Analyzing Students' Collaborative Regulation Behaviors in a Classroom-Integrated Open Ended Learning Environment

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Abstract: Identifying the effects of students' collaborative regulation behavior when working on a task is an important step towards a better understanding of how collaboration supports learning. We discuss a study where we combined analysis of students' dialogues with an automated analysis of their action patterns as they constructed science models in an open-ended learning environment. Our results show that students use different types of collaborative regulation behaviors, and that these behaviors affect their performance on the system as well as their pre-post learning gains. We also showed that groups, which adopt more shared regulation used different learning strategies than groups that did not.

Introduction

Research on collaborative learning has established that metacognitive processes are critical for group performance and individual learning (Volet, Vauras & Salonen, 2009; Saab, 2012). Computer-supported collaborative learning systems derived from open-ended learning environments (OELEs) (Land, 2000; Segedy, Kinnebrew, & Biswas, 2015) provide effective pedagogical contexts to support these processes, which, in turn allows researchers to examine and analyze these processes in greater detail. By providing students with tools and other resources to construct science models, combined with data logging capabilities we can identify behavioral patterns and make inferences on learners' cognitive and metacognitive processes.

The research presented in this paper assumes learners' action patterns (i.e. frequent action sub sequences) interpreted in the context of the learning tasks facilitated by the OELE, are indicative of their learning behaviors and strategies Thus, a contextual analysis of these action patterns may allow us making inferences on students' metacognitive processes (Kinnebrew, Segedy, & Biswas, 2014). There is growing consensus that metacognitive processes evolve as a series of events that can be derived from students' learning behaviors (Winne, 2010; Hadwin, et al. 2007).

In the study reported in this paper, 6th grade students worked in pairs using an OELE called Betty's Brain (Leelawong & Biswas, 2008) to construct a causal map of a complex science topic (climate change). The pair worked on a laptop, with shared input devices (mouse and keyboard) to build their models. The classroom teacher asked students to work together to build their models, and take turns in controlling the input devices. Betty's Brain adopts an open-ended approach to learning by modeling, and this prompts students to develop learning and problem solving strategies, along with metacognitive processes that help them monitor their learning and model building tasks. The system collects rich log data of students' action sequences and their performance on the system, thus allowing more detailed analyses of their behavior and performance.

Also, we leverage analytics and data mining techniques (Kinnebrew, Loretz & Biswas, 2013) to detect behavioral patterns, and combine them with an analysis of the dialogue between the students to study three forms of regulation: (1) *self-*, (2) *shared*, and (3) *other-regulation*. We hypothesize that groups that exhibit more shared regulation show greater awareness and better understanding of the task. As a result, they learn more and perform better. We perform a case study to determine if the data supports our claims.

Background

Metacognition and collaborative learning

In collaborative situations, one's metacognitive awareness and understanding may be extrapolated and projected for the active regulation of shared problem solving processes, such as contributing to goal setting, planning, progress monitoring, and reflection (Brown & Palinscar, 1989; Kinnebrew, Segedy, & Biswas, 2014). Collaborative work brings out the reciprocal nature of metacognitive activity and processes that is governed by dialogue structures that may include self-disclosure, feedback requests, and other-monitoring. A few studies have examined socially shared regulation or how a social setting affects individual metacognition. Goos et al. (2002), for example, argue that the social setting mediates metacognition by prompting an individual's metacognitive awareness, a process where transactive reasoning (i.e., reasoning on the reasoning of others) is critical. Other authors (e.g., Volet, Summar & Thurman, 2009; Iiskala, Vauras, Lehtinen & Salonen, 2011) define socially shared metacognition as inter-individual metacognition. Similar to an individual controlling her cognitive activity, socially shared metacognition "is consensual monitoring and regulation of joint cognitive processes" (Iiskala et al., 2011, pg. 379). Primers for metacognitive processes becoming shared are verbalizations of metacognitive experiences that prompt other group members to contribute to the regulation of the task. That individuals often profit from external regulation of their problem solving task is well established (e.g., Azevedo, Cromley & Seibert, 2004), and the assumption is that in collaboration, such regulation is partially accomplished by the collaborators. In consideration of the additional tasks related to coordinating collaborative activity, the question is how socially shared regulation affects group performance and individual learning. Like the study presented in this paper, recent work used mixed methods, combining the analysis of verbal interaction with trace methodologies to measure collaborative metacognitive regulation. Winters & Alexander (2011) found a significant positive relationship between students' regulatory behaviors and their learning gains. Schoor & Bannert (2012), in contrast, found no difference in the frequency of regulatory activities between high and low performing dyads. Järvelä, Malmberg & Koivuniemi, (2016) differentiated between self- and shared-regulatory activities related to task understanding, planning, strategy use, and motivation (cf. Winne and Hadwin, 1998), finding positive relations among socially shared regulation processes (planning and motivation) and performance. Importantly, Järvelä et al (2016) applied a temporal process analysis of student actions, and identified correlations between process patterns and high-performance groups: socially shared regulation of tasks is a critical factor for performance, but it needs to be supported by prior practice of individual regulation. The study also showed that students' sharing regulation of learning accrued more learning gains, especially if regulation was shared during the solution construction phase.

