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A Human-Inspired Collective Intelligence Model for Multi-Agent Based System

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ABSTRACT

The collaborative and competitive nature of multi-agent systems (MAS) is visible through the simple social mode of communication that emerges between human-agent interactions or agent-to-agent interactions. A simple mode of communication involves the fundamental actions carried out by individual agents in achieving their desired goal. The sum of these achievements contribute to the overall group goal. Comparatively, the collective intelligence (CI) of a MAS simply means that these agents should work together to produce better solutions than those made possible when using the traditional approach. In designing MAS with CI properties, formalisation of a higher level deliberation process is essential. A high level deliberation process refers to the judgement comprehension of tasks, reasoning and problem solving and planning. In this paper, we propose our Collective Intelligence Model, CIM, which has the potential to control and coordinate a high-level deliberation process of a MAS. CIM is inspired by the emerging processes of controlled discussion, argumentation and negotiation between two or more intelligent human agents. These processes screen and validate the deliberation process through a cross-fertilisation approach. The emergent property of the cross-fertilised ideas results in an intelligent solution that solves optimisation-related tasks.

Keywords: Argumentation, collective, cross-fertilisation, discussion, human, intelligence, multi-agent systems, negotiation, optimisation

INTRODUCTION

Our research aims at highlighting Collective Intelligence, CI, as the emergent property of intelligent social interaction rather than the combined behaviour of the participants in a group. This emergent property is influenced by two attributes, which are the behaviour of

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the participants and the level of cognitive capabilities engaged in intelligent social interaction (Gunasekaran, Mostafa, & Ahmad, 2013, November). We relate this to Personal Intelligence, (PI) (Gunasekaran, Mostafa, & Ahmad, 2013, December). The idea of this research is inspired by the need to understand the individual-to-individual form of collaborative work and to discover any emerging patterns that can be exploited for further enhancement. While much research work has been inspired by the collective behaviour demonstrated by swarms of insects such as ants and bees, our work investigates the characteristics of human interaction with respect to the 'knowledge' component of humans.

Our argument is that since humans are exceedingly more intelligent that insects, it would be more appropriate and necessary to discover a new approach to human collective intelligence that would produce exceedingly far better results than bio-inspired systems. We hoped to discover a generalized model of emergence of collective intelligence that could be tested on a community of software agents. Such a model is based on new concepts of knowledge components such as ideas, agreement and disagreement with multiple and cross-fertilization of ideas and knowledge.

We anticipated that a logically and mathematically complex mix of ideas, agreement and disagreement coupled with the existing knowledge of the entities would form a general model of emerging collective intelligence. We propose that if an algorithm could be developed based on the model and tested on a multi-agent system, similar results could be obtained in terms of collaborative efficiency, effective processes and possibly lower cost since the model is based on a successful outcome of decisions.

This paper attempts to study and analyze emerging collective intelligence among humans and to formulate a collective intelligence model that can be redeployed in a Multi-Agent-Based System. The following two hypotheses were tested in this study.

Hypothesis 1: There is an emerging collective intelligence in any interaction between two intelligent entities, however trivial that intelligence is.

Hypothesis 2: The emergence of collective intelligence is a consequence of the cumulative cross-fertilization of ideas and knowledge between a finite numbers of intelligent entities.

The objective of this research paper was to propose a collective intelligence model that is based on the outcome of interaction between collaborating entities.

As part of the model development, we needed to identify, study and analyze suitable and relevant face-to-face interaction between individuals and groups of people. Data gathering instruments were designed to capture the required information, characteristics, situations and context of discussion as possible variables of collective intelligence. High-impact collaborative activities were necessary to tease out the hidden concepts of collective intelligence. While we identified a few knowledge-related concepts, other concepts still need to be identified to truly model the process of arriving at a decision.

Background Study

The purpose of this background study is to learn and understand the mechanism of current CI models. We hoped to propose a CI model that uses a similar mechanism with the aim of eliminating uncertainties mainly during the simulation of MAS.

Collective Intelligence Models

Collective Intelligence (CI) models are based on streams such as self-organization, complex adaptive systems, multi-agent systems, population-based adaptive systems, swarm intelligence and swarm engineering. Some models are numerical in nature (Swarm Engineering), while others lean towards a conceptual approach (cellular automata). Here we describe the two common CI models, one inspired by nature and the other that is non-bioinspired, the Swarm Intelligence Model and the Multi-Agent System Model.

