizes.

This collective social brain hypothesis is important because, without an understanding of how to switch between these two reasoning types, any group decision-making (e.g., a survey) is inherently unable to remove bias in assessing a consensus. One example is the case of COVID-19, in which individuals who feel vulnerable might be biased toward prioritizing their right to be protected by their governments, and they might be strongly predisposed toward arguments that use Type I reasoning in adhering to the views espoused by those appointed as “experts” by individuals with the same cognitive bias they have. Individuals who feel responsible for their own protection as well as the protection of others, on the other hand, might not believe the government has as much ability to ensure all aspects of their well-being (physical, emotional, financial, etc.) as they do themselves. The natural result is that the first group will conclude that stronger lock-down measures are “logical”, while the second group will conclude that more freedom is “logical”. Any surveys or scientific research conducted by the Type I group will generally ignore the negative impacts on well-being that occur because of the measures they recommend (such as financial stability and mental health). Any surveys or scientific research conducted by the Type II group will generally ignore the fact that the people they are trying to convince (the Type I group) simply do not receive information that is not framed in terms of the rights of vulnerable groups to protection. However, GCI creates the capacity to measure all impacts of any intervention in the common universal terms of impact on the collective well-being, which HCFM measures as the collective fitness of individuals to execute all of their functions so that any reasoning that maximizes that well-being might be discovered regardless of which bias it came from.

This collective social brain hypothesis is then a critically important part of any GCI-based survey or other decision-making processes, as is the vastly greater intelligence possible through GCI. A GCI-based survey or other information-gathering tools

must be able to switch between reasoning types to have the capacity to discover optimal reasoning in terms of impact on collective well-being, regardless of polarization and an initial lack of consensus. A GCI-based survey or information-gathering tool must also be able to search through a vastly larger region of conceptual space for an optimal way to redefine the problem being addressed by the question, and it must be able to search through a vastly larger region of conceptual space to discover more optimal answers. These requirements mean an iterative process based on two-way communication that, over time, converges on the correct question and the correct answer.

## 5 Shortcomings of This Research and Future Directions

One shortcoming of this research is that it has not outlined specific timelines or conditions predicting when and why collective superintelligence is created. In the opinion of this author, the nucleus of a GCI platform capable of self-evolving into a collective superintelligence essentially already exists and can potentially be launched in days or weeks. The challenge is not a technological one but a social one, namely, the challenge of motivating sufficient participation. Because initially, after the concepts of HCFM and GCI have been broadly communicated, most GCI functionality will exist in the crowd members’ minds rather than in any platform. The crowd must be motivated to cause this collective concept to manifest in actual projects and technology. As for why it might be created, a collective superintelligence can potentially be incorporated into every product, service, or process along the entire business life cycle of any product or service, from research and development to recycling. Simply put, rather than deploying a single product, service, or project to achieve a modest and unsustainable impact on some outcome, GCI helps solve the problem of discovering massive intervention networks that together might be deployed to radically multiply that impact and make it self-sustaining. For example, healthcare processes could be optimized by automating the processes involved in the insurance industry and organizing groups of doctors and other healthcare providers to sell health insurance and to pay out that insurance with their own healthcare services (which might be called a form of “provider-based insurance”). Assuming that the health insurance industry and health claim handling result in 50% of healthcare costs in the United States alone, where over 3 trillion US dollar per year is spent on healthcare, GCI might be able to reduce domestic healthcare costs by enough to either radically improve healthcare in the US or pay for universal healthcare throughout much or even perhaps all of the developing world. With GCI, the task of finding these synergies becomes a well-defined problem.

By incorporating GCI in this way, groups of companies that cooperate to achieve mutual good might gain a potentially unbeatable competitive advantage over single monolithic companies that compete to maximize their individual outcomes. When incorporated into design processes, GCI is predicted to lead to products well beyond the level of complexity at which, as science fiction writer Arthur C. Clarke suggested, “any sufficiently advanced technology” becomes “indistinguishable from magic”<sup>[20]</sup>. When incorporated into basic science research, GCI is predicted to make research unrecognizably different. This result is easy to see in fields such as sociology, in which one might use GCI to solve the problem of poverty, and in response, the GCI might organize the group to explore many more solutions arising from the very many ways in which the components of every known

