Psychologie française 62 (2017) 293–311

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Original article

From learners' concept maps of their similar or complementary prior knowledge to collaborative concept map: Dual eye-tracking and concept map analyses☆

Comment deux apprenants coordonnent les représentations externes de leurs connaissances identiques ou complémentaires pour construire une carte collaborative : analyses des mouvements oculaires et des cartes conceptuelles

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ARTICLE INFO

Article history:
Received 28 November 2013
Accepted 7 November 2015

Keywords:
Computer-supported collaborative learning
Learning with multiple external representations
Prior knowledge distribution

ABSTRACT

The present paper describes the MUPEMURE (Multiple Perspectives on Multiple Representations; Bodemer, Author, Kapur, Rummel, & Weinberger, 2011) model as a conceptual framework for collaborative learning with multiple external representations. Within this framework, a study was conducted to examine how learners working in dyads translated between self-generated concept maps of their own and partner's prior knowledge to create a collaborative concept map. Before individual and collaborative concept mapping (CCM) sessions, prior information on the learning topic was

☆ Research topics: Computer-supported collaborative learning (CSCL), Collaborative multimedia learning, Group awareness tools for CSCL, Emotion awareness in CSCL.

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http://dx.doi.org/10.1016/j.psfr.2015.11.001

Collaborative concept mapping
Dual eye-tracking

distributed between dyad members in such a way that they had either similar ("same/shared prior knowledge" or SK condition) or different but complementary knowledge ("different/unshared prior knowledge" or DK condition). The dual eye-tracking method was used in this study, and eye movement data was examined in two time periods, the first and second half of the CCM session. Eye movement analysis was complemented with the analysis of concept map measures, such as achievement, individual-to-group transfer and group creativity. In the first half of the CCM session, eye movement behavior across the three maps was interpreted as reflecting initial externalization and divergent processes through which learners mutually compare their knowledge and engage in a process of modeling each other. The second half of the CCM session was identified as a convergent phase characterized by a decrease in eye movement transitions between maps, and a convergence of attention on the collaborative map. The results also showed that in the first half of the collaboration, learners of the DK condition transitioned more between their own and partner maps, and therefore had more difficulty coordinating their respective prior knowledge compared to learners of the SK condition. Participants with different/unshared prior knowledge also focused their attention mainly in their own map and explored less their partner map in the first half of the collaboration. This suggests that they worked in a less collaborative way compared to those with same/shared prior knowledge during the divergent phase.

RÉSUMÉ

Mots clés :
Apprentissage collaboratif médiatisé par ordinateur
Apprentissage à partir de représentations externes multiples
Distribution des connaissances initiales
Cartes conceptuelles
Eye-tracking

Cet article présente le modèle MUPEMURE comme cadre conceptuel pour l'apprentissage collaboratif à partir de représentations externes multiples. En lien avec ce modèle, une étude a été réalisée pour comprendre comment deux apprenants construisaient ensemble une carte conceptuelle commune à partir de cartes représentant leurs connaissances initiales respectives. Avant la collaboration, des informations sur le thème d'apprentissage ont été distribuées entre les co-apprenants de sorte à ce qu'ils disposaient de connaissances identiques ou différentes/complémentaires. Les mouvements oculaires pendant la collaboration ont été analysés ainsi que les cartes conceptuelles. Les résultats ont montré que la première moitié de la collaboration correspondait à une phase d'externalisation initiale et de divergence au cours de laquelle les co-apprenants ont comparé visuellement leurs cartes de connaissances initiales, tandis que la seconde moitié de la collaboration correspondait à une phase de convergence au cours de laquelle les co-apprenants ont concentré leur attention sur la carte commune. Nous avons également observé un nombre plus important de transitions oculaires entre les deux cartes de connaissances initiales, et donc une plus grande difficulté à coordonner ces dernières chez les co-apprenants avec des connaissances différentes. Ces derniers ont également porté plus d'attention à leur propre carte qu'à celle de leur partenaire dans la phase de divergence, ce qui suggère qu'ils ont travaillé de façon moins collaborative comparés aux co-apprenants qui possédaient des connaissances similaires.

1. Introduction

Collaborative situations are those that involve multiple agents working together towards a common goal. These situations require mutual efforts from multiple agents to synchronize and coordinate their respective – and probably different – internal representations so as to achieve a certain degree of shared understanding (Roschelle & Teasley, 1995). It is usual for multiple agents to generate and work with multiple external representations (MERs). Such kinds of collaborative situations may be referred to as "multiple agents, distributed or multiple internal/external representation situations", according to the work of Boshuizen and Tabachneck-Schijf (1998). In learning contexts, many tasks require students to synthesize information from multiple texts or critically analyze and combine information from multiple sources (texts, diagrams, tables, equations, etc.). That is especially the case in science education where the rapid and continuous emergence of new technologies provides students with a broader range of representational tools (dynamic/interactive visualizations, concept mapping tools, microworlds, simulations, etc.) that enable them to manipulate and create – alone or in groups – representational artifacts. Some research showed that learners could benefit from the multiplicity of external representations, since it may help them to construct a richer and more detailed mental model of the described topic. Other research indicated that it could be hard and resource consuming to use MERs, especially in computer-supported collaborative learning (CSCL) environments where learners must manage both cognitive and socio-relational demands of collaboration.