Swarm Intelligence. Swarm intelligence (si) is known for its collective problem-solving capabilities, which are inspired by the social capabilities of insects, birds, mammals, bacteria and microorganisms (bonabeau, dorigo, & theraulaz, 1999). It is the result of self-organization behavior in which the interaction of lower-level (microscopic level) components initiates the creation of a global-level (macroscopic level) dynamic structure that may be regarded as collective intelligence. It is interesting to note that using a simple set of rules in direct/indirect communication among participants in the colony leads to a global effect on the organization of the colony (matarić, 1995). Usually, local level information targets information about the local environment. The basis of si is derived from the four elements (bonabeau, sobkowski, theraulaz, & deneubourg, 1997) that structure the principle of self-organization. The elements are:

a) Positive Feedback
   This dictates a simple behavior that promotes the creation of convenient structures.
b) Negative Feedback
   This is the property to counterbalance positive feedback and help stabilize the collective pattern.
c) Fluctuation or Randomness
   This is the random walk error and the random task switching among swarm individuals that are vital for creativity and innovation.
d) Multiple Interaction
   This is interaction that involves many participants; there should be a minimum number of participants in interaction with one another to turn independent local-level activities into one interconnected living organism.

In order for this behavior to be intelligent, Millonas (1992) stated that five important principles should be evident, namely:

a) The swarm should be able to do simple space and time computations (the proximity principle).

b) The swarm should be able to respond to quality factors in the environment such as the quality of foodstuff or safety of location (the quality principle).
c) The swarm should not allocate all of its resources along excessively narrow channels and it should distribute resources into many nodes (the principle of diverse response).
d) The swarm should not change its mode of behavior upon every fluctuation of the environment (the principle of stability).
e) The swarm must be able to change behavior mode when the investment in energy is worth the computational price (the principle of adaptability).

A combination of the elements and principles have created a guideline for researchers to introduce SI optimization algorithms such as the Evolutionary algorithm, Ant Colony Optimization (ACO) algorithm, Particle Swarm Optimization (PSO) algorithm and the very recent Artificial Bee Colony (ABC) Optimization algorithm. These algorithms are deeply embedded in many applications such as the routing of traffic in telecommunication networks to the design and control algorithms for groups of autonomous robots.

Multi-Agent Systems. Multi-Agent Systems (MAS) consist of autonomous entities that are able to interact and share a common environment, which they perceive through sensors and upon which they act with actuators (Wooldridge, 2009). These autonomous entities are termed as agents. Russel and Norvig (Kaminka, 2007,pp.73) defined an agent as "an entity that can be viewed as perceiving its environment through sensors and acting upon its environment through effectors." Coen (Heylighen, 1999) viewed software agents as "programs that engage in dialogs and negotiate and coordinate the transfer of information." Wooldridge and Jennings (Bellifemine, Caire, & Greenwood, 2007) stated that an agent is "a hardware and/or software based computer system displaying the properties of autonomy, social adeptness, reactivity, and proactivity." Nwana and Ndumu (Goldstone & Janssen, 2005) defined an agent as "referring to a component of software and/or hardware, which is capable of acting exactly in order."
Wooldridge and Jennings (Parker, 2008) proposed two notions of agency: weak and strong notions. They defined the weak notion as agents having autonomous, sociable, reactive and proactive characteristics. The strong notion is exhibited by the mental characteristics of knowledge, belief, desire, intention and obligation. The strong notion is also known as intentional notion. Vigorous studies in this field are aimed at developing approaches that help in building complex systems comprising of autonomous agents. Each of these agents possesses information and the ability to perform actions that are coordinated to exhibit a desired global behavior (New Challenges in Computational Collective Intelligence, 2009). It is essential to note that a multi-agent based model differs from the SI model in terms of how the models have been inspired. Nevertheless the mechanism of MAS describes major similarities with SI.

The mechanism of a MAS is as follows (International Foundation for Autonomous Agents and Multiagent Systems, 2010):

a) Agent design
Numerous MAS have been designed in different ways that consists of individual agents.

b) Environment
Agents must be able to deal and interact with their environments, which can be either static or dynamic.

c) Perception
The data that are accessed from the sensors for the agents in MAS are usually distributed.

d) Control
The control in multi-agent systems is normally decentralised.

e) Knowledge
In multi-agent systems, the amount of knowledge about the current state of the environment for every agent can differ substantially.

f) Communication
Multi-agent systems are often represented by some form of communication or interaction but normally, communication in multi-agent systems is represented as a two-way process, with senders and receivers of messages. This involves direct communication in which the agent is equipped with antennas or receptors.

