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THE EFFECT OF COLLABORATIVE KNOWLEDGE MODELING AT A DISTANCE ON PERFORMANCE AND ON LEARNING

Josianne Basque, LICEF-CIRTA Research Center, Télé-université, Canada
Béatrice Pudelko, LICEF-CIRTA Research Center, Télé-université, Canada
Email: jbasque@teluq.uquebec.ca

Abstract. This study examines the effect of co-elaborating a knowledge model in dyads at a distance on performance and on learning. Participants (N = 48) were trained to represent knowledge taken from a text, using an object-typed knowledge modeling editor software tool. Knowledge modeling is similar to concept mapping, except that the former is based on a typology of knowledge objects and a typology of links, and that the structure of the knowledge representation is not necessarily hierarchical. After a 75-minute training session to knowledge modeling, each participant constructed a knowledge model individually. The experimental session consisted of elaborating a knowledge model in dyads. In the first condition, participants constructed and shared the knowledge model at a distance, using a whiteboard and a chat tool (synchronous group). In the second condition, participants elaborated one knowledge model with a turn-taking approach; they used e-mail to share their work-in-progress (asynchronous group). In the third condition, participants worked face-to-face at the same computer (control group). Pre- and post-tests were administered to measure learning in the domain. Results show that the quality of the knowledge models was better for dyads in the face-to-face condition than for the ones in the asynchronous condition, but only for the score related to knowledge objects (and not for the score related to propositions). We did not find a significant between-group difference on learning, but results indicate a tendency that working at a distance in a synchronous mode was more beneficial than working face-to-face and synchronously at a distance. These results should be interpreted with caution considering the short duration of the experiment and the low familiarity of participants with the targeted domain and with knowledge modeling.

1 Introduction

The construction of concept maps by learners is an educational strategy whose efficiency has been shown in several studies (Holley & Dansereau, 1984; Horton *et al.*, 1993; Novak & Gowin, 1984; Okebukola & Jegede, 1988). Creating concept maps favors significant learning (Novak & Gowin, 1984), allows learners to define implicit links of various concepts which are often confused by learners (Fisher, 2000), involves learners in deep knowledge-processing (Jonassen, Reeves, Hong, Harvey, & Peters, 1997) and leads them to ‘’learn how to learn’’ (Novak & Gowin, 1984).

Based on socioconstructivist and distributed learning theories, some researchers have started to investigate collaborative concept mapping. They claim that such a strategy triggers discussions and sociocognitive conflicts which are beneficial to learning. Thus, van Boxtel, van der Linden, & Kanselaar (2000) observed a greater number of such discussions with students who constructed collaborative concept maps than participants who produced a poster. Osmundson, Chung, Herl & Klein (1999) also observed buoyant arguments and discussions in small teams of 10-11 year old children who were creating computerized concept maps. Moreover, collaborative concept mapping triggers negotiation of meaning, a critical activity in the learning process (Osmundson *et al.*, 1999). Roth & Roychoudhury (1993) found that co-constructed maps allowed college students to ensure they were discussing the same concepts. Maps also made it easier to express mental representations than spoken language only. Concept maps have been described as a kind of “social glue” that brings participants to share a common representation of the task (Roth & Roychoudhury, 1992; 1994). However, studies addressing collaborative concept mapping situations are still scarce. Many of them have focused on the study of interactions among knowledge mappers (Roth & Roychoudhury, 1992 ; Sizmur & Osborne, 1997; van Boxtel *et al.*, 2000). But we know very little about the effect of this activity upon learning and on task performance, whether it is compared to individual learning situations or to other collaborative learning activities. Moreover, results are contradictory. Hence, Okebukola & Jegede (1988) have shown that maps created collaboratively were of better quality than those produced individually and that participants in the collaborative group achieved better results on a post-test measuring higher levels of Bloom’s taxonomy of learning objectives. However, van Boxtel *et al.* (2000) did not find any significant difference in comprehension post-test scores with participants who produced a collaborative concept map, compared to those who produced a poster collaboratively. Participants involved in the Suthers & Hundhausen (2001) study who produced a specific type of concept map (an ‘’evidential map’’) with the Belvedere tool did not outperform those who used a textual or matrix representation to analyze collaboratively various hypotheses of a problem. However, Osmundson *et al.* (1999) showed that written essays produced by 10-11 year olds after a three-week-long collaborative concept mapping activity were of better quality than those of students who had participated in other collaborative learning activities. Other researchers have assessed learning by using a post-test measure that consisted of asking participants to produce an individual map after the collaborative activity. Osmundson *et al.* (1999)

included such a measure. Scores associated to the individually-produced maps following a collective production were higher with participants involved in collaborative concept mapping. Stoyanova & Kommers (2002) obtained similar results with university students.