Analyzing students' actions

As learners' cognitive and metacognitive processes are not directly visible, a common approach is to infer these processes from patterns of learners' actions and the context in which they invoke these actions (Winne, 2010, Kinnebrew, Segedy, & Biswas, 2016). In OELEs, such as Betty's Brain (see Figure 1), actions occur on explicitly designed interface features that enable the analysis of their activities in more specific task-related contexts. For example, students may access a *Science Book* by clicking on a tab of the main interface, an action that is an indicator of acquiring information to learn about the science topic; accessing the *Quiz* tab is linked to the more general task of solution assessment and monitoring; by working in the *Causal Map* page, students construct their solution (Leelawong & Biswas, 2008; Segedy, Kinnebrew, & Biswas, 2015).

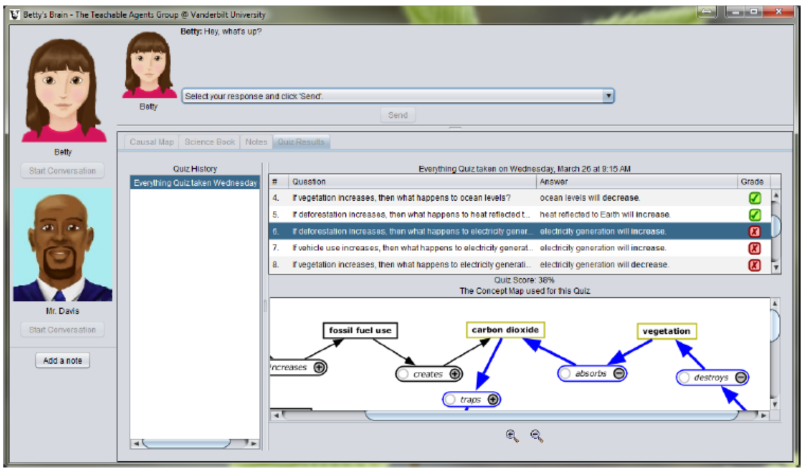

Figure 1. The Betty's Brain system. The page shown in the figure is the Quiz page.

Analyzing students' action sequences in learning research

Increasingly, researchers are utilizing trace methods to analyze learners' actions in an effort to make inferences on their metacognitive processes. The underlying rationale is that metacognitive processes are best studied by examining the effects of metacognitive control. Other methods, such as questionnaires, typically provide post-hoc accounts of metacognitive experiences and processes, and are less suited to capture the dynamic nature of regulation processes.

A new development in this respect is using sequence mining techniques to detect patterns of recurring actions. These techniques are especially applicable to examine differential use of actions and action patterns in varying groupings of learners. For example, high-performing students are much more likely to read information and use that information to make progress in a problem solving task than are their lower-performing peers who may find it difficult to connect their reading to their problem solving task requirements (Kinnebrew, Segedy, & Biswas, 2014).

Sequential characteristics describe the learning activities a student typically uses and they inform the actual process of self-regulated learning (Johnson, Azevedo, & D'Mello, 2011). To examine the links between actions produced by shared or individual regulation, action sequences have to be examined in context and their relation to each other. Weak or no relations between actions that make up a pattern suggests that learners' cognition is broadly un-regulated. This may imply the learners are applying a trial and error approach without a specific focus or direction. In contrast, regularity and coherence relations among actions and frequent use of action patterns suggests that the learner(s) are exerting control, derived from strategies (Kinnebrew, Segedy, & Biswas, 2016). Thus, a first important analysis concerns whether regularly occurring action sequences can be detected; subsequently we examine whether action patterns resulting from shared, other-, or self-regulation differ.