These operations mobilize MAS to display the characteristics below, which make it a potential CI model:

a) Each agent has incomplete information or capability for solving the problem and, thus,has a limited viewpoint.
b) There is no system for global control.
c) Data are decentralized.
d) Computation is asynchronous.

METHOD

We used the qualitative approach to explore the phases, behaviours and tasks of a group of humans working together through intelligent social interaction. Once these behaviours and tasks were identified at the local level, our intention shifted to formalising them into adaptive sequential phases to support the global formation of the model. We strongly believed that by observing their intelligent social interaction, we would be able to tap into the behaviours and cognition activities that constitute the emerging effects of Collective Intelligence. The qualitative method strategy used was Entrography. This method allowed us to be engaged through the participative observation method, which enabled us to perform direct observation on a group of subjects in an environment that we recorded using technological gadgets such as a camera and video recorder. We also took notes and carried out informal interviews to clarify certain matters.

For the purpose of this research, we identified nine meetings. The nine meetings included five research-based meetings, two department meetings and two electrical design meetings. Out of the five research-based meetings, two were data mining projects whose goal was to predict a group of students who were weak in their studies so that early preventive measures could be taken to help them improve. The participants of this meeting were five lecturers from Universiti Tenaga Nasional, UNITEN, and one information technology manager from the Information Technology and Multimedia Services, ITMS, division at UNITEN. The other three research-based meetings were also on a data mining project that aimed to predict and tap into the problem of electricity service payments by Tenaga Nasional Berhad (TNB) customers. The participants of this meeting were five lecturers from UNITEN and two officials from TNB. The two academic meetings were the department meetings of UNITEN academic staff involving 15 academic staff holding various positions. The last two electrical design meetings involved a team of 15 engineers (electrical, mechanical, design, etc.) with different levels of technical, ground and managerial expertise from MMC GAMUDA.

All these meetings involved participants at various positional levels (manager, senior electrical engineer, professor, senior lecturer). For the purpose of discretion, we did not disclose the goals and details of the meetings. The procedure involved in direct observation comprised five steps.

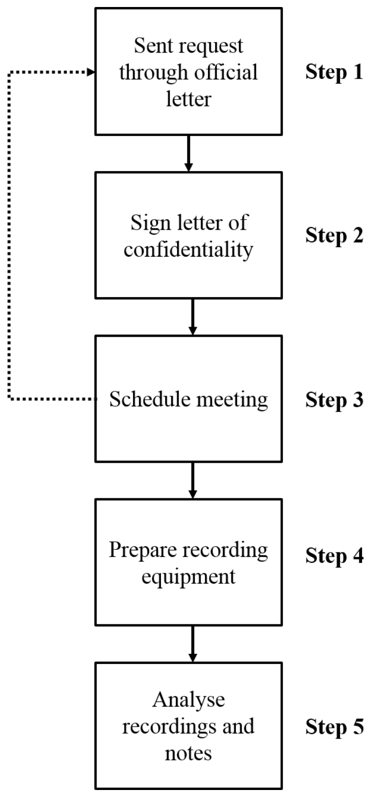

Figure 1. Observation procedure

RESULTS

In the first screening of the recorded meetings, we were able to derive the behaviour and tasks of intelligent social interaction. Table 1 below shows these behaviour and tasks as the emergent property of the nine meetings that we observed.

Table 1
Behaviour and task table

No.	Meeting	Behavior				
		Problem Understanding		Idea Reasoning		Idea Delivery
		Task				
		Knowledge Understanding	Propose Idea	Agree/ Diagree	Counter Idea	Throw Ideas
1.	Research Meeting 1	Y	Y	Y	Y	Y
2.	Follow-Up of Research Meeting 1	Y	Y	Y	Y	Y
3.	Research Meeting 2	Y	Y	Y	Y	Y
4.	Follow-Up of Research Meeting 2	Y	Y	Y	Y	Y
5.	Follow-Up of Research Meeting 2	Y	Y	Y	Y	Y
6.	Department Meeting 1	Y	Y	Y	Y	Y
7.	Follow-Up of Department Meeting 1	Y	Y	Y	Y	Y
8.	Electrical Design Meeting 1	Y	Y	Y	Y	Y
9.	Follow-Up of Electrical Design Meeting 1	Y	Y	Y	Y	Y

