General Collective Intelligence and the Transition to Collective Super-Intelligence

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ABSTRACT

For at least a decade a general collective intelligence factor measuring the general problem-solving ability (intelligence) of groups has been hypothesized by many to exist. General Collective Intelligence or GCI has recently been defined as a platform that combines individuals into a single collective cognition that may have vastly greater intelligence than any individual, and a vastly greater general collective intelligence factor than is innate to any group. A novel Human-Centric Functional Modeling approach has been used define both a model for this collective cognition, as well as a method for assessing the intelligence of a system of individual or collective cognition, in order to quantify this potential increase in intelligence as exponential. From the functional modeling perspective, the transition from animal intelligence to a human intelligence, is a well-defined phase change. The transition from human intelligence to GCI, the transition from GCI to second order GCI, and so forth to Nth order GCI, are also potential phase changes. The functional modeling approach clarifies the fundamentally different nature of the general problem-solving ability provided by GCI as opposed to the narrow problem solving ability of tools such as computation (including artificial intelligence) that can be applied to any general problem. This comparison suggests that entire categories of problems cannot reliably be solved without this phase change to GCI. However, this same functional modeling approach suggests that GCI is too big and complex, and requires too great a degree of flexibility, to be reliably implemented in a top-down way without GCI, so instead must be evolved in a self-assembling process that relies on GCI itself.

Keywords: General Collective Intelligence, collective intelligence, Artificial General Intelligence, super intelligence, phase change, Human-Centric Functional Modeling, Functional Modeling Framework

1 INTRODUCTION

Interest in swarm intelligence (Luitel and Venayagamoorthy, 2010), (Majhi et al., 2008), (Panda et al., 2007), decision-systems (McHugh et al., 2016), (Gilliland and Landis, 1992), (Kraiger and Wenzel, 1997), (Iandoli et al., 2009), and all other fields related to collective intelligence (Georgi and Jung, 2012), (Grasso and Convertino, 2012), (Malone and Bernstein, 2015), has been steadily growing. And the areas in which collective intelligence has been applied, such as in health care (Wolf et al., 2015), education (Lee, 2020), business models (de Castro Neto and Santo, 2012), resource management (Diggle, 2013), crowdsourcing (Buecheler et al., 2010), political theory (Peters and Heraud, 2015), social media (Schoder et al., 2013), and even sustainable development (Elia and Margherita, 2018), are continually increasing. More generalized approaches to designing collective intelligence systems continue to emerge as well (Musil et al., 2015), (Kornrumpf and Baumöl, 2014), as have models for evaluating their effectiveness (Suran et al., 2019). The concept of a general collective intelligence or c factor as an emergent property of groups has been explored in a variety of contexts (Woolley et al., 2010). And the concept of collective super-intelligence having the potential to vastly increase this property has also been explored (Malone, 2018).

Although the concept of a "general collective intelligence factor" (Woolley et al., 2010) describing the general problem-solving ability of groups has been in use since at for least a decade, a model of General Collective Intelligence or GCI with a well-defined mechanism creating the potential capacity to greatly increase this factor has only been elaborated over the past year (**?**), (Williams, 2020d), (Williams, 2020i). Because this model is so new, much of the work exploring the applications of this model belongs to this author as the creator of that model. The goal of this paper is to disseminate knowledge of GCI in order to ensure that a sufficient number of researchers are aware of GCI, and have the baseline knowledge required to participate in any upcoming large-scale research projects based on GCI, so that a self-assembling process to evolve a GCI can potentially be deployed.

2 USING HUMAN-CENTRIC FUNCTIONAL MODELING TO REPRESENT COGNITION

Functional modeling has long been used to facilitate the design of large complex systems by decomposing such systems into functional components with well-defined interfaces that remove the need for specialists in one area to have to understand all other areas. Human Centric Functional Modeling (HCFM) (Williams, 2020k) represents all the functionality of a system that can be observed within human awareness as forming a discrete set of functions through which the system can transform itself. Since all behaviors through which the system can transform itself are a composite of these functions, the possible states achievable form a "functional state space". As the system's state changes, the system moves through this functional state space.