With the increasing popularity of telelearning and online learning in all educational circles and levels all over the planet, the remote, computerized collaborative construction of concept maps has also sparked researchers' interest over the last few years. Many researchers have focused on the interactions and processes which occur in such a context (Chiu, Wu, & Huang, 2000; Chung, O'Neil, & Herl, 1999; Fischer & Mandl, 2000, 2002; Reinhard, Hesse, Hron, & Picard, 1997; Suthers, Girardeau, & Hundhausen, 2002; van Boxtel & Veerman, 2001). Very few researchers have addressed the quality of the maps produced and the effects of such an activity on comprehension and learning. Moreover, all of these studies are limited to synchronous communication. Some studies highlight the low quality of collaborative maps while using a chat tool (Chung *et al.*, 1999). Slow typing (Chiu, Huang, & Chang, 2000), split-attention effect (Chung *et al.*, 1999) and lack of deictic affordances (Fischer & Mandl, 2000; Suthers *et al.*, 2002; 2003) could explain some of these issues. Most studies do not compare collaborative maps produced by live participants with those produced in remote interactions. Suthers *et al.* (2002; 2003) found no significant difference at a memory-for-factual-information post-test between participants who collaborated remotely to build an evidential map and those who worked face-to-face, although the participants in the face-to-face group wrote better essays. This paper presents a study where three situations of knowledge modeling[1] in dyads are compared, that is two remote scenarios (synchronous and asynchronous) and one face-to-face situation. This study investigates (1) collaborative knowledge modeling task performance, (2) individual learning as measured by a content-related test, and (3) the metacognitive interactions between members of dyads. This paper reports results related to the first two issues.

2 Methodology

2.1 Participants

Forty-eight adults (19 females, 29 males) of 19 to 57 years old (mean age: 34.6) participated in the study. Half of them were postsecondary full-time students in a variety of disciplines; others were workers with a postsecondary diploma and/or studying part-time at university. All were familiar with e-mail and most of them had already used chat software. Their self-declared prior knowledge in the targeted domain (cognitive information processing: CIP) and experience with knowledge modeling or concept mapping software were limited. Participants were randomly distributed into three groups: synchronous distance group (SYNCH; N=16), asynchronous distance group (ASYNCH; N=16) and face-to-face group (CONTROL group; N=16). They performed the collaborative knowledge modeling task in dyads (N=8 in each group). Pairing was assigned randomly and members of each dyad did not know each other before the experiment. Participants were paid to take part in this investigation.

2.2 Collaborative Knowledge Modeling Task

The collaborative knowledge modeling task consisted of co-elaborating a knowledge model in dyads immediately after having read individually, for 5 minutes, a short text (1 page) describing the principal components of a CIP system (sensory memory, short-term memory, long-term memory) and the CIP process as described in typical course material. Dyads had 50 minutes to construct their knowledge model using an object-typed knowledge modeling software called MOT developed at LICEF Research Center (Paquette, 2002).[2] In MOT, four types of knowledge objects are distinguished by using different graphic shapes: *concepts* (rectangles), *procedures* (ovals), *principles* (hexagons) and *facts* (rectangles with indented corners). These knowledge objects are linked to each other with arrows, the arrowhead indicating the link direction. Letter labeling is used to specify the link type: *Composition*, *Regulation*, *Specialization*, *Precedence*, *Input/Product (I/P)* and *Instantiation*. The software constrains the type of links that users can create between two specific types of knowledge objects. For example, a specialization link can only be used between two objects of the same type. Consequently, the specialization link is not accessible from the menu when the user is in the process of labeling

[1] A knowledge model is similar to a concept map as defined by Novak & Gowin (1984), except that, in a knowledge model, different types of knowledge objects (not just concepts) are represented with different shapes and a typology of predefined links is used.