The results of the analysis indicated the emergence of three specific behaviours, which were problem understanding, idea reasoning and idea delivery. During problem understanding, it is pertinent to note that each participant's contribution is influenced by two factors. Firstly, the participant's knowledge reflects upon the idea of PI. Each participant's knowledge is different based on their diverse PI capacity regarding the subject matter. Secondly, the monopolisation of the meetings shows biasness by participants who have seniority and therefore, greater authority. Authority as a property is reflected by the position held by the participant in the organisation. Their positions are awarded based on the extent of their tenure. Further observation revealed that second-level behaviour involved bargaining on ideas among the participants. At this point, the tasks, 'propose idea', 'agreement/disagreement' and 'counter idea' took place. Noticeably, each of the proposed ideas was further discussed to identify its pros and cons; during this discussion, the ideas went through the agreement-disagreement process. To support ideas, specific guidelines were followed and shared by participants who were experts in that particular area. In some circumstances, external expertise was sought to support the validity of the ideas. The meeting ended when the idea that had the most pros was identified; this selection was coded as idea delivery behaviour.

Two observations were made. Firstly, there was more refined behaviour and tasks involved in regulating the communication flow of intelligent social interaction. Secondly, there was absolute meaning to the behaviour and tasks. In order to justify our observation, we conducted informal interviews with the 43 participants of the meetings. The interview was conducted at the end of the follow-up meetings and lasted 30 minutes.

The results of the interviews were threefold. First, it enabled the renaming of observed behaviour. Secondly, the behaviour and tasks could be further elaborated on and phased and thirdly, the definition of each behaviour and task was finalised. The behaviour identified was problem understanding, idea reasoning and idea delivery; these were renamed discussion, reasoning and decision making, respectively. The purpose of the renaming or rephrasing was to provide a better naming convention to represent the different behaviour. In addition, the behaviour of reasoning was seen to comprise two extended behaviours, which were argumentation and negotiation. As for the tasks, the task of knowledge understanding could be further refined to domain identification, domain familiarity and formation of a common goal, task identification, task familiarity and idea identification. Within reasoning behaviour, an additional task was added, which was idea organisation. Finally, within the decision making behaviour, the 'throw idea' task was refined to idea execution and idea storage. The number of tasks, therefore, increased from five to 13. Table 2 shows the phase, behaviour and task relationship.

Table 2
Phase, behaviour and task relationship

Phase	Behavior	Task	
Pre-Fertilization	Discussion	1.	Domain Identification
		2.	Domain Familiarity
		3.	Formation of a Common Goal
		4.	Task Identification
		5.	Task Familiarity
Pre-Fertilization	Discussion	1.	Idea Identification
Cross-Fertilization	Discussion	1.	Propose Idea
	Argumentation	1.	Disagreement
		2.	Counter Idea
	Negotiation	1.	Idea Organisation
		2.	Agreement
Post-Fertilization	Decision Making	1.	Idea Execution
		2.	Idea Storage

We were able to finalise the behaviour for the nine meetings in Table 3 below.

Table 3
A detailed version of phase, behaviour and task

No.	Meeting	Behavior												
		Phase												
		1					2	3					4	
		Discussion					Discussion	Discussion	Argumentation		Negotiation		Decision Making	
		1	2	3	4	5	1	1	1	2	1	2	1	2
1.	Research Meeting 1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
2.	Follow-Up of Research Meeting 1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
3.	Research Meeting 2	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
4.	Follow-Up of Research Meeting 2	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
5.	Follow-Up of Research Meeting 2	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
6.	Department Meeting 1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
7.	Follow-Up of Department Meeting 1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
8.	Electrical Design Meeting 1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
9.	Follow-Up of Electrical Design Meeting 1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

The third screening of the recorded meetings revealed that the participants of the meetings incorporated PI in pursuit of a common goal, and this resulted in the recursive behaviour of discussion, reasoning and decision-making. This behaviour and the tasks followed a recursive structure in order to stimulate a positive outcome, which ultimately represented the emergent collective intelligent. This proved the first hypothesis. Interestingly, this observation led to three important discoveries, a discussed below. (Further explanation of the definition of the behaviour and task can be read in Gunasekaran, Mostafa and Ahmad [2015]).