HCFM has been used to define a functional approach to modeling the entire human system. While the human system is one physical system, in this Functional Modeling Framework (FMF) (Williams, 2020e) that physical system is represented as consisting of multiple functional systems. One functional system is human cognition, which is representing as moving through a space of concepts or a "conceptual space".

3 HUMAN INTELLIGENCE AND GENERAL COLLECTIVE INTELLIGENCE

From the perspective of this model of cognition, human cognition navigates a conceptual space. This navigation is governed by a cognitive awareness function that optimizes fitness to execute all reasoning functions. While reasoning, and the path through conceptual space that represents it might be non-deterministic and chaotic, ability to achieve all cognitive functions must be stable in that it stays within a bounded region of fitness. Since this stability takes into account a number of dimensions of cognitive well-being, this stability is also defined as existing within it's own state space, the "cognitive well-being space" (Williams, 2019a), (Williams, 2019b). Similarly, the model of collective cognition navigates a collective conceptual space, and that navigation is governed by a collective optimization function so that individual reasoning is assembled into a coherent collective reasoning process that optimizes fitness to achieve collective outcomes, where that collective reasoning might include information and reasoning from any individual in the group.

Since reasoning in this model consists of a sequence of paths between concepts in conceptual space, then assuming intelligence can be defined as the volume of conceptual space that can be navigated per unit time, the number of potential paths through conceptual space is related to intelligence. Generalization from the functional modeling perspective increases the region in conceptual space representing a concept. As the ability of a cognitive system to generalize increases, at some point the initial concept and the final concept can be contained within a single generalization. At this point reasoning can become isomorphic, and the number of potential reasoning paths increases exponentially (Williams, 2020f). The transition from animal intelligence to a human intelligence capable of a sufficient level of abstraction to develop science and other concepts, and capable of exchanging and accumulating the value of those abstractions to achieve exponentially greater impact on the external world therefore defines a phase change in intelligence.

From the perspective of this model of collective cognition, as the ability of the collective cognition to generalize increases to the point at which collective reasoning can become isomorphic, the number of potential reasoning paths again increases exponentially (Williams, 2020f). Capacity to generalize depends on the number of concepts and reasoning processes that generalization can be applied to, which in a GCI depends in part on the number of individuals that can be engaged in the collective reasoning. In order to increase capacity for generalization so that this potentially exponential increase in the general collective intelligence factor is reliably achievable, GCI not only defines a collective reasoning optimization function to create a single coherent collective reasoning process, but also introduces functionality to remove limitations on the number of individuals and the amount of resources that can be engaged in that collective reasoning. Depending on the number of individuals involved, GCI then might represent a kind of "super-intelligence".

4 QUANTUM AND OTHER SUPERCOMPUTERS AS OPPOSED TO SUPER-INTELLIGENCE

From this functional perspective, the larger magnitude of narrow problem-solving ability that can be achieved by humans with the assistance of systems of computation such as quantum or classical supercomputers can be represented in conceptual space and compared to the magnitude of general problem-solving ability that might be achieved through Artificial General Intelligence (AGI) or GCI. Any specific set of problems that a programmer might solve through software must be conceived by that programmer first. If the set of solutions achievable with a particular computing program represents a nearby set of paths extending the programmer's conceptual space, then the volume in conceptual space corresponding to such narrow problem-solving ability might resemble a narrow rod. If a quantum computing version of the program is a billion times faster then the extension of the rod by the quantum computer might be a billion times longer, and the narrow problem-solving ability corresponding to the narrow volume in conceptual space that can be navigated might be correspondingly greater.

However, an AGI or GCI with exponentially greater general problem-solving ability using that same quantum computer as a tool creates an exponential increase in ability to replicate that rod of narrow problem-solving ability in all directions, including to the problem of designing a better quantum computer as well. The programmer might apply quantum computing to any general problem, but the process of applying quantum computing must fit within their individual cognition so replicating that rod in a new direction faces the limitations of human cognition as a bottleneck. In the case of an AGI or GCI, the process of replicating that rod of narrow problem-solving ability representing quantum computing (i.e. the process of applying quantum computing to all other problems) can be conducted by an exponentially larger artificial or collective cognition.