Despite considerable research on individual learning with MERs, there is still little knowledge on how people can learn together with multiple representations, and on how to support collaborative learning with MERs. In the present paper, we investigate how learners working in dyads use and coordinate the self-generated external representations (individual concept maps) of their respective prior knowledge to co-construct an external representation (a collaborative concept map) that reflects their shared understanding. Prior to the individual and collaborative concept mapping sessions, dyad members were provided with either identical (same/shared prior knowledge condition) or different but complementary information (different/unshared prior knowledge condition) on the learning topic. We study how the distribution of prior knowledge among dyad members impacts the way they translate between concept maps and from individual to collaborative phases.

The Introduction is divided in four sections. We first give an overview of individual and group processes involved in collaborative learning (Section 1.1). In Section 1.2, we present research on the effect of external representations in both individual and collaborative learning, and then we introduce the MUPEMURE–"sharing MUltiple PErspectives on MUltiple REpresentations"–model (Bodemer, Kapur, Author, Rummel, & Weinberger, 2011; Author, Bodemer, Kapur, Rummel, & Weinberger, 2011; Weinberger, Bodemer, Kapur, Author, & Rummel, 2011) which investigates approaches that can support collaborative learners in the construction and coordination of multiple representations. Section 1.3 focuses on collaborative concept mapping and also presents previously published results from the present study. In Section 1.4, we finally describe the research objectives and questions addressed in this paper.

1.1. Collaborative learning processes and representations

This section refers to three theoretical models recently proposed to describe how individuals learn and construct knowledge through social interaction, namely the Stahl's model (2000), the Cress and Kimmerle's model (2008), and the collaborative information processing (CIP) model (Jorczak, 2011). Stahl's model is a cognitive theory of learning as a social process, initially developed as a basis for the design of CSCL interfaces. Cress and Kimmerle (2008) have proposed a model of collaborative knowledge building with wikis that combined a systemic approach of external and internal processes with Piaget's theory of equilibration. In his model, Jorczak (2011) adopted an information processing view of collaborative learning, and focused on the sequencing of divergent and convergent group processes. The common denominator of these models is that they considered the relationship and mutual influence between individual cognitive processes and collaborative group processes. This section is not a complete description of each framework. Instead it proposes a synthesis of these models with a focus on core processes involved in collaborative learning.

Collaborative learning is defined as an iterative and multiple-phase process (Jorczak, 2011; Stahl, 2000), and is characterized by an interplay of mental (internal) and external representations. In his model, Stahl (2000) described two interrelated cycles of learning processes: a cycle of personal understanding and a cycle of social knowledge building.

1.1.1. Personal cycle of collaborative learning

Externalization and internalization are described as individual cognitive processes that take part in this cycle (Cress & Kimmerle, 2008). Such processes can themselves result in learning as they both involve transformations of internal representations.

Externalization occurs when learners use verbal and non-verbal language (speech, gestures, etc.) or other external representation systems (pictures, diagrams, etc.) to transform their personal mental models (of the domain/task/problem) into public statements (Stahl, 2000). In collaborative learning settings, learners have to communicate their knowledge in a way that is relevant to the task, and understood by their collaborative partners (Horton & Gerrig, 2005). It is assumed that learners need to construct a mental representation of what their partners know (also called a peer knowledge model) to adjust the way they externalize their own knowledge accordingly (Author, Sangin, Nüssli, & Dillenbourg, 2009; Sangin, Author, Nüssli, & Dillenbourg, 2011).

Internalization occurs when new information from the social interaction is integrated into learners' prior knowledge. This new information can come directly from partners (who shared it to the group) or can be co-constructed by the group. The internalization process results in emergent knowledge that "represents collaborative knowledge building which is more than mere knowledge sharing" (Cress & Kimmerle, 2008, p. 112).

1.1.2. Social cycle of collaborative learning

The social cycle consists in building and maintaining a "negotiated and shared conceptual space" (Roschelle & Teasley, 1995, p. 70). In the CIP model, the social cycle is composed of three main phases: an initial externalization phase followed by a divergent phase, and then a convergent phase (Jorczak, 2011).

The divergent phase is described as an elaboration phase in which information is diversified based upon the learners' existing knowledge. In the divergent phase, learners compare their understanding of the subject matter with their partners, and this confrontation of multiple perspectives may lead to conceptual conflicts that learners must resolve to achieve the common goal.