[2] MOT stands, in French, for "*Modélisation par Objets Typés* », which means « *Object-typed modeling* ». The LICEF Research Center, based at Télé-université in Quebec, Canada, is a laboratory dedicated to cognitive informatics and training environments. For further details on MOT, refer to the LICEF website: http://www.licef.teluq.uquebec.ca

a link between two different object types. However, users can put their own label on what is called an "untyped" link. A specific shape is also provided for "untyped" objects. It is also possible to link a "comment" to a knowledge object or a link. Some authors argue that a constrained approach to concept mapping adds more precision, exhaustiveness and coherence to the knowledge representation, thus facilitating its interpretation and communication (Gordon, 1996; Moody, 2000; Paquette, 2002; Reader & Hammond, 1994).

Partners of a dyad in the SYNCH group communicate with each other via the *NetMeeting* software. The screen was divided in two windows (see Figure 1). In the MOT window, partners of each dyad co-constructed their knowledge model. Only the one "with the hand" could work on it, the other acting as an observer. In the chat window, they could send messages to each other at any time during the session. The sent and received messages appear in different colors. Participants in the ASYNCH group used e-mail to send the co-constructed knowledge model to their partner. Thus, each member of the dyad could not see in real-time the work done by their distant partner. While waiting for the knowledge model from their partner (i.e. the one "with the hand"), participants were instructed to help their partner by sending him messages, to think about what to do next or to re-read the text. Dyads in the CONTROL group worked side by side at one computer. In all groups, one member of each dyad was identified randomly as the one "with the hand" at the beginning of the session. They were told that they could exchange the hand as often as they wished during the session.

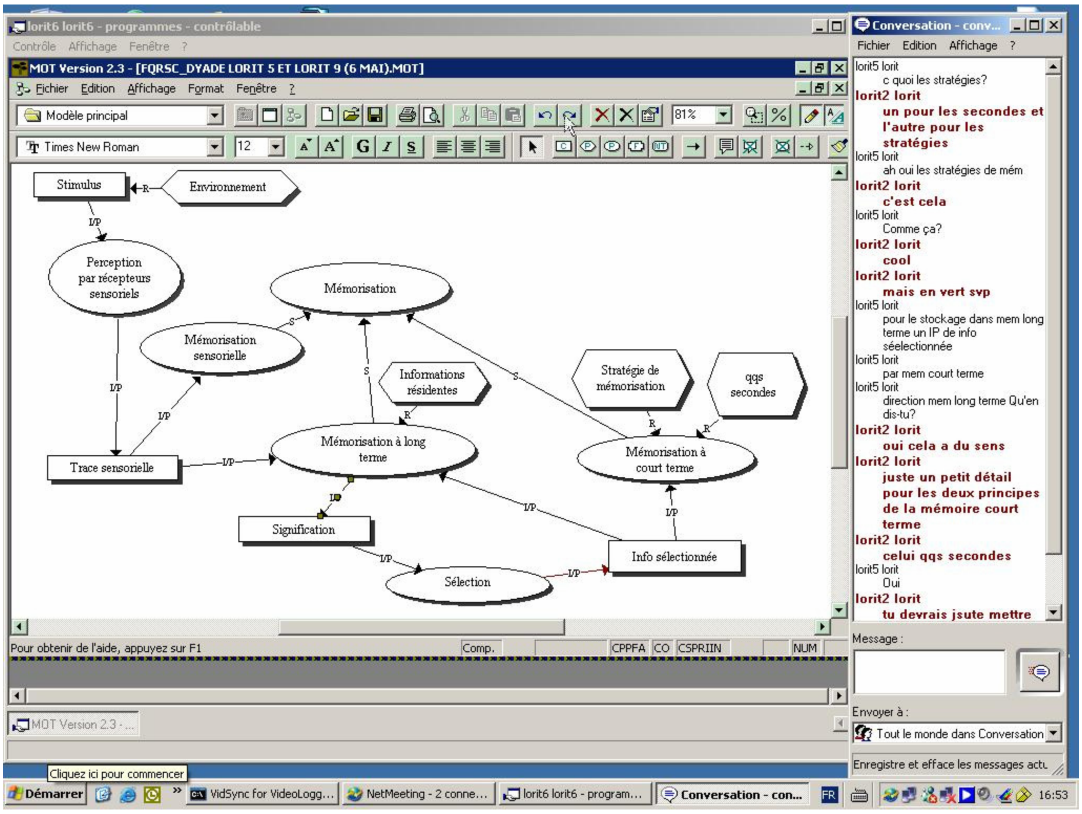

Figure 1. Screen capture of the NetMeeting window (SYNCH group)