5 THE PROBLEM OF TRANSITIONING TO GENERAL COLLECTIVE INTELLIGENCE

In order to incentivize participation in projects to implement GCI functionality it is essential to build mind share regarding the importance of GCI. One of the challenges with communicating a compelling argument justifying the reader to conclude or to believe that GCI has the potential to significantly increase general problem-solving ability over that of any individual, is the problem of complexity. GCI is described by a simple functional model, rather than requiring any detailed technical language that takes a great deal of time to learn, and therefore might not appear be as complex as other subjects such as abstract mathematics or theoretical physics. But according to the underlying model of cognition, the problem of proving that GCI has the potential to significantly increase general problem-solving ability might be broad enough and complex enough to exceed the limits of individual human cognitive capacity. Even more so than such complex topics.

As if figure 1, the model represents the state of cognitive systems as moving through a "conceptual space", and represents the level of intelligence of the cognitive system (its general problem-solving ability) as being the volume of conceptual space it can navigate per unit time. As shown in figure 2, if the information that must be communicated in order to convey a concept covers too great a range of conceptual space then its breadth exceeds the capacity of any individual mind.

Or if requires too many steps in conceptual space at too high a resolution in conceptual space, then its complexity exceeds the capacity of any individual mind. In either case, if a proof or any other concept is too broad or too complex to be within the capacity of any individual mind, then it cannot reliably be communicated. Furthermore, if the concepts involved are too broad or too complex then problems cannot be defined. And as shown in figure 3, reasoning paths representing solutions cannot then be discovered.

To understand why, consider that human cognition utilizes two types of reasoning processes. These are type 1 (fast or intuitive) reasoning, and type 2 (slow or rational methodical reasoning) (Kahneman, 2011). If a problem is defined as a gap between one point in conceptual space representing one concept, and a point in conceptual space representing another concept, a solution is then a path between those two points.

Objective proof requires the use of rational methodical reasoning to define a step-wise path through conceptual space in which each element of reasoning can be objectively assessed to be correct, so the reasoning is therefore repeatable and communicable. Intuitive reasoning can potentially connect any two points in conceptual space directly, and therefore can subjectively "solve" any conceptual problem. But intuition must be trained by the individual's past experience and is therefore subjective. Subjective reasoning cannot be objectively assessed to be correct. One might mistake that intuitive reasoning for objective reasoning if one shares the same intuition, and in that case one might choose to believe that reasoning constitutes proof. But it is not repeatable and communicable proof to others having different intuitions or to other who don't use intuition for that specific problem at all.

Demonstrating the capacity for GCI to greatly increase the general problem-solving ability of a group then requires either objective proof, or requires demonstrating a sufficient number of mechanisms by which impact on a great many problems might be significantly increased across a sufficiently great many topics to train the collective intuition, so that a great capacity to increase in general problem-solving ability can be subjectively agreed upon by the group. If providing objective proof of the potential for increased general problem-solving ability using rational methodical reasoning is above the cognitive capacity of any individual human in the communication process, then that proof cannot be communicated and/or understood. If that objective proof is too broad or too complex for any human cognition then the problem cannot even be sufficiently well-defined to be solvable by either the author or the recipient of such a communication. In this model of cognition, the limit to the complexity that can be navigated by an individual can be represented graphically.

If the audience is using intuitive reasoning, then the communicator must provide enough examples to satisfy the audience's subjective criteria for the reader to believe their argument. To the audience, or in the case of written material to the reader or to an individual trusted by the reader to be expert and whose opinion the reader will accept, the author must demonstrate the ability to increase impact on problem-solving ability in each specific topic, and must do so for whatever number of topics required for the reader's intuition to be trained so they become convinced of the capacity of GCI to greatly increase a group's general problem-solving ability. While it might be reliably achievable to demonstrate a single mechanism by which impact on a specific problem in a specific topic might be greatly increased using GCI, when the number of specific problems, and number of specific areas required for the reader to believe GCI has the potential to significantly increase general problem-solving ability is higher than the number of areas that can be addressed by any individual or team without GCI, then this belief cannot be reliably conveyed.

