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Collective intelligence ratio: Measurement of real-time multimodal interactions in team projects

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Collective intelligence ratio

Measurement of real-time multimodal interactions in team projects

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Abstract

Purpose – With a team interaction analysis model, the authors sought to identify a varying range of individual and collective intellectual behaviors in a series of communicative intents particularly expressed with multimodal interaction methods. In this paper, the authors aim to present a new construct (i.e. collective intelligence ratio (CIR)) which refers to a numeric indicator representing the degree of intelligence of a team in which each team member demonstrates an individual intelligence ratio (IR) specific to a team goal.

Design/methodology/approach – The authors analyzed multimodal team interaction data linked to communicative intents with a Poisson-hierarchical generalized linear model (HGLM).

Findings – The study found evidence of a distinctive IR for each team member in selecting a communicative method for a certain task, ultimately leading to varying degrees of team CIR.

Research limitations/implications – The authors limited the type and nature of human intelligence observed with a very short list of categories. Also, the data were evaluated by only one subject matter expert, leading to reliability issues. Therefore, generalization should be limited to situations in which teams, with pre-specified team goals and tasks, are collaborating in multimodal interaction environments.

Practical implications – This study presents potential ways to directly or indirectly optimize team performance by identifying and incorporating IRs and CIRs in team composition strategies.

Originality/value – In the literature of team cognition and performance, the authors offer a new insight on team schema by suggesting a new task-expertise-person (TEP) unit integrating information on who uses what communicative methods to best tackle on what cognitive task (i.e. optimum cognition with least cognitive burden). Individual and collective intelligence ratios should be considered as new extensions to conventional transactive memory systems in multimodal team interaction scenarios.

Keywords Intelligence, Team performance, Communication technologies, Team working

Paper type Research paper

Introduction

With advancing information and communication technologies (ICT) coupled with synchronous conferencing applications and social network services, various innovative team interaction and collaboration environments have emerged in recent years. Organizations adopting new interaction possibilities (e.g. asynchronous, synchronous, hybrid, multimodal communication, collaborative knowledge augmentation and

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management) often seek strategies to enhance and extend the cognitive capacities of own teams. Zara (2009) labels such types of innovation as “amplified intelligence technologies.” In such technology-enabled team interaction environments participants engage in and contribute to team discussions generally with specific team goals and measurable outcomes in mind. Furthermore, team interaction processes can be enhanced in purposeful real-time team interactions, where each team member demonstrates a varying range of intellectual behaviors through a series of communicative intents particularly expressed with multimodal interaction methods. In this era of digitally afforded multimodality and highly networked society, people “integrate words with images, sound, music, and movement to create digital artifacts that do not necessarily privilege linguistic forms of signification but rather draw on a variety of modalities – speech, writing, image, gesture and sound – to create different forms of meaning” (Hull and Nelson, 2005, pp. 224-225). In the context of multimodal interaction analyses, these communicative intents are the building blocks of the individual’s intelligence, defined as “the aggregate or global capacity of the individual to act purposefully, to think rationally and to deal effectively with his environment” (Wechsler, 1944, p. 3). Interestingly, contemporary younger generations appear to be more adept at interpreting meaning in sound, music, still and moving images, and interactive components than older generations (Jenkins, 2009) in computer-supported real-time multimodal communication environments.

In our research context, a real-time multimodal interaction (RMI) refers to a synchronous online interaction in an environment where each participating member can lead or support team discussions by expressing an observable communicative intent through voice, text, gesticulation, graphical drawing, or external stimulus. Within an RMI environment, team members who are spatially dispersed can engage in different tasks in pursuit of a common team goal. In our study, the aim is to develop a multimodal interaction analysis model to identify potential evidence of individual intelligence (i.e. as a result of interactions with team members, communication tools, and environmental stimuli) in a series of communicative intents linked to the process of progressive ideation, knowledge augmentation, or solution design in a team project.

The overarching assumption of this paper is that by analyzing evidence of varying degrees of observable individual intelligence in a series of team project sessions, one could infer an individual intelligence ratio (IR) specific to recurring patterns of communicative method choice with given tasks in team projects. In order to quantify and measure an IR, we employ a classification of the levels of observable intellectual behaviors based on a five-stage critical thinking and problem-solving model proposed by Garrison (1991). This particular classification system could be better understood and put into the context of analyzing individual intellectual behaviors if paralleled with earlier models developed by Bloom (1956) and Henri (1991). Table I presents a comparison between the three models.

IRs of multiple individuals (i.e. specific to communicative methods and given tasks in a team project) are necessary elements to numerate a collective effort of team interaction, capability, or performance. Thus, a collective intelligence ratio (CIR) in this study refers to a numeric indicator representing the degree of intelligence of a team in which each participant demonstrates an individual IR specific to a team goal. In essence, it is an attempt to analyze the interaction of “people gathered for a specific purpose” or as defined by Malone *et al.* (2009), “groups of individuals doing things collectively that seem intelligent” (p. 2).

Based on Garrison's theory of critical thinking and Henri's critical reasoning skills, Newman *et al.* (1997) developed a content-analysis technique to measure critical thinking in computer-supported cooperative learning. However, in such online discourse analysis scenarios, most data units are mere texts from asynchronous discussion settings. To date, the analysis of critical thinking and problem solving in a synchronous online team interaction scenario (i.e. integrating multiple modalities that allow visual aid, drawing, and gesture as a whole communication environment) has not made to the mainstream research of interaction analysis. Nonetheless, the use of online tools for RMI is rapidly increasing in many sectors including business and academic communities as the need for internet-based teleconferences (e.g. WebEx) is increasing.

In this paper, we present how one can derive an intelligence analysis model that takes into account habitual patterns of intellectual behaviors reflected in repetitive uses of communication modalities in five categorical tasks over multiple interaction sessions and projects. The tasks linked with team goals require team cognition, leveraging the interactional context (e.g. team members with idiosyncratic talent, communication method preference, and dynamic stimuli). This paper demonstrates the analysis model development process and the analysis results.