solution might be combined. No one would be able to assess whether any of these solutions is correct by following the minutia of any collective reasoning process. No one would be able to accurately assess correctness if they measure poverty according to any given set of external criteria, such as earning a certain amount of money, which might not be relevant or applicable in all cases. Instead, they will most accurately assess correctness by learning to look inward to observe whether well-being (the level of fitness to execute all functions) has been optimally achieved. This reality might more resemble existentialist traditions, such as meditation or yoga, than the current manifestation of social science. In the same way, when GCI can explore all possible reasoning in physics in the hope of discovering the theory that is the fittest at explaining an observation, or when GCI can explore all possible medical interventions to suggest the correct brain surgery, then individuals need not have any knowledge of medicine or physics to make discoveries that modern science might consider miraculous. When the volume of facts and reasoning is barely large enough to be outside the grasp of any individual human, the requirement for a different approach might be obfuscated. When the volume of facts and reasoning is much larger than any individual can navigate, it becomes clear that the problem is not learning to recognize facts but learning to represent problems in a universal way using human-centric functional state spaces and learning to look inward to recognize truth as a pattern in each functional state space describing the particular problem. This reality again might make physics and/or medicine more resemble existentialist traditions.

In the author's opinion, the most important future direction for this research is cracking the problem of building a massive mind share for the concepts of HCFM and GCI and their potential impact. Each set of GCI functionality that is deployed is intended to provide a new narrowly defined problem domain with narrow problem-solving ability at the group level so that over time, these sets of GCI functionality might accumulate to provide general problem-solving ability at the group level. GCI platforms are intended to allow massive networks of cooperation to self-assemble to execute whatever collective reasoning processes the platforms are capable of at their current level of deployment. This self-assembly requires building sufficient mind share among potential participants in those massive cooperation networks. With these cooperation networks, GCI is predicted to facilitate an exponential increase in general problem-solving ability, which means an exponential increase in the ability to solve any problem in general. Because this exponential increase in ability to affect problems is not predicted to be achievable by any other known means, GCI is potentially the most important innovation in the world today regarding a wide variety of problems that are "collective optimization" challenges in that they involve optimizing some collective outcome. The larger importance of communicating these HCFM and GCI approaches to a critical mass of people is that "collective optimization problems" describe perhaps all of the existential challenges presently facing civilization. The challenge in conducting research and writing academic articles on this topic is that creating the potential for an exponential increase in general problem-solving ability that applies to every problem in every field makes this approach heavily multidisciplinary (involving a great many fields). Thus, anecdotally, this potential to exponentially increase problem-solving ability often cannot be demonstrated by any one person in sufficient detail to reliably convince experts in any field because no person has sufficient expertise and credibility in every field involved. Therefore, this task must be broken up, and

collaborations must be formed to complete it. However, collaborations require either money or motivating interest, either of which requires creating mind share. This circumstance is a catch-22. No one knows about GCI, and sources of funding for unknown work that is too different are not readily available, so forming collaborations is difficult. Thus, perhaps the biggest potential source of impact on every collective problem (GCI as opposed to CI) remains unknown and unexplored.

## 6 Conclusion

In summary, even if a survey or other information-gathering process begins with a question that poorly captures the relevant issues and is conceived solely within the echo chamber of a given bias, a GCI-based process might reliably converge on a much better question or set of questions. Furthermore, rather than forcing individuals of one bias to reason in terms of the opposite bias, which the collective social brain hypothesis suggests they are not reliably capable of, GCI uses a model for collective well-being to discover answers across both biases so that discovery of optimal solutions might be reliably achievable. Organizing the cacophony of different information-gathering processes that might be performed to address a particular question, in addition to organizing the even greater cacophony of answers, requires a single model in which even the most wildly different individual reasoning processes become coherent parts of a single collective reasoning process. To accomplish this task, GCI models the distributed adaptive processes through which individual neural cells, which are very unintelligent, potentially become vastly more intelligent human brains capable of coherent thought. This approach involves mimicking the same abstract functional model of bias hypothesized to be presented in an individual human brain and reusing it to allow bias to be used productively within a single coherent group-reasoning framework, and it involves mimicking the same abstract functional model of well-being hypothesized to be presented in individual reasoning and reusing it to define a model for collective well-being. With this approach, for the first time in the history of human civilization, a group of individuals might soon be able to organize themselves to discover their collective super-genius, as they form a vastly more powerful collective cognition capable of coherent collective reasoning.