In other words, in order to reliably communicate that GCI creates the potential to significantly increase general problem-solving ability, GCI might be necessary to create the capacity to reliably exceed the limits preventing this understanding from being reliably communicated. This is just one of the "chicken and egg" problems involved in transitioning to GCI. Other such problems surround creating networks of cooperation able to create sufficient value through aligning cooperation to sustain such a large implementation effort (Williams, 2020g). Or understanding how products and services might leverage GCI so they optimize outcomes for every individual user (Williams, 2020h), as well as understanding what platform might be required for them to do so (Williams, 2020j), or understanding how GCI applies to any research or development or other process, including to the process of developing GCI itself (Williams, 2020g).

To solve this chicken and egg problem an evolutionary process has been proposed. In this process, the small subset of GCI functionality that can reliably be created by a single individual or team is used to demonstrate the ability to increase impact on a specific problem and to engage a larger community to leverage this GCI functionality in order to build more GCI functionality to demonstrate the ability to increase impact on a more general problem, on a larger number of specific problems, or some combination, in an iterative way.

There might be a number of additional reasons that deploying GCI might not be reliably achievable through a top-down process, but instead might likely be more akin to a collective organism that must essentially be grown through such an iterative and evolutionary self-assembling process. For example, assuming that deploying a GCI requires a great deal of resources, the potential sources of such resources, namely centralized entities such as governments or large donors with agendas set by often inflexible, ideology-driven, and bureaucratic policies, might not have the capacity to ”do what works”, that is, to predict collective outcomes, to measure collective outcomes actually achieved, and to shift collective action radically according to whatever maximizes those outcomes. The model of GCI suggests the functionality of GCI is required infrastructure to achieve this collective optimization. In addition, the fact that a genome and gametes, as well as algorithms implementing all other basic life processes (homeostasis, reproduction, etc.) (Williams, 2020c) can potentially be defined for a GCI based civilization, supports this concept of a collective organism. Current work continues to explore how decentralized mechanisms such as the cryptocurrency of a cognitive blockchain platform (Williams and Visconti, 2020) might also be deployed in an iterative way, beginning with the small initial subset of GCI and leverage the growing functionality in each GCI iteration to make deployment of GCI sustainably self-funding.

6 APPLICATIONS OF GENERAL COLLECTIVE INTELLIGENCE

From this functional perspective, any problem of understanding the behavior of that system can be represented as the problem of how to navigate from one point in functional state space to another. Any solution might involve not only basic functions of the system, but functions defined by interactions with those functions. That is, it might involve interactions of second order or higher. When the order of these interactions is sufficiently high that those interactions are no longer understandable within any individual human cognition, those interactions have been described as being of “higher order” complexity.

Within the conceptual space of a single individual, a single representation of a problem, or a single representation of a solution might suffice. The individual’s cognition might generalize that single representation of a problem so that multiple solutions that each solve that problem in different ways can be reused where they apply. Or the individual’s cognition might generalize different solutions so that they can be reused to solve a single problem. However, the increased ability of a GCI to generalize is based on the capacity of a GCI to incorporate many individuals into the collective reasoning process. This implies the ability to abstract any solution discovered by any individual into a more general one that might be reused by any other individual to solve any other problem where it applies, as well as implying the ability to abstract any problem defined by any individual to a more general one so that any other individual might discover solutions.