Background

This section is by no means a comprehensive overview of all relevant research on collective intelligence or multimodal interaction analysis; at best, it is an abridgment of relevant studies that loosely defines and broadly addresses some of key elements referred in this study. Among many areas, as a pioneering attempt, the focus of this study is more on the development of the interaction analysis model and the analysis of the results. In sum, interchangeable terms and unfamiliar acronyms of this study show how young this research field is and calls for more in-depth studies in the future.

Collective intelligence and critical thinking

Smith (1994) stated the reasons that people normally form collaborative groups – the task is too large to be completed by an individual within limited time and no one possesses all of the skills and knowledge required. Through collective intelligence, groups of individuals often work collectively so as to acquire new knowledge on a just-in-time basis (Jenkins, 2009). Levy (2000) described the potential of "collective

Garrison's stages	Bloom's categories	Henri's cognitive skills	Description
Identification	Knowledge	Elementary clarification	Observe, recall and identify information
Definition	Comprehension	In-depth clarification	Understand underlying meanings, values, assumptions
	Application		Use of a learnt concept in a novel situation
Exploration	Analysis	Inferencing	Concepts are separated and understood by their propositional structure
Evaluation	Evaluation	Judgment	Decision-making, evaluation, criticism
Integration	Synthesis	Application of strategies	Build from diverse elements to create a new structure

Table I. Comparison of the five-stage model of critical thinking by Garrison (1991) with the cognitive learning categories of Bloom (1956) and the cognitive skills in problem-solving by Henri (1991) intelligence" as "everyone knows something, nobody knows everything and what any one person knows can be tapped by the group as a whole." In regards to the motivation of collaborative behaviors, Brown and Lauder (2001) defined collective intelligence as a basis for an empowerment opportunity: "pooling of team intelligence to attain common goals or resolve common problems" (p. 603). Teams often create novel and unexpected combinations of knowledge in ways that individuals could not (Hargadon, 1999). Such opportunistic team cognition becomes more possible when there is a collective critical thinking process. In other words, outcomes (e.g. augmented intelligence, new knowledge, innovative solution) led by iterative team reflections and cognitions qualify to be the result of collective intelligence because such critical thinking processes involve the analysis of premises, arguments, and evidence arising from team interactions (Kamin *et al.*, 2001).

However, when we assemble a group, we inherently create other problems and questions. For example, we often ask how we can make a virtue of the pooling knowledge within the intellectual construct developed by a group or how we can avoid the lack of intellectual integrity leading to even worse outcomes (Smith, 1994). Many team discourses can turn into pointless drifting episodes no matter how many intelligent individuals interject numerous useful ideas in team interactions. When ideas are not well expressed or understood; supportive diagrams or gestures are counterintuitive; or discussions lack structures or goals, such sessions can often lead to fruitless endings. Therefore, what may cause optimal critical thinking to occur or how team collaboration might lead to a constructive, creative, or innovative idea or product design has been a topic of many research studies. Especially, in terms of defining or analyzing critical thinking evidence, there have been decades of research studies originated from as early as John Dewey's (1933) work.

John Dewey is probably one of distinguished pioneers in the study of critical thinking who stressed the importance of "active" and "reflective" thinking (Dewey, 1919, 1933). Dewey is contrasting the kind of thinking in which people just receive knowledge in a passive and unreflective way. Instead, he believes that critical thinking is essentially a process in which people are encouraged to give reasons and evaluate reasoning. A widely used definition of critical thinking is proposed by Norris and Ennis (1989) who asserted that critical thinking is reflective thinking that is focused on deciding what to believe or do. Accordingly, four categories of critical thinking skills were identified by Ennis (1987) and Norris and Ennis (1989). In their definition and model of critical thinking, they addressed intellectual behaviors such as clarifying information, assessing evidence, judging inferences, and applying appropriate strategies and tactics. A more historical source of critical thinking can be found in Bloom's cognitive taxonomy of educational objectives (Bloom, 1956). The top three of Bloom's categories (analysis, synthesis and evaluation) are comparable to the definitions of critical thinking by Kennedy *et al.* (1991). Apparently, Bloom's work substantially influenced the later work of other scholars. For example, there are comparable classifications such as four categories of critical thinking skills (Norris and Ennis, 1989), five-phases of cognitive presence (Garrison, 1991), and five critical reasoning skills (Henri, 1991). Therefore, the critical thinking analysis criteria are often presented analogous to each other, especially in the higher levels of critical thinking (Hara *et al.*, 2000). See earlier Table I that presents the similarities between the three models.

Team cognition

Many team projects are knowledge-driven so they involve a high degree of critical thinking in which contextual knowledge is gathered, interpreted, and understood (Koskinen, 2004; Chiocchio, 2007). According to Johnson and Johnson (1986), there is persuasive evidence that people in cooperative teams often achieve and demonstrate higher levels of critical thinking while retaining information longer than people who work as individuals. The collaborative work scenarios often provide team members an opportunity to engage in discussion, take responsibility for their own learning, and help them become critical thinkers (Totten *et al.*, 1991).

Team collaboration is seen as an essential aspect of cognitive development since team cognition cannot take place in isolation from the relevant social context. Having its roots in Dewey's reflective inquiry approach to learning, Garrison (1991, 1993, 1997) incorporated social context elements in their collective inquiry model (i.e. community of inquiry model). This model has been often discussed as one of effective models to demonstrate collective critical thinking processes in a computer-mediated group-learning environment (Anderson and Garrison, 1995; Garrison, 1991; Anderson and Garrison, 1995). Interestingly, Newman *et al.* (1997) also looked at various significant differences between computer-mediated conferences and face-to-face meetings in critical thinking. They concluded that computer-mediated conferencing facilitates higher levels of critical thinking while face-to-face interactions encourage more creative and higher volumes of interaction. For this regard, Newman *et al.* (1997) also provided discrete evidence for each phase of Garrison's (1991) critical thinking model and a specific scenario in which teams tackled explicit problem-solving tasks.