a) **Knowledge as the focal interaction attribute**
In our proposed CIM, we embarked on the principle of representing each participant as having his/her own PI. PI represents mental consciousness over physical and neurological capability, which is knowledge, and enabling this mental consciousness to stimulate the social structure in order to achieve goals. Success due to PI is often influenced by how one's knowledge is utilised in achieving a goal. Hence, as our CIM describes, each participant in intelligent social interaction is governed by various PI due to variant degrees of knowledge. This knowledge is shared between these participants for attaining effective decision-making solutions.

b) **Knowledge transformation process**
In effective communication, knowledge is transferred from one participant to another. There is an inherent process that guides knowledge transformation into meaningful decision-making options. The transformation takes place when experience transforms into knowledge and when that knowledge is used correctly through the execution of ideas, transforming it into intelligence. Figure 2 below shows the idea, knowledge, experience and intelligence conversion.

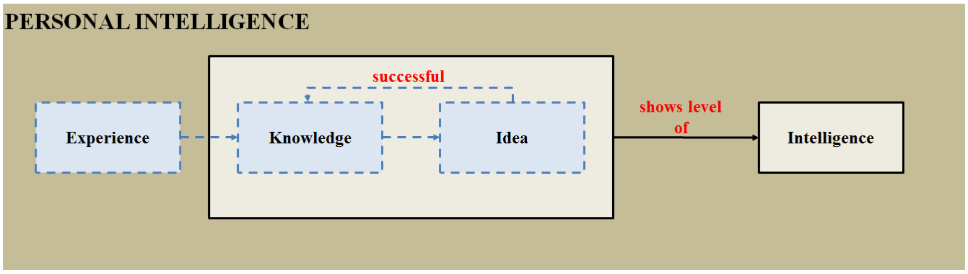

Figure 2. Idea, knowledge, experience and intelligence conversion

From our observation, it was evident that a meeting was often initiated with a discussion and proceeded when a participant in the group began the topic of discussion by conveying the initial idea on the subject matter to the other participants of the group. The purpose of this gesture was to share knowledge based on one's experience of the topic of discussion in the form of a lingual proposal. However, during the course of discussion, each participant would argue the validity and effectiveness of the proposed idea and other corresponding ideas by referring to legitimate reasons.

Consequently, the interaction turned into argumentation when other participants would suggest counter proposals of fresh new ideas. Here, argumentation was the process of diminishing an idea with specific reasons that supported its purpose. While some group reasoning progressed smoothly, most of these reasoning processes met with a string of arguments that were ultimately resolved through negotiation. This negotiation process ensured that an agreement was reached for the purpose of decision making. Agreement progressed into action performance or more discussion depending on the potential of discussion to solve the problem. This observation indicated the existence of a knowledge transformation process in CIM. During the discussion, knowledge was extracted from prior experience and presented as ideas. Further in the reasoning behaviour, these ideas were manipulated in an iterative manner through argumentation and negotiation. Manipulation involved collaborating, competing or polarising the ideas. Collaboration reflected on the option of combining and executing the various ideas one at a time. This scenario was prevalent when both the participants had equal depth of knowledge in the domain area. Competing reflected on targeting the best idea to be selected in the decision-making behaviour. This scenario was prevalent when either one of the participants had a greater depth of knowledge in the domain or enjoyed greater authority. Polarisation reflected on the outcome of new ideas through the assimilation of two or more ideas. This scenario was prevalent when the nature of an intelligent social interaction involved immense idea generation between various participants. These collections of ideas were refined for optimal solutions requiring a continuous set of agreements, disagreements, proposals and counter proposals. Overall, once an idea or a combination of ideas had been agreed upon, a decision was made to implement the idea. In this work, if the idea contributed to a successful action-performing outcome, we called the process of manifesting the outcome as CI; otherwise, the decisions of the outcome went through another cycle of discussion, agreement and negotiation. The successful idea was then transformed into knowledge and stored in the memory for future retrieval.