In other words, where one individual cognition might understand an abstraction of an abstraction internally, they can only reliably communicate information to another individual cognition, not understanding. In order to reliably communicate understanding of an abstraction of an abstraction to another individual, and in order to collectively reason in terms of such higher abstractions, a more powerful collective cognition and its semantic modeling are required. As mentioned GCI is the only model of collective cognition meeting these requirements. Without GCI the level of complexity that can be navigated by any individual or group is limited to those problems not requiring the ability to abstract any concepts defined by any individual so they can be applied to concepts abstracted by any other individual in this way. Individuals or groups of individuals without GCI cannot solve problems of higher-order complexity than individual human cognition can reliably navigate. Reasoning involving abstractions of abstractions might be of such higher order complexity. Examination of a few examples of reasoning requiring abstractions of abstractions suggests that concluding such problems are higher order (and therefore not reliably solvable without GCI) might be correct. For example, identifying all sustainability processes, and defining all design and manufacturing processes for all products and services, then abstracting those processes, and reusing the abstracted sustainability processes in the abstracted design and manufacturing processes to achieve pervasive sustainablity in design and manufacturing of all products or services has not yet proved to be achievable. In another example, defining abstractions of all scientific concepts in one scientific discipline, and reusing those concepts in abstractions of all other disciplines to achieve convergence across all disciplines science, has also not proved to be achievable.

In addition to scaling capacity to navigate complexity, GCI also scales the capacity for cooperation, as well as scaling the capacity to sustain processes. Where the value of cooperation is positive, outcomes can potentially be scaled by scaling cooperation. Where cooperation processes can be aligned, outcomes can potentially be increased through this alignment to the point that cooperation is self-sustaining. Scaling cooperation and scaling alignment of cooperation processes to the point that cooperation reliably becomes self-sustaining might require GCI. With GCI, problems are not limited to those requiring a greater ability to harness information or reasoning collectively, or to those requiring a greater ability to sustain collective reasoning, than any individual or group without GCI might have. Having removed these limits it might then be possible to direct far greater collective resources towards solving any collective problem in general. Examination of some examples of reasoning requiring a great ability to harness information or reasoning collectively, or requiring a great ability to sustain collective reasoning, suggest the conclusion that such an ability might be outside the capacity any individual or group without GCI might be correct. For example, a proposed Collective Intelligence based Program to Accelerate Achievement of the Sustainable Development Goals (CIPAA-SDGs) aims to make development sustainably self-funding at the scale required to be globally transformative. However, as of the time of this writing, despite the massive increase in impact on sustainable development that conceptual case studies suggest to be achievable through such an approach (up to 750X increase in impact per program dollar (Williams, 2020a)), and despite that impact potentially being self-sustaining as opposed to conventional programs whose impacts often stop when the program ends, the failure of any organization or group of organizations to launch this or a similar program, and the failure of any organization to even assess the possibility of such a program, suggests a lack of ability to harness information or reasoning collectively, and lack of the ability to sustain reasoning collectively until all available proposals and the reasoning behind them can be assessed.

One property that a General Collective Intelligence or any other system with general problem-solving ability must have is the capacity to address both computable and uncomputable problems. Computable problems are those that can be solved by deterministic algorithms. Any well-defined methodical (type 2) reasoning process can be automated, that is, can be represented by such an algorithm in a software program. Computable problems can be addressed by conventional computing methods as well as by cognitive computing. From the Human-Centric Functional Modeling point of view, intelligence involves a cognitive awareness process that provides the potential ability to navigate all possible reasoning processes. Where cognitive computing differs from conventional computing is that this cognitive awareness process also must provide the ability to solve uncomputable problems through awareness of what the solutions are or have been observed to be. In the human mind, detecting solutions by observing current or past patterns is type 1 (fast) or intuitive reasoning, whereas computing solutions using methodical processes is type 2 (slow) or rational methodical reasoning. The cognitive awareness process of this model enables both types of reasoning processes to potentially be combined into a library that it can use to increase it's general problem-solving ability (Williams, 2020b).

General problem-solving ability is then needed for any problems in which some degree of unpredictability results in solutions being computable only part of the time. General problem-solving ability might also be the most sustainable way to solve problems given finite resources. Even if the solution to a problem is computable, a given computing system might not have the resources to execute any specific computational algorithm. In that case, the solution is effectively uncomputable. However, if the system has general problem-solving ability, it can simply choose another algorithm that can compute some answer, perhaps with less precision, but doing so within the computational resources available.