Analysis of face-to-face interaction scenarios

There have been a notable number of studies focused on interactions in face-to-face scenarios. Among leading researchers in this micro-field, Francis Quek at Virginia Tech has been a more active researcher in analyzing video recorded interactions. For example, Quek *et al.* (2002b) analyzed interactions incorporating gesture and speech in order to understand the interplay between the two distinctive modalities and the way in which they support communication. Also, in another study, Quek *et al.* (2002a) analyzed gestures of participants extensively because they believed that in natural conversation between individuals, gesture and speech function together as a co-expressive whole and therefore, human multimodal communication coheres topically at a level beyond the local syntax structure. In a later study, Quek *et al.* (2005) analyzed multimodal meetings by reviewing "hyperphrase" or "catchment" as minimal data units in 30 to 90-second video data segments. In addition, for a fine-grained analysis of communicative intents involving gesticulation and speech, the researchers employed a set of motion tracking devices to track body, torso, head, and hand motion while video-taping the entire group interaction session. The study showed which participant demonstrated a pattern of leading role in overall group interactions and how an interaction hierarchy was established in the team. Based on Quek's early work, Chen *et al.* (2006) investigated interactions among speech, gesture, posture, and gaze in meetings. However, there was no particular team goal or problem solving task which might trigger the team to demonstrate any evidence of collective team cognition or critical thinking.

Real-time (synchronous) multimodal interactions

Kress (2003) offers a definition of multimodality of new media. He asserts that modern literacy requires the ability to express ideas across a broad range of contemporary media including spoken or written words, moving or still images and 3D models. He views that each medium has its own representation and a unique method for producing and transferring knowledge. When team projects are knowledge-driven and involve a high degree of learning and interaction (e.g. new product development or scientific research projects), a proper information transfer is of great importance (Chiocchio, 2007). Maznevski and Athanassiou (2003) find that teams perform well if there is an efficient flow of tacit and explicit knowledge. While identifying or defining explicit knowledge (e.g. project task or function description) belongs to the lower level of the critical thinking classification model (see Garrison, 1991), communicating tacit knowledge requires a complex set of skill (i.e. requiring multiple intelligence or higher critical thinking competencies). In the latter scenario, voice intonations, hand drawings and even body language are often employed to help people understand all the subtleties of tacit knowledge in team projects (Chiocchio, 2007).

In addition, as an identified challenge in online interactions, a significant body of literature reveals that team interaction and collaborative learning at a distance inhibits the development of critical thinking and active involvement because participants often passively assimilate knowledge rather than critically examine and construct it (Lauzon, 1992; Burge, 1988; Garrison, 1993). In this regard, Gunawardena and Zittle (1997) address that "social presence" is a strong predictor of satisfaction with computer-mediated communications. According to Garrison's theory of Community of Inquiry, participants should find strategies and media to present their personal characteristics into the communication channels (i.e. in order to be viewed as "real people"), otherwise the goal of affective involvement and cognitive learning cannot be realized (Garrison, 1993). For this, Kuehn (1993) and Walther (1994) suggest that it would be ideal if a computer-mediated discourse environment can enable interactions involving affective components (e.g. emotions and other unconventional symbolic displays).

Visual communication

Text-based discourses through mobile communication or knowledge-repositories integrating videos are proliferating in today's communication media channels. Interestingly, McKim (1980) stress that the ability to think visually is also a necessary skill for developing innovative solutions. For example, Song and Agogino (2004) find that the volume of total sketches and especially the number of three-dimensional sketches has an increasingly positive effect on the final design outcome. Similar to the off-line face-to-face interactions in which people use speech, gesture, hand drawings, diagrams, or artifacts that can carry meaning, today's online synchronous multimodal communication environments do integrate whiteboard features for people at a distance to interact while sketching or drawing collaboratively for team projects. Moreover, the use of mobinar (e.g. smartphone with whiteboard conferencing) is making it possible for people to express whatever, whenever, however, they want to communicate. However, analyses of online multimodal synchronous interactions are still rare.

Task appropriate modality

In the era of information and intelligence, making a choice among multimodal communication methods can be a challenge for a team. Effective interactions of a project team supported by communication technologies depend largely on a proper match between the task demands and the communication methods that the team considers (Straus and McGrath, 1994). According to Riopelle *et al.*'s (2003) longitudinal case study of six virtual teams, it is appropriate to use reliable media-rich synchronous interactions (e.g. videoconferencing or groupware), if a task is complex and also requires a great deal of information exchange and reciprocal feedback. When tasks are less complex and more independent, asynchronous communication media such as e-mail and web-based discussion forums may be more appropriate (Riopelle *et al.*, 2003). In addition, Takahashi *et al.* (2009) assert that it is crucial for practitioners or researchers to identify various roles of not only formal communication media, but also informal online communication channels to understand their implications.

Overall, with the advancement of information and communication technologies, team interactions are no longer confined in physical or geographical boundaries. At the same time, team reflections and collective cognition (i.e. through in and out of formal and informal communication channels) can leverage much more than just speech or text as a communication modality. Moreover, team discourses (i.e. involving body or hand gestures, hand-drawn sketches, pictures of artifacts, tables or diagrams, or computation results from external processes) can be recorded and analyzed not only as they lead to a project outcome, but as the development of collective intelligence is taking place.

Method

Participants

Six participants were all master's degree students in the following majors: one computer science, one electrical engineering, and four learning technology (education) students. The education and computer science major students were in the first year of their program and the electrical engineering student was in the second year of his program. The average age of the team was 26. The data analyzed in this study was from one of three teams in a class of total 18 students who were all enrolled in a graduate level course (i.e. an elective course for a Master's degree in learning technology design) offered at a private university in the Fall of 2007.