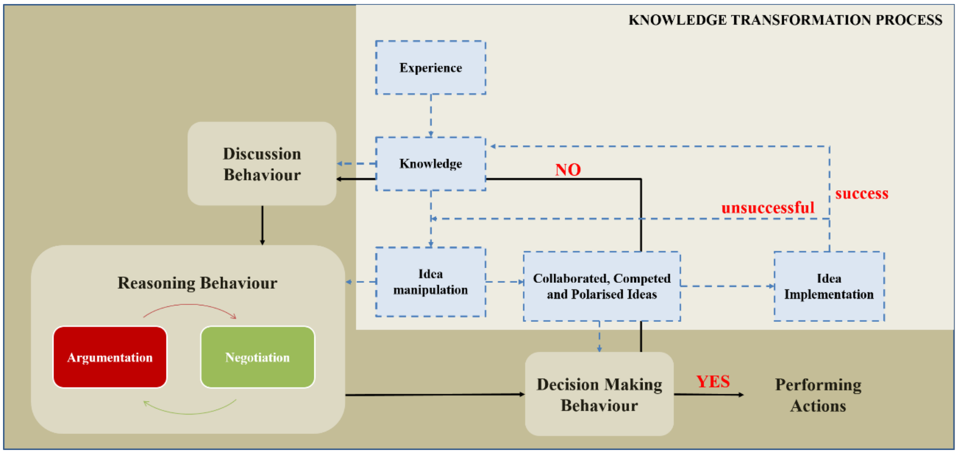

Figure 3. Knowledge transformation process

c) **Cross-Fertilisation.** Knowledge is communicated iteratively to achieve collective intelligence (goal attainment). In our proposed CIM, the intention was to derive to ideas either through collaboration, competition or intersection of the knowledge of various participants in intelligent social interaction. It was pertinent that the cross-fertilisation process took place. This proves the second hypothesis.

Our observation suggested that the cross-fertilisation process underwent three phases: the pre-fertilisation phase, the cross-fertilisation phase and the post-fertilisation phase. The categorisation of the phases with the corresponding behaviour and tasks are shown in Table 4.

Table 4
Phase, behaviour and table relationship

Phase	Behavior	Task	
Pre-Fertilization	Discussion	1.	Domain Identification
		2.	Domain Familiarity
		3.	Formation of a Common Goal
		4.	Task Identification
		5.	Task Familiarity
Pre-Fertilization	Discussion	1.	Idea Identification
Cross-Fertilization	Discussion	1.	Propose Idea
	Argumentation	1.	Disagreement
		2.	Counter Idea
	Negotiation	1.	Idea Organisation
		2.	Agreement
Post-Fertilization	Decision Making	1.	Idea Execution
		2.	Idea Storage

The pre-fertilisation phase sanctions the PI component of each participant. During this phase, each participant was capable of verifying the knowledge he/she had in accomplishing the given task. In the cross-fertilisation phase, the participants initiated interaction by communicating their individual knowledge to the other agents. In our observation, the cross-fertilisation phase underwent three levels of order.

The first level of order in the cross-fertilisation phase occurred when competition for the best ideas prevailed during the intelligent social interaction. The second level of order occurred when collaboration of ideas prevailed in the intelligent social interaction. The third level occurred when polarisation of ideas was prevalent in the intelligent social interaction. As such, each participant was equipped with varied levels of PI. As discussion, argumentation and negotiation behaviour is iterative, knowledge is diffused from one participant to another and transformed and eventually polarised. We termed this process as knowledge intersection. The diffused knowledge was deliberated concisely and acted as an added value for current and future task execution.

In the post-fertilisation phase, the participants reached a mutual decision to execute the cross-fertilised idea that was best suited for accomplishing the given task. The success of the cross-fertilised idea determined whether the idea was converted to knowledge and stored in the agent's memory for future usage. If a cross-fertilised idea is unsuccessful, it undergoes the reasoning cycle all over again.

Figure 4 is based on this and shows the proposed CIM.