Actions in Betty's Brain

In Betty's Brain, students' information acquisition, map building, and map checking actions are recorded in log files. In addition, students can also add and view notes (NOTESVIEW; a 'note' is a text box in which to collect or summarize information from the science book deemed to be relevant); and ask Betty to explain her answers to quiz questions (EXPL). The most common actions and their labels are listed in Table 1.

Table 1: Actions in Betty's Brain and their log labels

Action description	**Action log label**
Reading the resources to learn about the domain of study	*READ*
Adding or Viewing a Note	*NOTESVIEW*
Adding a concept	*CONCADD*
Adding a causal link	*LINKADD*
Removing a concept	*CONCREM*
Removing a link	*LINKREM*
Indicating that a link is believed to be 'correct';	*CLMARKCORR*
Have Betty take a quiz about the map	*QUIZTAKEN*
Highlight the part of the causal map that Betty used to answer a quiz question	*QUIZVIEW*
Ask Betty to explain her answer	*EXPL*

Some logged actions are further characterized by attributes. Relevant for this study are 2 attributes. If the period between a READ action and an immediately following action is below 3 seconds, the READ action is logged as READ-SHRT (for 'short reading'). Short reads are interpreted as shallow skimming over the learning material. Actions on links (adding or removing) are associated with the change in map score that these actions entail. A link action increasing the map score is logged with the suffix –EFF (for 'effective'), an action decreasing it with the suffix –INEFF (for 'ineffective').

All actions are classified in higher-level categories corresponding to cognitive process that, when combined, constitute metacognitive strategies. Building on prior work (Kinnebrew, Segedy, & Biswas, 2016), actions are classified as the cognitive processes of Information Acquisition (READ, NOTESVIEW), Solution Construction (all actions on the causal map, e.g. LINKADD) and Solution Assessment (QUIZ actions). The actions listed in table 1 constitute the elements of action sequences; in the Results section we will present the action sequences in the terms they are recorded by the system.

The study

The focus of the study conducted in this paper revolves around two primary research questions:

RQ1*: Do the extent of groups' self-, other and shared regulatory activities correlate with their* *performance? (RQ1.1); and do students' self-, other and shared regulatory activities correlate with their pre-posttest learning gains? (RQ1.2)*

***RQ2**: Do students' action patterns differ when they adopt socially shared regulation strategies as opposed to working more on their own?*

We discuss our methods to answer these questions below.

Method

Participants

14 middle school students (6th grade) from an academic magnet school in Southern USA participated in the study. To enroll in this school, students need an average grade of B+ during the previous academic year. All participating students were in a self-contained class taught by the same teacher. Overall, the study lasted 7 days. On day 1, students were introduced to the science topic (climate change), provided an overview of the idea of concept maps, and given hands-on training with the system. On day 2, students were tested on their knowledge of climate change, of reading comprehension and introduced to causal maps, and reasoning with causal maps. These tests constituted the pre-test. Then students of equal academic capability who were deemed compatible following the teacher's suggestions were paired to work together. The grouping yielded 3 single-sex dyads (all male-male dyads), and 4 mixed-sex dyads. On days 3 to 6, the dyads then worked on the system constructing the causal map. We call these days *study days*. They lasted on average 50 minutes per day. Students were instructed to collaborate, i.e. to discuss and take decisions jointly. These instructions were occasionally repeated during the study sessions. On day 7, students took a post-test consisting of the same items as the pre- test.

Data collection

Groups worked at a single computer with one student controlling the mouse. The teacher explained that one student in the group should have control of the mouse, the primary input device, for half a study day, and then let the second student take over control of the mouse. Talk and behavior (e.g., attention to the other student) was recorded using Camtasia as audio-video data from web-cams synced to a screen capture video. Student-system interactions were automatically logged by the system. The log files recorded the action (e.g. adding a causal link, accessing a specific page in the Science Book) with the group ID with corresponding time stamps on a central server.

Transcript analysis

Students' talk was transcribed with the turn-of-talk as the smallest unit of analysis. The time stamp of each turn was recorded manually to allow synchronization with action logs. When a student-system interaction was carried out immediately after or during talk, talk and action were transcribed as a single turn-of-talk. Transcription yielded a total of 5774 turns-of-talk (mean: 825, *SD*: 157).