There was no particular reason to pick one team's data over other teams because all teams performed similarly and produced comparable outcomes. The comparison of team performance among teams was left out for the future iteration of the study (i.e. analyzing team performance variations and other affective measures).

The students participated in the course for ten weeks in both offline meetings and online interactions. The instructor-led online interactions took place on a commercial communication management system. However, students in the class participated in numerous discussions and meetings using their own choice of synchronous and asynchronous messaging and interaction systems.

Team projects

In order to meet the requirements of the course, students had to discuss various learning technology solutions as team projects and come up with solution prototypes. Multiple learning technology solutions were discussed by the teams in the course and their solutions included an English language learning microphone for adults, mobile cognitive training solution for children with ADHD, web-based HIV/AIDS education program, creative story making software for early literacy development, PDA-based stomach ulcer management program, floor-mat based phonics game, financial math training game using mobile phone, etc.

For project discussions, students met online and discussed each project in three different session times as scheduled by each team. The team submitted their project discussion results (i.e. three recorded sessions in three movie files) to the instructor by the final day (i.e. tenth week) of the course.

The overarching aim of this study was to devise a statistical model and analyze multimodal interactions linked to critical thinking processes ultimately contributing to collective intelligence building. With the analysis model, the researcher sought to identify patterns of intellectual behaviors presented with a particular modality in a given task. In order to accomplish the goal, the researcher coded the real-time multimodal interaction (RMI) data collected from observations of three projects involving six participants who discussed each project in three separate sessions as shown in Figure 1.

The three-separate-session with three-separate-project structure with the same six participants was employed in this study in hopes to find recurring patterns of communication behaviors. In other words, this time-series-like sequence of observations was devised to identify possible consistent intellectual behavior patterns accompanying modality choices for a series of given tasks.

Each subject had the option to choose from five different communication methods (e.g. text, speech, digital gesticulation, body gesture, introduction of external artifact or stimulus). When each participant contributed to the overall team discussion with a

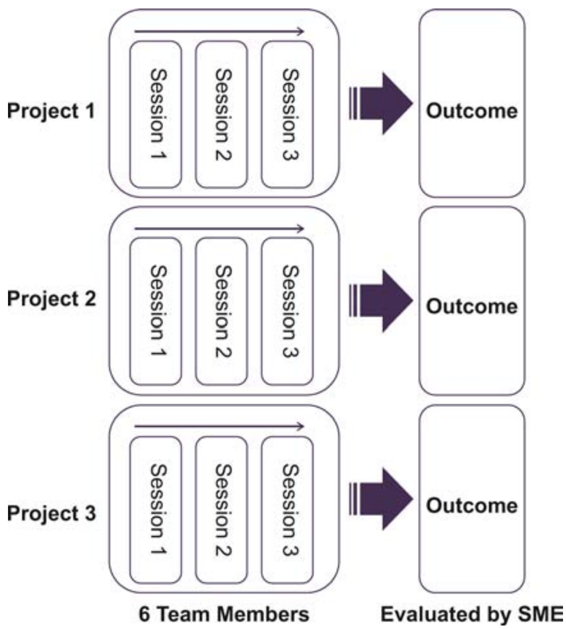

Figure 1.
Team project process

communicative intent using one of five communication methods, each intention vector was tallied as a data unit.

Communication environment

The team interaction sessions through a web-based communication environment (see Figure 2), which incorporated audio, web cam video, whiteboard, text discussion, and file upload (i.e. to upload images, external files), was captured though a computer screen capture software. Each segment of sessions lasted about 35 to 50 minutes.

A total of nine sessions were collected for the analysis. Each participant was at a remote location using a headset, webcam, and mouse pointer to participate in the online team interaction sessions. Prior to the first session in the first project, there were two orientation and practice sessions for all participants to become familiarized with the communication environment. Most of the participants were already familiar with web-based conference environments.

Data

Descriptive statistics of the data are shown in Table II. It provides mean and standard deviation of the number of positive contributions for each task and method. Total mean of the number of positive contributions is 2.782. The number of contribution varies method by method. Speech seems to be the most frequently used method of communication on average in the overall RMI with the team (Figure 3).

Intelligence ratio analysis

Based on Garrison's (1991) five-category model of critical thinking, this study adopted the coding method developed from Newman *et al.* (1995) to measure group interactions. In short, Newman *et al.* (1995) model proposed a way of computing critical thinking ratio (CTR): $CTR = (X^+ - X^-)/(X^+ + X^-)$, where X^+ is the count of communication intents contributing to critical thinking for a given category and X^- is the count of communication intents detracting from critical thinking. Although there are several