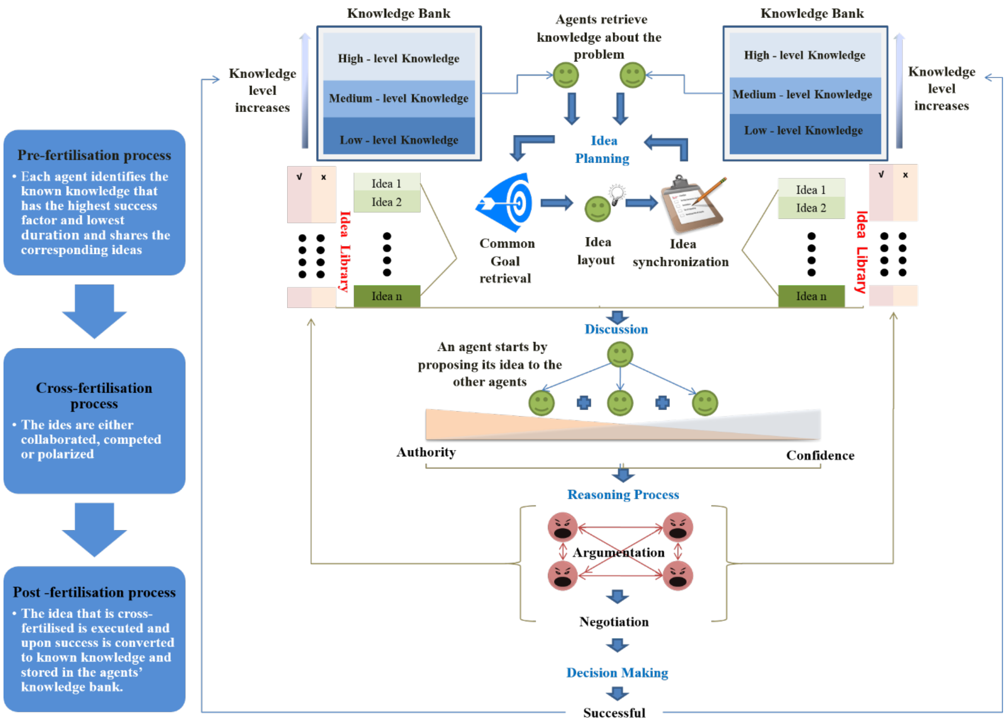

Figure 4. Collective intelligence model (CIM)

DISCUSSION

While there are many workable CI systems to support many applications, none has actually been built on a model that captures the exchanging process of intelligent behavior and cognition of interacting humans (West, 2007; Sun, 2006). All of these models are inspired by either the study of epigenetics, neurology, animals, insects, microorganism or engineering technology. Von Neumann's cellular automata focus on self-reproduction of cells; McCulloch's neural computation mobilizes the principle workings of the human brain; Darwinian evolutionary computation draws its inspiration from the dynamics of an entire species of organism; and Bonabeau and Meyer's swarm intelligence features the swarm behavior of biological organisms. All of these models focus primarily on a group-based behavioral approach.

In general, we understand that a CI model consists two levels. First is the local level that reflects the individual participants of a group. Second is the group organization, which is composed of the collective effort of the various participants at the local level. This constitutes intelligent social interaction involving a group of humans, with each human PI represented at the local level. The various PIs communicate iteratively, which ultimately results in cross-fertilized knowledge at the global level. Both models discussed above lack this characteristic.

The SI model and the MAS focus on the collaboration factor, in which a simple mode of communication involves the fundamental actions carried out by participants to achieve their desired goal at the local level. The sum of these achievements contributes to the overall group goal. Comparatively, the collective intelligence aspects of an SI and MAS simply mean that these participants should work together to produce more efficient solutions than are possible using the traditional approach. Our challenge lay in identifying the local attributes that contribute to the global component of the new CI model.

CONCLUSION

From this case study, we were able to justify the emergence of behaviour and tasks from intelligent social interaction. Behaviour displayed was governed by two properties, authority and confidence. While authority reflected on the position the participants held in the intelligent social interaction, confidence related to their PI level. These properties created an avenue for continuous recursive behaviour to normalise the occurrence of knowledge inconsistencies among the participants. Eventually, this influenced the formation of the knowledge transformation process. The knowledge transformation process was essential in two areas. Firstly, it enabled us to construct the meta-rules to represent our CIM and secondly, it helped in strengthening the idea of cross-fertilisation, which acted as the basis of our CIM.

In conclusion, there are a few factors that describe our CIM. At the local level, each agent had differing PI. PI is influenced by the properties, authority and confidence. PI includes the sub-component of knowledge, which evolves through experience.

At the global level, the inconsistency in the knowledge depth of each participant influences the recursive behaviour of discussion, reasoning and decision making. This recursive behaviour encompasses the knowledge transformation process. The knowledge transformation process defines the three phases of cross-fertilisation, pre-fertilisation, cross-fertilisation and post-fertilisation. The cross-fertilization process manipulates the knowledge sub-component, producing an ultimate solution that acts as the precursor for collective intelligence. Knowing these factors enables us to proceed with further work on our Collective Intelligence Model that will fine-tune the model for use by multi-agent communities.

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