2.3 *Procedure*

The experiment took place in 2003 at the LORIT, a distance learning engineering research laboratory based at Tele-universite, Canada.[3] To simulate distance in the experimental conditions, computer workstations were isolated from each other with partitions to ensure that participants could not see one another. Several sessions were organized, six students participating in each session (3 dyads). At the beginning of the session, participants were reminded about the research objectives and confidentiality issues. Second, a short pre-test (6 open-ended questions about CIP) was administered. Third, a 75-minute training session on the MOT software and on

3 For more information about the LORIT: http://www.licef.teluq.uquebec.ca/lorit/eng/index.htm.

knowledge modeling took place. During this training, participants did eight short exercises of increasing complexity (for example, identifying concepts, procedures and principles[4] in a sentence; linking those knowledge objects; reproducing a small MOT knowledge model in a text format, etc.). At the end of the training session, they were asked to represent individually a short text (6 lines) describing two waste-elimination methods in a knowledge model format using MOT. Twenty minutes was provided for this task. After a 15-minute break, participants performed the collaborative knowledge modeling task. Prior to this task, those in the experimental groups were briefly introduced to the online tool to use (chat or email). After a second break (20 minutes), participants filled out the post-test (identical to the pre-test).

2.4 Data Collection

The data collected during the experiment include the following: (1) pre- and post- measures of content-related knowledge; (2) the 8 exercises completed during the training session on MOT and on knowledge modeling; (3) individual knowledge models created after training on MOT, as a measure of knowledge modeling ability after training; (4) knowledge models created in dyads; (5) screen captures (with Windows Media Encoder) of the collaborative knowledge modeling sessions and (6) video capture of the collaborative knowledge modeling sessions (CONTROL group only). In this paper, we focus on pre- and post-test measures and on the evaluation of the individual and collaborative knowledge models produced.

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2.6 Data Analysis

Pre-tests and post-tests. Two independent coders scored the participants' answers to the 6 open-ended questions included in the tests. The maximum score was 21. Inter-rater agreement, as calculated with the Holsti's formulae (1969) on one-third of the total tests, was high (.89).

Knowledge models. Participants' knowledge models were compared to an "expert model" that was built by content experts and MOT experts[5] who performed the knowledge modeling task, first individually (same time limit constraints as the participants) and then collaboratively (without time limit[6]). Two scores were determined. The *Knowledge Objects score* (KO score) was calculated by summing up the total number of participant's knowledge objects that were also represented in the experts' knowledge model; for each knowledge object, 2 points were attributed if it was present and correctly typed and 1 point if it was present but incorrectly typed. The maximum score for the waste-elimination model was 30, and 82 for the CIP model. The *Propositions score* (P score) [7] was calculated by adding the total number of experts' knowledge propositions represented in the participant's knowledge model; for each proposition, 1 point was attributed if the same two knowledge objects were paired (regardless of the link); 1 point for each correctly typed knowledge object included in the proposition; 1 point if the link was correctly typed and 1 point for the correct link direction[8]. The maximum score for each proposition was 5. The maximum score was thus 72 for the waste-elimination model (18

[4] Due to time constraints, participants were not introduced to the ''fact'' knowledge objects.

[5] For the waste-elimination model, participants were two MOT experts and one content expert. For the CIP model, participants were two MOT experts and two content experts (also knowledgeable in knowledge modeling). Experts were instructed not to use the "fact" objects.

[6] The experts were told that they had to come to a consensus in constructing a knowledge model, which took 25 minutes for the waste-elimination model and 64 minutes for the CIP model.