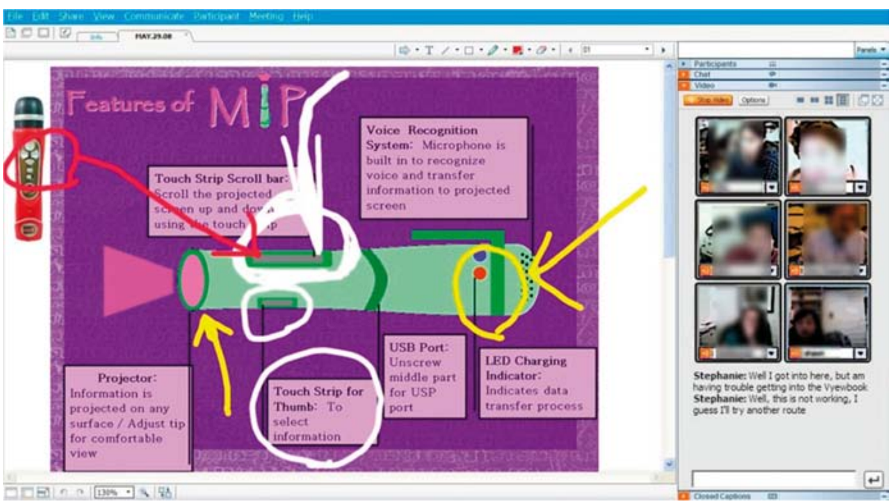

Figure 2.
A sample screen shot of one of multimodal discussion sessions

Table II.
Descriptive statistics

	Text		Speech		Digital gesticulation		Body gesture		External artifact		Mean
	n	SD	*n*	SD	*n*	SD	*n*	SD	*n*	SD	
Identification	2.13	1.61	3.69	2.25	2.46	1.37	1.52	1.14	0.69	1.11	2.10
Description	1.96	1.26	5.19	2.17	3.80	2.18	2.15	1.32	0.31	0.70	2.68
Exploration	2.19	1.40	5.17	1.89	4.09	2.00	2.72	1.35	1.61	1.50	3.16
Application	3.78	1.25	5.31	2.17	2.87	1.55	1.11	0.84	0.87	0.95	2.79
Integration	4.54	1.68	5.65	2.36	3.81	1.86	1.63	1.20	0.30	0.46	3.19
Mean	2.92		5.00		3.41		1.83		0.76		2.78

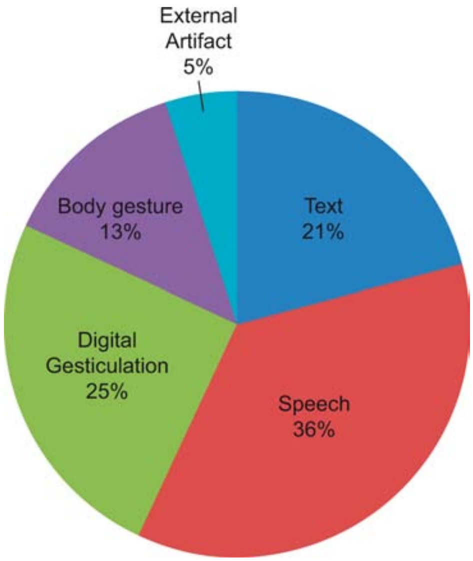

Figure 3.
Overall RMI percentages by modalities

issues with complexities in judgments (e.g. inter-rater reliability and manual labor in coding), this coding method has been adopted by many studies such as Marra *et al.* (2004) or Hara *et al.* (2000) in analyzing online discussions. Given that the total number of positive communicative intents in our study is large ($n = 3,091$), it is necessary to simplify rater's work on data collection without taking account of the negative or irrelevant units of intents. Unlike data units defined in previous studies where there are $\pm$ per unit count based on contribution, any communicative intent that was not relevant or deemed constructive (i.e. by subject matter expert with the help of research assistants) in its nature was not counted in this analysis. Therefore the data collected in this study were only the accumulation of " $+$ "s, indicating meaningful contributions toward the problem solving and project completion. Each data unit was categorized into one of five critical thinking sub tasks based on Garrison's (1991) five-stage taxonomy (see Figure 1): problem: identification (task 1), definition (task 2), exploration (task 3), evaluation (task 4), and integration (task 5).

In this study, the responses are the number of positive contributions of an individual in a team so that generalized linear models (GLMs) could possibly be considered in analyzing such data (i.e. instances of intellectual behaviors). However, the traditional GLMs are often not suitable for the complex data structure like human performance appraisals because GLMs cannot best reflect the correlation among the repeatedly measured variables in a set interval with the same individuals. Lee and Nelder (1996) proposed a broad model class, hierarchical generalized linear models (HGLMs) to account for correlations of repeated measures from the same subjects by allowing random effects for traits (i.e. pattern of behaviors, thoughts, preferences, and emotion often contributing to performance) of individuals as well as fixed effects in GLMs. Furthermore, HGLMs are extension of hierarchical linear models or multilevel models (Goldstein, 1995) to non-normal responses.

Lee *et al.* (2006) assert that models incorporating individual and treatment-individual interactions as fixed parameters perform poorly in ranking performance of individual's traits. These traits can be treated as random, involving a random sample from a suitably defined population (Lee *et al.*, 2006). In this study, we employ a Poisson-HGLM (P-HGLM) with normal random effects because Poisson distribution is often recommended to analyze count data such as our collection of communicative intents in non-overlapping independent set intervals.

We believe that each team member demonstrates idiosyncratic talents (e.g. expressed intelligence in multiple tasks), which can be regarded as random variables. At the same time, such traits lead to a set of communicative method preferences for a given task. Therefore, our research goal, analyzing count data and possible interactions between method choice and task, seems to be best met by P-HGLM models. Here is how we approach to develop the P-HGLM model to analyze the data.

Let y_{ijktm} denote the number of positive contributions through intellectual behaviors for the ith individual in the jth project of the kth session, taking the tth quasi-sequential stage (critical thinking category or in short "task") and the mth method of communications. ($i = 1, \ldots, 6, j, k = 1, \ldots, 3$ and $t, m = 1, \ldots, 5$). Let v_i be the trait of individual, u_{it} be the trait-task interaction, w_{im} be the trait-method interaction and r_{itm} be the trait-task-method interaction:

(1) Condition on random components $(v_i, u_{it}, w_{im}, r_{itm})$, y_{ijktm} follows the Poisson distribution with the conditional mean $E\{y_{ijktm}|v_i, u_{it}, w_{im}, r_{itm}\} = \mu_{ijktm}$. With the log link we have:

$$\begin{aligned}\eta_{ijktm} &= \log(\mu_{ijktm}) \\ &= \mu + \alpha_j + \beta_k + T_t + M_m + TM_t + v_i + u_{it} + w_{im} + r_{itm},\end{aligned} \tag{1}$$

where $\mu, \alpha_j, \beta_k, T_t, M_m$ and TM_{tm} are fixed effects for the overall mean, effects of the project, session, task, method and the task-method interaction, respectively.