A small set of transcribed talk was first coded by two authors of this article. Verbal data were the primary source for coding, although visual gaze, nodding or other non-verbal behavior was occasionally also examined for coding. Differences in coding were discussed until a consensus on the definition of the coding categories was reached. Then, one author coded all remaining transcripts, while the other coded 20% of transcripts selected from different groups and study days. Inter-rater agreement (Cohen's kappa) was .87. By most accounts (e.g., Bakeman, Quera, McArthur, & Robinson, 1997), a kappa value above .81 is considered "excellent agreement."

Coding proceeded by first identifying initiative-response relationships between turns of talk (Kneser, Pilkington & Treasure-Jones, 2001). We argue that this lens is helpful to capture whether a discussion is reciprocal (i.e. both students initiate ideas and contribute constructively to the discussion) or not (when one student is dominant, the other is silent or may carrying out the instruction).

We relied to prior analysis schemes as a guide to develop our coding categories (Volet, Summer, & Thurman, 2009; Hadwin et al. 2011):

Socially Shared Regulation (SSR, figure 3): turns-of-talk were coded as SSR when the students question or elaborate on their partner's initiative or with an alternative. This is the case, for example, when proposals are not passively accepted, but negotiated and may lead to more protracted discussions. Discussions include various topics, such as what to do next, how a proposed action fits into an overall plan, how to proceed after an assessment, and so on. In these discussion, students are likely to verbalize their strategies (e.g. "how do we link incorrect quiz answers to incorrect links in our map?") and demonstrate metacognitive awareness and processes

("Have we read about sea level rise?", "Should we check our map now?"). Goals, plans, and strategies are co-constructed, and regulation is distributed and shared with multiple ideas being weighed and negotiated (Miller and Hadwin, 2015).

Other-Regulation (OR, figure 2): in this form of regulation, a student is temporarily dominant and instructs the other. This form of regulation occurs frequently when the less dominant student is in control of the mouse. When this student just performs suggested actions without discussion, we code it as OR. Importantly, instructions are almost never accompanied by verbalizations of rationales, plans or strategies, or metacognitive experiences.

Self-Regulation (SR): Self-Regulation occurs when a student is temporarily in full control of problem solving, with no contribution from the other student. The Self-Regulation code can only be applied to a student in control of the mouse. The partner may be absent, may not be contributing or interested in contributing, or the student controlling the mouse may disregard the partner's attempted contributions and suggestions.

S Talk and Actions	Code
Adam: "We should add a link"	OR
John: [Activates link button]	OR
Adam: "No, go back to the science book"	OR
John: [Opens science book]"What should we read?"	OR
Adam: [Reads from the page and tells John]	OR

S Talk and Actions	Code
Hana: "We got 4 right and 2 wrong" (students are viewing quiz results)	SSR
Sam: "Let's edit it" [marks the causal link between 'ice and ocean level' as 'maybe wrong']	SSR
Hana: "So, we should fix all of these links?" (points to the links)	SSR
Sam: "Yes, we need to do more work" "Let's go to the science book"	SSR
Hana: [Opens science book to search for 'ocean levels']	SSR

Figures 2 and 3. Transcript extracts illustrating other-regulation (figure 2, left figure) and socially shared regulation (figure 3, right figure). Interface actions were noted in the transcript in square brackets (e.g. [Opens Science Book]). These actions are automatically recorded in the log files as well and are the data on which the sequence mining algorithm is applied.

Results

We report briefly the quantitative profiles of all groups. In two groups, students jointly carried out the task – groups 1 and 7; mean percentages: 68% SSR (SD = 4.2%), 23% SR (SD = 2.1%), 9% OR (SD = 3.5%); in two others it was often only one student – groups 5 and 6; mean percentages: 21% SSR (SD = 2.8%), 73% SR (SD = 9.1%), 6% OR (SD = 6.3%). In the three remaining groups, joint and individual regulation is balanced – groups 2, 3 and 4; mean percentages: 40% SSR (SD = 9%), 48% SR (SD = 6.8%), 12% OR (SD = 4.5%). OR occurs infrequently in all groups.

RQ1.1*: Do groups' self-, other and shared regulatory activities correlate with their performance?*
To address this question, the Pearson correlation coefficient between self-, other- and socially shared regulation of learning per group (sum of all days) was calculated. A significant positive relationship between the frequency of SSR and the map scores ($r = 0.75, p < .05, SE = 0.31$) was found.