[7] Novak & Gowin (1984) defined a proposition as " two […] concept labels linked by words in a semantic unit" (p. 15).

[8] If the link was not correctly typed, we put 0 for direction because, in MOT, some types of link have a predefined direction (for example, a specialization link goes from the more specific knowledge object to the more general one). As some dyads in the ASYNCH group constructed more than one knowledge model, we also coded the knowledge objects and propositions that were individually introduced by each participant and added them to the dyad score.

propositions) and 260 for the CIP model (52 propositions). Two independent raters scored the knowledge models with this method. Inter-rater agreements, as calculated with the Holsti's formulae (1969) on one-third of the knowledge models, was very high (waste-elimination: .96 for KO score and .97 for P score*;* CIP: .95 for KO score and .98 for P score).

3 Results

Group equivalence for knowledge modeling ability. The total score attributed to the exercises completed by the participants during training does not differ significantly among groups, $F(2,47) = .190$, $p > .05$. Performance to the post-training individual knowledge modeling task is also equivalent for all groups on both measures: KO score, $F(2,47) = .035$, $p > .05$; P score, $F(2,47) = .642$, $p > .05$. Based on these results, we concluded that groups' knowledge-modeling ability was equivalent before the collaborative knowledge-modeling task. The mean score for the exercises is relatively high (mean = 42.08, SD = 10.39; participants' maximum score = 56/56), but performance at the post-training individual knowledge mapping task is low, especially for P score (mean = 22.48, SD = 12.08; participants' maximum score = 48/72); the mean KO score is 15.71, SD = 4.19; participants' maximum score = 23/30). Thus, participants were genuine novice knowledge modelers. Regarding the total score of the exercises, we found a positive correlation with the two scores of the individual knowledge-modeling task (KO score: $r = .477$, $p \leq .01$; P score: $r = .524$, $p \leq .01$). Those last two scores are not significantly correlated to the self-reported content knowledge (KO score: $r = .110$, $p > .05$; P score: $r = -.105$, $p > .05$).

Effect of modality of collaborative knowledge modeling on task performance. Table 1 shows descriptive statistics for the two performance scores of the collaborative knowledge modeling task. The ANOVA reveals an omnibus significant difference only on the KO score, $F(2,23) = 4.10$, $p \leq .05$. There are no between-group significant difference on the P score, $F(2,23) = .262$, $p > .05$). Post-hoc analyses (Tukey's HSD) reveal that the KO score is significantly higher for dyads in the CONTROL group than in the ASYNCH group ($p \leq .05$). If we consider the two sub-scores of the KO score (Number of KO and Type of KO), there is a significant difference only for the Type of KO variable, $F(2,23) = 4.13$, $p \leq .05$. Between-group difference for the total number of knowledge objects is not significant, $F(2,23) = 2.95$, $p > .05$.

	SYNCH (N = 8)		**ASYNCH** (N = 8)		**CONTROL** (N = 8)	
Scores	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Knowledge objects (KO) score	25.63	6.16	21.75	4.80	29.00	4.00
Number of KO	13.63	3.25	11.75	2.66	15.13	2.03
Type of KO	12.00	3.34	10.00	2.51	13.88	2.10
Propositions (P) score	26.50	10.04	26.00	12.76	30.25	15.21
Number of P	6.63	2.45	6.38	3.25	6.5	3.30
Type of paired KO	12.13	4.26	11.13	5.79	12.88	6.40
Type of link	4.75	2.71	5.50	2.83	5.88	2.75
Direction of link	3.00	2.14	5.13	2.30	5.00	3.16

Table 1: Descriptive statistics of collaborative knowledge modeling task performance scores

Effect of modality of collaborative knowledge modeling on learning. Not surprisingly, as showed in Table 2, content-related knowledge has been enhanced in all three groups after the collaborative knowledge-modeling task, although it remained relatively low. The ANOVA results indicate that the difference between post- and pre-test scores is not significant between groups, $F(2,47) = 2.84$, $p > .05$, although descriptive statistics shows that this difference is higher for the SYNCH group than for the other groups. This result is almost significant ($p = .069$).