(2) The random components follow normal distribution:

$$v_i \sim N(0, \sigma_v^2), u_{it} \sim N(0, \sigma_u^2), w_{im} \sim N(0, \sigma_w^2), r_{itm} \sim N(0, \sigma_r^2)$$

In HGLMs, $\theta = (\alpha^T, \beta^T, T^T, M^T, TM^T)^T$ are parameters for fixed effects, $\tau = (\sigma_v^2, \sigma_u^2, \sigma_w^2, \sigma_r^2)^T$ are parameters for variance components, and $b = (v^T, u^T, w^T, r^T)^T$ are random effects. For the absence of random effects we can test the nullity of variance components. For example, if $\sigma_v^2 = 0$, all $v_i = 0$ (the absence of v_i component). In the test for the variance component, the testing hypothesis is onthe boundary of the parameter space (e.g. $\sigma_v^2 = 0$), the critical value is $\chi^2_{1,2\alpha}$ for a size α is the $1 - 2\alpha$ quartile of χ^2_1 distribution (Lee *et al.*, 2006). For size 0.05 test, the critical value is $\chi^2_{1,0.9} = 2.706$. Table III shows the results of deviance tests for variance components based on the residual likelihood (Lee *et al.*, 2006). The deviance difference for the hypothesis $\sigma_r^2 = 0$ is 0.09 which is less than 2.706 so that $\sigma_r^2 = 0$ is not rejected. Similarly, $\sigma_u^2 = 0$ and $\sigma_v^2 = 0$ is not rejected. However, because the deviance difference 22.07 is greater than 2.706 for the hypothesis $\sigma_w^2 = 0$, we can reject the null hypothesis $\sigma_w^2 = 0$. Hence, the results indicate that the random individual effect v_i, the random individual-task interaction u_{it}, and the random individual-task-method interaction r_{itm}, are not present. Therefore, the individual intelligence ratio represented in a linear predictor, removing all insignificant random effects is as follows:

$$\eta_{ijktm} = \log(\mu_{ijktm}) = \mu + \alpha_j + \beta_k + T_t + M_m + TM_t + w_{im} \quad (2)$$

Also, in order to test the absence of fixed effects, we use one of the deviance tests based on the likelihood using "Laplace approximation" model by Lee *et al.* (2006). Table IV summarizes the sequential analysis for selecting the fixed effects through the backward elimination. Since the deviance difference follows approximate χ^2 distribution in which degrees of freedom (df) is the difference of the number of parameters, we can test whether each fixed effect is significant or not. Because the deviance difference 211.10, is greater than the critical value under 0.05 significance level (i.e. $\chi^2_{2,0.95} = 5.991$), the null hypothesis $\alpha = 0$ is rejected. Similarly, the null hypothesis, $\beta = 0$ is also rejected (the deviance difference $7.98 > 5.991$) and $TM = 0$ is also rejected (the deviance difference $199.97 > \chi^2_{16,0.95} = 26.996$). Hence, we conclude that all of the fixed effects are necessary in the final model. Because task-method interaction TM_{tm} are significant, the corresponding main effects T_t and M_m are included in obtaining the individual intelligence ratio.

Results

Table V shows the estimates for the effects of projects and sessions. The team demonstrated higher collective intelligence ratios (CIR) as they were moving from the initial project to the final project.

There was no statistically significant difference between session 1 and 2. However, the team performed the best in session 3 with the highest CIR. The estimates of $T_t + M_m + TM_t$ are shown in Figure 4. For exploration (task 3), the number of positive contributions tends to be larger compared with other tasks, resulting in more collective efforts in completing the task with specifically shared team goals in mind.

Hypothesis	Deviance	Deviance differences
No zero variance components in model (1)	4503.68	
$\sigma^2_r = 0$ in model (1)	4503.77	0.09
$\sigma^2_w = 0$ in model (1)	4525.75	22.07
$\sigma^2_u = 0$ in model (1)	4503.75	0.07
$\sigma^2_v = 0$ in model (1)	4504.42	0.74

Table III. Tests for variance components

Hypothesis	Deviance	Deviance difference (df)
No zero fixed effects in model (2)	4418.01	–
$\alpha = 0$ in model (2)	4629.11	211.10 (2)
$\beta = 0$ in model (2)	4425.99	7.98 (2)
$TM = 0$ in model (2)	4617.98	199.97 (16)

Table IV. Tests for fixed effects

For description (task 2) and integration (task 5), the evidence of positive contributions is greatly varied with respect to the various methods in team interactions. Particularly, when external artifact (e.g. uploaded diagram or picture) was used, the description and integration (task 2 and task 5) have the lowest ratio whereas the team demonstrated the best ratios in speech.

Overall, speech was the most effective method for overall tasks for the team. In the model (2), random effects w_{im} represent the ith individual's intelligence ratio (IR) for the mth method. Because $\sigma_v^2 = 0, \sigma_u^2 = 0$ and $\sigma_r^2 = 0$ in the final model (2), all of v_i, u_{it} and r_{itm} are not present in this analysis. The estimates of w_{im} are given in Table VI.

Table V.
CIR estimates of fixed effect for projects and sessions

Parameter	Estimate	Standard error	t value
Project 1	0	–	–
Project 2	0.275	0.044	6.26
Project 3	0.583	0.041	14.13
Session 1	0	–	–
Session 2	− 0.015	0.041	− 0.37
Session 3	0.089	0.040	2.24