RQ1.2*: Do students' self-, other and shared regulatory activities correlate with their learning gains?*
To answer this question, the Pearson correlation coefficient was calculated between the frequency of SSR and SR of a group, and the students' learning gains. There was a significant positive relationship between individual learning gains and frequency of socially shared regulation ($r = 0.59, p <.05, SE = 0.32$), and a significant negative relationship between individual learning gains and the frequency of self-regulated actions ($r = - 0.54, p < .05, SE = 0.31$). These results lend some support to the claim that individual students learn more when they jointly regulate the task.

RQ2*: Do action patterns differ when a group jointly regulates the task compared to when in a group individual students often work on their own?*
To answer this question, we employed a differential sequence mining technique (Kinnebrew, Loretz & Biswas, 2013) that detects recurrent action patterns in a set of action sequences. We selected two groups (1, 7) which consistently demonstrated high frequencies of shared regulation (the *bothStudents* profile) and two groups (5, 6)

where one student worked often by themself (self-regulation), or instructed the other (other-regulation). This set is called the *oneStudent* profile. We justify aggregating instances of Self- and Other-Regulation by pointing out that in Other-Regulation students rarely verbalize their metacognitive experiences or provide rationales for their instruction.

The sequences of logged actions of all groupings (oneStudent and bothStudents) were analyzed with a gap size constraint of 1, yielding a very large set of action patterns (~ 60,000). A gap size constraint of 1 means that between each consecutive pair of actions in a frequent pattern, the mining algorithm allows up to 1 of additional actions. A sequential pattern with such an optional (small) gap (e.g., the pattern A → B → C) means that each subsequent action in the pattern is performed shortly after the previous action even if there were intervening actions that are not part of the pattern. For example, a student performs A, followed by B, then D, then C; i.e. the actions A, B and C are followed in close, but not necessarily direct, succession, and the single action D is treated to be irrelevant.

Associated with each pattern are the following values: for each pattern, a value representing in how many groups was the pattern detected regardless of frequency (S-frequency), and a value of how frequently a pattern occurred by an 'average' group (I-frequency). The 'average' group is calculated using the actual data used in this study. Patterns are ordered by I-Frequency of the oneStudent grouping and assigned an index starting from 1 and increasing as that I-frequency decreases. Patterns with low indices occur very frequently in the oneStudent condition; patterns with a very high index (40k-60k) occur with high frequency in the bothStudent condition. We computed the difference in I-frequencies and their ratio to identify 1) frequently occurring action patterns and 2) action patterns occurring with high I-frequency differences or ratio differences relative to the two groupings.

We first report the most and least frequent action patters in both groupings. The most frequent patterns for the oneStudent grouping are short or longer map edits (e.g. ADDCONC; ADDCONC; ADDLINK; ADDCONC) (1). and explanations (e.g. pattern 96, table 2). Sequences of only explanation actions and only map edits (up to 7 consecutive actions) occur at much higher frequencies in the oneStudent grouping than in the bothStudents grouping. The I-frequency ratios (oneStudent:bothStudents) averaged over all action patterns with only map edit or only explanation actions, regardless of length, are 5.1:1 and 5:1, respectively. The most frequent action patterns in the bothStudent grouping involve READ actions. Action patterns with only READ actions (up to 7 consecutive actions) occur on average 2.6 times more often in the bothStudent grouping. For this grouping we also identify distinct action patterns that involve taking and viewing notes (VIEWNOTES), and marking a causal link as 'correct' or 'incorrect' on the causal map (CLMARKCORR). This latter action is an expression of the belief that a link is correct (or not), and thus can be interpreted as a progress marker (if marked 'correct') or as an organizer of future activity (if marked 'incorrect). Action patterns involving the VIEWNOTES action occur 5 times more often in the bothStudents groups; those involving marking actions occur almost never in the oneStudent grouping.

We then examined the sequence mining results to identify action patterns that span distinct high-level process elements, such as patterns that involve reading *after* taking a quiz, or taking a quiz *after* adding elements on the map. With regard to strategies involving information acquisition and subsequent actions, we found that students' in the bothStudents grouping identify important information and then work only briefly on the map more often those in the oneStudent grouping. More in general, in the bothStudents grouping, the students read the Science Book or their notes, and then add one or very few concepts or links (e.g. pattern 51919). Students in the oneStudent grouping, in contrast, read in the Science Book, then work on the map adding several concepts or links without returning to the Science Book (pattern 635). This finding generalizes to several action patterns involving READ followed by MAPEDIT actions.