7 CONCLUSIONS

Although the concept of a "general collective intelligence factor" describing the general problem-solving ability of groups has been in use since at for least a decade, a model of General Collective Intelligence or GCI with a well-defined mechanism creating the potential to exponentially increase this factor has only recently been elaborated over the past year. Because this model has been defined from first principles, and because it is so new, much of the work exploring the applications of this model belong to a single author, the creator of that model. Solving the challenge of building mind share for a model that is largely unconnected to the existing literature might itself require GCI. However, in order to escape this "chicken and egg problem" an evolutionary methodology might be used to self-organize research projects into self-supporting networks able to iteratively implement such a concept so that transitioning to this collective super-intelligence is reliably achievable.

CONFLICT OF INTEREST STATEMENT

The authors 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.

AUTHOR CONTRIBUTIONS

This paper is the sole work of the author.

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FIGURE CAPTIONS

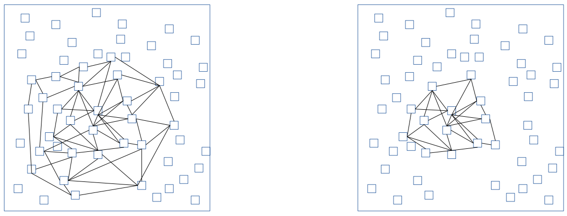

Figure 1. A larger volume of conceptual space navigated per unit time (left) represents higher general problem solving ability. A smaller volume of conceptual space navigated per unit time (right) represents lower general problem solving ability.

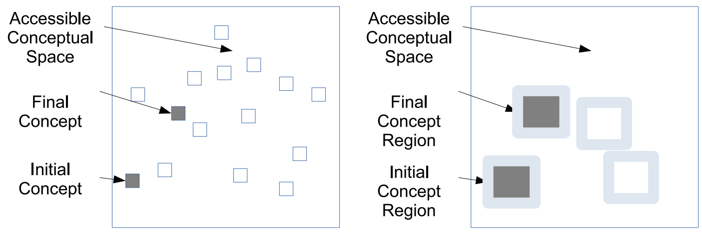

Figure 2. Problems are not definable if the initial and/or final concepts in problem definition are not within the accessible region of conceptual space (right). Initial, final, or intermediate concepts in problem definition not sufficiently revolvable (left).

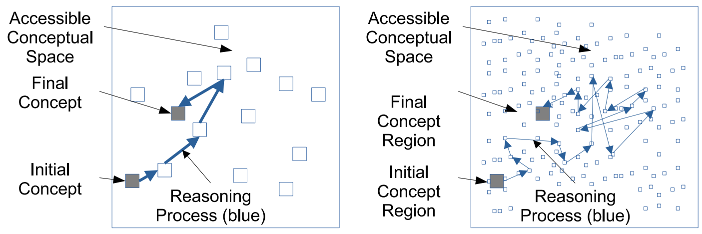

Figure 3. Solutions are not discoverable if the required reasoning exits accessible conceptual space (left), or if the initial, final, or intermediate concepts in reasoning are defined at too high a resolution to be located (right).

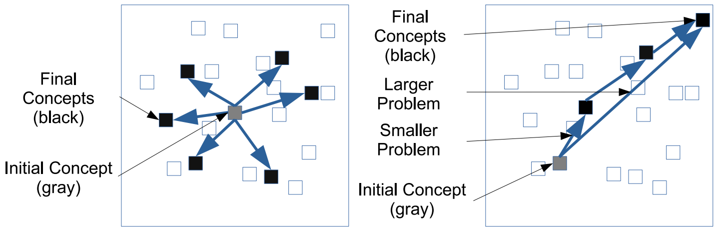

Figure 4. Problems are defined by gap between initial and final concepts. Breadth of problem solving ability is defined in the FMF as the capacity to navigate from an initial concept to many different final concepts (left). Magnitude of problem solving ability is defined in the FMF as the capacity to navigate from an initial concept through reasoning steps a representing a solutions to a smaller problem, towards a distant concept representing the solution to the larger problem (right).