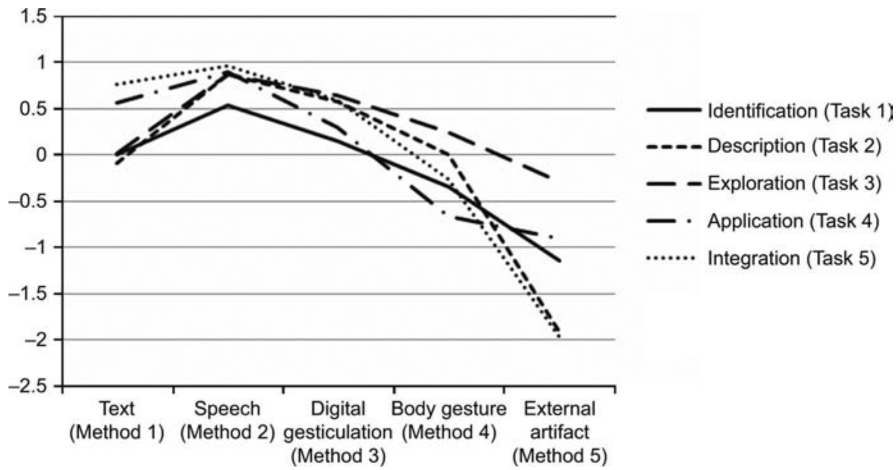

Figure 4.
Estimates of $T_t + M_m + TM_t$

Table VI.
Highest individual IR ratios in each method of communication

	Text	Speech	Digital gesticulation	Body gesture	External artifact
Subject 1	− 0.060	− 0.026	− 0.142	− 0.121	− 0.167
Subject 2	0.023	0.376[a]	0.074[a]	− 0.113	0.003
Subject 3	− 0.095	− 0.080	− 0.063	0.019	0.050[a]
Subject 4	0.097[a]	− 0.026	0.051	0.033	0.027
Subject 5	0.007	− 0.128	0.041	0.091	0.050[a]
Subject 6	0.040	− 0.107	0.051	0.106[a]	0.050[a]

Note: [a] Highest IR ratio in each method

Figure 5 clearly shows that subject 2 outperformed all other members in speech. Subject 6 performed the best with body gesture in which subject 2 performed poorly. For external artifact, the subject 3, 5 and 6 are the best. Nonetheless, we find that subject 2 demonstrated the highest estimate for the overall intelligence ratio $\frac{1}{5}\sum_{m} w_{im}$.

In sum, with the log link we can present the relationship as follows:

$$\mu_{ijktm} = \exp(\mu + \alpha_j + \beta_k + T_t + M_m + TM_t)\exp(w_{im}).$$

Thus, the exponent of the individual IR is multiplicative. For example, for the text method, the estimate of w_{im} of the subject 1 is -0.060, so that the subject 1 presents $\exp(-0.060) = 0.942$ times less intelligence ratio than the collective intelligence ratio in the Text method. This is how we can derive a perspective on IR between the individual and the collective.

Discussion

The findings illustrate how CIRs vary in sessions and projects, and how IRs vary in tasks and methods. Clearly, the team demonstrated a higher collective intelligence ratio (CIR) as they were moving from the initial project to the final project while the IRs of subjects varied over different communication methods and tasks. Interestingly, for exploration (task 3), the number of positive contributions of the team tends to be larger compared with other tasks, resulting in the evidence of more collective efforts. Unsurprisingly, speech was the most frequently used and effective method for overall tasks for the team, but it is interesting to observe how each subject demonstrates different levels of IR (i.e. more or less constructive to the overall collective cognition and performance) with different methods of communication during the team project process. The findings in this study may apply to only a limited domain with specific tasks. However, we can safely predict that people, with different traits and preferences, would not be able to best demonstrate most optimal IRs with a mere single type of communication channel (i.e. particularly for team cognition and performance in a synchronous virtual workspace).

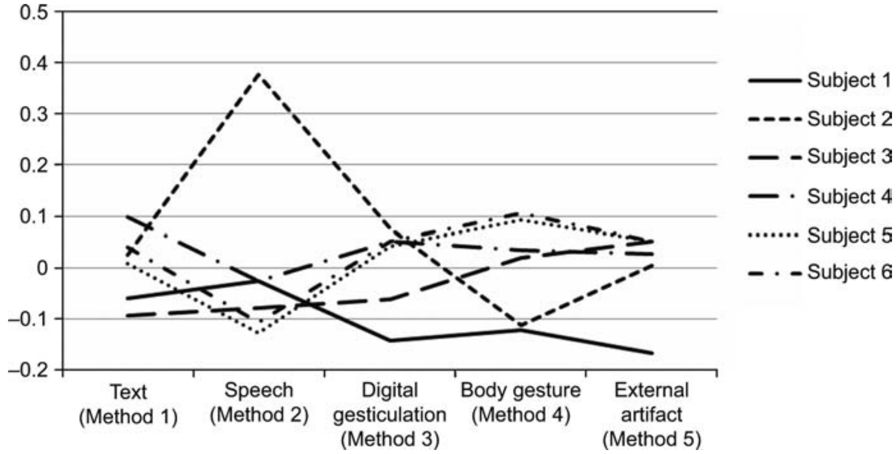

Figure 5. Overall individual IR in each method of communication

The present study offers implications for a few strands of future research. One strand may be in the discussion of transactive memory (TM) especially with the extension of transactive memory systems (TMS) and another strand may be in the study of team composition strategies for optimized team cognition. Wegner *et al.* (1985) came up with the concept of TM as a shared system in which group members develop for learning, storing, and retrieving information from different domains. During the past decade, TMS has attracted substantial attention because it has shown the positive effects on successful team outcomes (Wegner *et al.*, 1991; Moreland and Myaskovsky, 2000; Austin, 2003), including task performance, team learning, speed to market and team satisfaction. CIR identified in our study can serve as an indicator of the degree of flow efficiency of TM within a team. While conventional TMS may be inexplicitly constructed and recognized when teams are formed or reformed to work on multiple projects over time, IRs and CIRs could be more explicitly measured and recognized. Also, if TMS is subject to domain expertise, perhaps, IRs and CIRs are subject to media literacy, perceived media efficiency, or habitual traits.