Of particular importance are strategies carried out after a progress assessment. For strategies involving the QUIZ as the first action we find that in the bothStudents grouping, the students return to the Science Book after a QUIZ much more frequently than students in the oneStudent grouping (e.g. pattern 51581). This strategy indicates that the students in the bothStudent grouping were better able to interpret the results of a quiz in terms of missing understanding, which they seek to address by reading. Students in the oneStudent grouping, in contrast, either immediately work on the map (including by removing concept, see pattern 76) or by asking Betty for an explanation (pattern 71). Working on the map after a quiz results is very likely indicative of a trial-and-error strategy.

Students' application of information and actions after assessment generalizes to strategies involving all multiple different high-level process elements. Students in the bothStudents grouping are more likely to carry out an IA, SC, SA strategy (e.g. pattern 52028 and 49062); students in the oneStudent grouping demonstrate a strategy that involves multiple quiz views and map actions (pattern 1376), a validation of our earlier suggestion that these students are more likely to solve the task through trial-and-error.

Table 2: Action patterns with high differences in I-frequency (reported as ratio) relative to the two groupings. Patterns are listed by ascending index

Index	Pattern	1S:2S ratio
49062	LINKADD-INEFF;READ; QUIZTAKEN;READ;	1:1.9
51581	QUIZTAKEN;QUIZVIEW;REA; READ;READ;LINKADD;	1:2.4
51897	LINKADD-EFF;QUIZTAKEN; QUIZVIEW;READ;	1:2.1
51919	READ-SHRT;READ; LINKADD;	1:1.9
52028	READ;LINKADD;QUIZTAKEN; QUIZVIEW;	1:2.6

Index	Pattern	1S:2S ratio
71	QUIZTAKEN;QUIZVIEW;EXPL; EXPL;	5:1
76	QUIZTAKEN;QUIZVIEW; CONCREM;CONCREM;	7.6:1
96	EXPL;EXPL;EXPL	4.3:1
635	READ;CONCADD;CONCADD;LI NKADD;LINKADD;LINKADD;	5.3:1
1376	QUIZVIEW;CONCADD;LINKAD D;QUIZTAKEN;QUIZVIEW;	2.2:1

Discussion

This study set out with the aim of analyzing students' collaborative regulation behaviors in an OELE and linking the behaviors to students' metacognitive strategies. Our quantitative analyses show that students who adopted more shared-regulation strategies demonstrated better task performance and learning gains than those that do not. We thus confirm other's findings on the importance of collaborative metacognitive regulation (Winters and Alexander, 2011) and socially shared regulation (Järvelä et al., 2016).

By detecting frequent action patterns and how they occur with differential frequency in the two groupings, our study contributes to the question of *how* socially shared regulation affects performance and learning gains. Our results indicate that sharing regulation affects students' strategies with important implications on when and how they acquire knowledge, apply acquired knowledge, assess progress and react to that assessment. Evaluating differential frequencies of strategies based on Winne & Hadwin's (1998) model, we find that students sharing regulation adopt a) improved information acquisition and application strategies (reading followed by working on a single or only a few element of the map, then returning to the Science Book) b) better monitoring strategies (when to check the correctness of the current causal map), and c) improved strategies on how to react to assessments (reading followed by working on the map, instead of immediately altering the map).

We also identify action patterns that are distinct for each grouping, which further the question on the construct of socially shared regulation. As note taking and marking are much more frequent in the bothStudent groups, these actions can be interpreted as organizing collaborative activity. These groups seek external markers to summarize what they have read together, to mark what they have accomplished and to organize future joint activity. With regards to the identification of potential benefits of sharing metacognitive processes, the effect of such markers will need to be taken into account. Benefits may result from activities intended to organize collaboration – rather than strictly organizing problem solving. Iiskala, Vauras & Lehtinen (2004) argue that socially shared metacognition is a distinct process that cannot be reduced to the contribution of individuals to joint activity. Our study allows to qualify this assumption. Activities aimed at regulating and coordinating group activity prompt sharing of metacognitive awareness. Whether sharing metacognitive processes emerges from such coordination activities, from transactive processes (Goos et al., 2002) or from the projection of individual metacognitive awareness onto the group activity (Iiskala et al., 2011) is a question that warrants further examination.

Endnotes

(1) ADDCONC: added a concept to the causal map; ADDLINK: added a link to the causal map

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