	SYNCH (N = 16)		**ASYNCH** (N = 16)		**CONTROL** (N = 16)	
Scores	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Pre-test	3.56	3.16	3.81	1.60	5.31	3.00
Post-test	11.81	2.69	9.75	2.91	10.75	2.79
Difference between both tests	8.25	3.53	5.94	3.42	5.44	3.72

Table 2: Descriptive statistics for pre- and post tests scores and for difference between both tests

4 Discussion

In summary, our study shows (1) that performance at the collaborative knowledge modeling task is superior for dyads working at the same computer than for those who communicated asynchronously at a distance, but only in terms of the knowledge objects represented in the knowledge model (and more precisely in terms of specification of the type of the knowledge objects), not in terms of the propositions elaborated and (2) that groups do not differ on learning, although we found a tendency for remote partners who communicated synchronously to have learned more than participants in the two other groups.

The three conditions of this study can be distinguished in terms of "what is shared" in the interaction. In the face-to-face group and in the synchronous distance group, the knowledge construction *process* via a common workspace is shared. In the asynchronous distance group, only the *results* of the knowledge construction process are shared. The difference between the face-to-face group and the synchronous group lies in the speed and the facility of the sharing process, which are lower in the last group, probably due to slow typing (Chiu, Huang, & Chang, 2000), split-attention effect (Chung *et al.*, 1999) and lack of gestural deixis (Suthers *et al.*, 2002; 2003), three factors that could substantially affect the quantity and the nature of messages produced. Thus, the communication process was probably more fluent in the face-to-face condition. It is interesting to note that what seems to make a difference between groups on task performance is not the total number of knowledge objects nor the propositions represented in the models, but the specification of the type of the knowledge objects. Considering the low degree of familiarity of participants with content-knowledge and with MOT, and the complexity and short duration of the task, it is possible that participants of all dyads had enough time to identify a similar number of knowledge objects, but only those interacting in face-to-face had sufficient time to negotiate and reach consensus around the specification of the types of those objects.

No significant between-group differences were found for the Proposition score. It may be that the method used to evaluate the knowledge models underestimates the participants' capacity to elaborate valid propositions. For example, we observed that experts systematically represented all the inputs and outputs of each procedure represented in the two texts. Many participants put, instead, "precedence" links between the procedures. Although those propositions were valid (although less complete and less informative than the ones represented in the expert model), they were not considered as such in our coding scheme based on the comparison with an expert model. This could explain in part the very low performance on the Proposition score. Moreover, this method does not tell us much about participants' misconceptions in the target domain. We are currently elaborating another method based on cognitive semantics theories (Pudelko, Basque & Legros, 2003; Basque & Pudelko, 2003).

How can we interpret the lack of between-group difference on learning ? Some authors argue that sharing processes is more beneficial to learning than sharing only results. For example, Stoyanova & Kommers (2002) conclude from their study on the effect of three types of knowledge and resources sharing (shared, moderated and distributed) during a collaborative concept mapping activity on subsequent individual performance that "*learning effectiveness depends on the extent to which students share their learning, not only as results, but also as a process of knowledge acquisition and creation by a direct interaction*" (p. 131). Our results do not allow us to attest to this conclusion, as participants who seem to have learned the least (although this is only a tendency) are those who either shared the knowledge modeling process the most (CONTROL group) or the least (ASYNCH group). Results closely reflect Stoyanova & Kommers' conclusion for the ASYNCH group but not for the CONTROL group. It may be that if, as we hypothesized, partners working at the same computer spent more time negotiating about the type of the knowledge objects, they probably paid more attention to the MOT metalanguage than to the domain-related knowledge. However, we do not conclude that the use of the metalanguage is not beneficial to learning and text comprehension, as we think that the duration of the task was probably insufficient and the complexity of the task probably too high for novice knowledge modelers to allow participants to take advantage of this metalanguage. Another type of learning measures (for example, a written essay) could also lead to different results, as in the Suthers *et al.* studies (2002, 2003). Further research is needed to investigate the effects of using a metalanguage like the one in MOT on comprehension and learning. It seems necessary to analyze more in depth the process of collaborative knowledge modeling and the interactions between partners of dyads. This constitutes the next phase of our investigation, based on screen captures and video recordings of the collaborative knowledge modeling sessions.

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