Akgun *et al.* (2005) find that effective TMS occurs in a new product development (NPD) team when team members remain on the team from the pre-prototyping stage throughout the whole product development process. Also, the TMS would develop sooner if group members have prior personal interaction before the project team is formed (Akgun *et al.*, 2005). In this regard, a hybrid team[1], the transition model between a traditional and a virtual team is more likely to establish TMS better. However, there is no evidence in CIRs showing that the hybrid team progressively builds TMS as soon as they launch the first session (e.g. the CIR in session 2 was lower than the CIR in session 1). Another phenomenon may arise when it comes to a scenario where TMS is poorly or immaturely established. Interestingly, Majchrzak and Malhotra (2004) argue that multi-channel synchronous communication may help teams effectively share knowledge even with poorly developed TMS in the early stage. Nonetheless, the real-time multimodal communications could potentially play an important role in helping the team to compensate for the early gaps in the team's TMS. Certainly in future studies, it will be worthwhile to compare TMS flows with varying degrees of CIRs between face-to-face team interactions and multimodal team interactions as the teams work on multiple projects.

Additionally, the outcome of the present study expands the work of Brandon and Hollingshead's (2004) task-expertise-person (TEP) unit. Brandon and Hollingshead (2004) proposed that the basic units for a TMS are task-expertise-person (TEP) units, which link tasks to the expertise of team members. This construct also reflects the development of relevant literature in the fields of knowledge management and information sharing, increasingly adopted and developed in the research of team performance (Liang *et al.*, 1995; Hollingshead *et al.*, 2002; Moreland and Argote, 2003). They define task representation as the major attribute of transactive memory at a macro level while TEP unit as a microelement defining the connections between expertise and team member. Thus, TM relies upon a true recognition of task-expertise-person relations in a team (i.e. in order to effectively distribute cognition responsibilities accurately). However, Brandon and Hollingshead (2004) admit that such accuracy can be difficult to achieve given that there may be no objective measure of real expertise in teams. A suggested way is to ask team members to conduct peer assessments on knowledge (i.e. cognitive task-related experiential knowledge or expertise) responsibilities (Hollingshead, 1998; Moreland *et al.*, 1998). Given that the peer evaluation is still rough recognition and perception, in our study, we provide IRs for TEP units and CIRs as more objective additional references for a team TMS. Furthermore, based on a computed CIR, an optimized team composition might be devised to avoid a scenario where all members are good at identifying a particular problem, but none knows how to "apply" or attempt to adequately "integrate" presented ideas to complete projects (see Table VII). As it is reflected in Wegner *et al.*'s (1985) assumption, TM is more useful when members perform different functions and less useful when they perform the same functions. Perhaps, a smaller optimized team may perform more efficiently and effectively than larger un-optimized teams. Such concept will require future in-depth analyses with multiple team compositions. Overall, there are many other ideal scenarios that can be derived from the findings of this study, but speculations of such call for further experiments and in-depth analyses.

Another implication from this study relates to cognitive interdependence in a form that one member's output becomes another member's input (Thompson, 1967; Brandon and Hollingshead, 2004). As individuals work within a team, they must be able to utilize others' knowledge as well as develop their own (Bhappu *et al.*, 2001; Griffith and Neale, 2001). Participants in our study demonstrated a varying degree of individual intelligence from a very basic level to a higher-order level by taking advantages of individual's strengths in specific communicative methods (i.e. media-specific IRs). The preferable methods (i.e. they are interchangeably using for appropriate tasks) probably meet the demand of reducing cognitive burden on individual members and thus deepening their understanding towards the whole project and designing a solution in the overall team cognition environment. Therefore, team schema, backed by expanded TEP units on who uses what communicative methods to best tackle on what cognitive task (i.e. optimum cognition with least cognitive burden), could be made explicit and used by a team to devise ideal distributed cognition systems within a team.

Overall, IRs and CIRs stem from optimal choices and combinations of communicative methods for given cognitive tasks. The degree of efficiency in media choices may increase as media literacy improves. We view that identified IRs and CIRs certainly influence team performance outcomes in many team project scenarios. Therefore, the capability of dynamically combining the most optimal media to creatively and effectively respond to communication needs in various problem solving situations is a form of media intelligence.

Limitations

Unfortunately, this study presents several shortcomings. First of all, by reviewing and categorizing the data into five critical thinking categories, we limited the type and

	Text	Speech	Digital gesticulation	Body gesture	External artifact
Subject 2	0.023	0.376[a]	0.074[a]	−0.113	0.003
Subject 4	0.097[a]	−0.026	0.051	0.033	0.027
Subject 6	0.040	−0.107	0.051	0.106[a]	0.050[a]

Note: [a] Highest IR ratio in each method

Table VII. Optimized team composition based on CIR nature of human intelligence within a very short list of categories. Second, the data was evaluated by only one subject matter expert, leading to reliability issues. Third, the body gestures observed in webcam videos could not possibly reflect free gestures that can be demonstrated in unconstrained space. Fourth, the data coding was done by complete manual labor and took an extensive amount of time to review the recorded sessions. Lastly, we only explored a limited number of participants who had clear goals in mind. In a conventional social networking setting, collective intelligence may involve a much larger group of participants without clear goals to achieve or specific tasks to work on in a sequential manner. Therefore, the merit of this study may be simply in offering a possible multimodal interaction analysis model and interpretation example. Therefore, it certainly invites future studies addressing the shortcomings.

The multimodal interaction analysis model can be improved by integrating additional factor analysis components to understand the overall interactions among other variables that may directly or indirectly contribute to the overall team performance and project outcome. Also, the RMI data coding process may be improved by employing a set of video annotation tools and semantic analysis models.

In sum, with the rapid advancement of information and communication technology, team interaction modalities and real-time communication environments will continue to evolve. In turn, such advancement will allow people to enhance team cognition, interaction, and performance with more dynamic and augmented collective intelligence. In order to become more effective in team interaction and performance in future multimedia-rich communication environments, people might have to acquire and develop media intelligence. In our future research, we hope to identify and study innovative ways of using multimodal interaction tools to improve productivity in future teamwork scenarios.

Note

1. Griffith and Neale (2001) exam the development of transactive memory across three types of teams (traditional, hybrid and virtual). We find that the team in our study is closer to the type of hybrid team because six team members met each other in the class but conducted all of the group discussions via RMI workplace like other virtual teams.

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