## Dates

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## References

- [1] W. Zhang, *State-Space Search: Algorithms, Complexity, Extensions, and Applications*. New York, NY, USA: Springer, 1999.
- [2] M. E. J. Newman, *Networks: An Introduction*. Oxford, UK: Oxford University Press, 2010.
- [3] P. Gardenfors, Conceptual spaces as a framework for knowledge representation, *Mind and Matter*, vol. 2, no. 2, pp. 9–27, 2004.
- [4] A. W. Woolley, C. F. Chabris, A. Pentland, N. Hashmi, and T. W. Malone, Evidence for a collective intelligence factor in the performance of human groups, *Science*, vol. 330, no. 6004, pp. 686–688, 2010.
- [5] T. W. Malone and M. Klein, Harnessing collective intelligence to address global climate change, *Innovations: Technology, Governance, Globalization*, vol. 2, no. 3, pp. 15–26, 2007.
- [6] A. E. Williams, Human-centric functional modeling and the unification of systems thinking approaches: A short communication, *Journal of Systems Thinking*, doi: 10.54120/jost.v1i1.1369.

- [7] A. E. Williams, Defining a continuum from individual, to swarm, to collective intelligence, and to general collective intelligence, *International Journal of Collaborative Intelligence*, vol. 2, no. 3, pp. 205–209, 2021.
- [8] A. E. Williams, A generalized model for distributed, autonomic and self-organizing computing, in *Proc. 2022 International Conference on Frontiers of Artificial Intelligence and Machine Learning (FAIML)*, Hangzhou, China, 2022, pp. 27–33.
- [9] A. E. Williams, Innate collective intelligence and the collective social brain hypothesis, <https://doi.org/10.31234/osf.io/upgfw>, 2022.
- [10] G. -J. Qi, C. C. Aggarwal, J. Han, and T. Huang, Mining collective intelligence in diverse groups, in *Proc. 22<sup>nd</sup> International Conference on World Wide Web*, Rio de Janeiro, Brazil, 2013, pp. 1041–1052.
- [11] R. P. Mann and D. Helbing, Optimal incentives for collective intelligence, *Proceedings of the National Academy of Sciences*, vol. 114, no. 20, pp. 5077–5082, 2017.
- [12] C. Yu, Y. Chai, and Y. Liu, Literature review on collective intelligence: A crowd science perspective, *International Journal of Crowd Science*, vol. 2, no. 1, pp. 64–73, 2018.
- [13] A. W. Woolley, I. Aggarwal, and T. W. Malone, Collective intelligence and group performance, *Current Directions in Psychological Science*, vol. 24, no. 6, pp. 420–424, 2015.
- [14] T. Buecheler, J. H. Sieg, R. M. Füchslin, and R. Pfeifer, Crowdsourcing, open innovation and collective intelligence in the scientific method: A research agenda and operational framework, in *Proc. 12<sup>th</sup> International Conference on the Synthesis and Simulation of Living Systems*, Odense, Denmark, 2010, pp. 679–686.
- [15] D. C. Brabham, Crowdsourcing as a model for problem solving: Leveraging the collective intelligence of online communities for public good, PhD dissertation, the Department of Communication, University of Utah, Salt Lake City, UT, USA, 2010.
- [16] D. C. Brabham, *Crowdsourcing*. Cambridge, MA, USA: MIT Press, 2013.
- [17] T. Buecheler, R. Lonigro, R. M. Füchslin, and R. Pfeifer, Modeling and simulating crowdsourcing as a complex biological system: Human crowds manifesting collective intelligence on the Internet, in *Proc. 11<sup>th</sup> European Conference on the Synthesis and Simulation of Living Systems (ECAL 2011)*, Paris, France, 2011, pp. 109–116.
- [18] A. E. Williams, Are wicked problems a lack of general collective intelligence, *AI & Soc.*, vol. 38, pp. 343–348, 2021.
- [19] A. E. Williams, Approximating an artificial general intelligence or a general collective intelligence, *International Journal of Collaborative Intelligence*, vol. 2, no. 3, pp. 210–223, 2022.
- [20] A. C. Clarke, *Profiles of the Future: An Inquiry into the Limits of the Possible*. London, UK: Harper & Row, 1973.