The convergence phase aims at resolving socio-cognitive conflicts and achieving the common goals. There are different types of social interactions in which learners may engage to reconcile and integrate their different points of view; these include clarification, argumentation, and knowledge negotiation (Stahl, 2000). These productive interactions are recognized as playing a crucial role in learning (Weinberger, Stegmann, & Fischer, 2007), and were identified by Cress and Kimmerle (2008) as participating in a process of mutual adaptation by assimilation and accommodation. Jorczak (2011) described information convergence as the result of identification and selection processes by which externalized information is reduced to only mutually accepted knowledge relevant to the achievement of the shared goals. The outcome of convergence processes is an increase in the similarity of co-learners' knowledge structures (Jeong & Chi, 2007) in relation with an increase in convergence of information expressed during interaction. It is also hypothesized that information convergence results in group learning only when it is preceded by sufficient divergence between learners.

Fig. 1 depicts the personal (externalization, internalization) and social (divergent and convergent processes) cycles of collaborative learning. In the present paper, we are concerned with the externalization of prior knowledge in the form of concept maps, and with the use of individual knowledge maps during collaborative concept mapping (i.e., with the relationship between the personal and social cycles). We are particularly interested in how the use of individual maps for the construction of the collaborative map differs between the divergent and convergent phases.

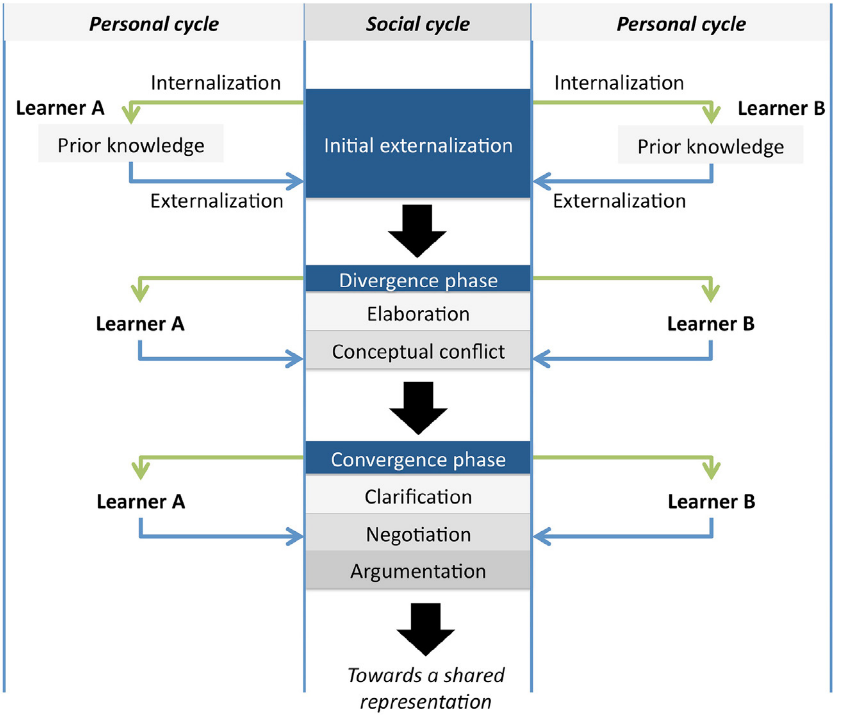

Fig. 1. The personal and social cycles of collaborative learning.
Adapted from the Stahl's model (2000), the Cress and Kimmerle's model (2008), and the collaborative information processing (CIP) model proposed by Jorczak (2011).

1.2. *Collaborative learning with multiple external representations*

When learners collaborate on a complex subject matter, such as science or mathematics, they are usually presented with multiple forms of external representations of the subject matter, and/or they may be asked to construct together different external representations. External representations (ERs) are defined as configurations of (material) inscriptions (De Vries & Masclet, 2013) used to externalize cognitive activities and conceptual understanding. Current cognitive science research mainly focuses on two types of ERs: descriptive (symbolic) representations (e.g., spoken/written texts, equations) and depictive (iconic) representations (e.g., pictures, animations, diagrams, graphs). It is widely accepted that ERs can enhance cognitive performance and communication. They can be used as memory aids, but beyond that they can facilitate reasoning and problem solving as they provide "perceptual input which gives access to knowledge and skills that are otherwise unavailable to us" (Acartürk, 2009, p. 23). They are also recognized as participating in the construction of new knowledge.

Research on the role of ERs in supporting learning largely remains focused on individual learners. Goldman (2003) identified two generations of work on ERs, the first focusing on "consistencies in the processing of verbal and visual information" (p. 240) and the other on "the impact of multiple forms of representation on learning" (p. 241). The first generation includes research based on an information processing approach to understand how learners select, organize and integrate information from verbal and visual representations. For instance, Mayer (2005) developed the cognitive theory of multimedia learning with the aim of providing guidelines on how to arrange text and pictures so as to promote active processing that takes into account working memory limitations. In the second generation of research, the focus relates on the interactions between affordances of external representations and processes of learning (Schnotz & Kürschner, 2008; Wu & Puntambekar, 2012). External representations with different characteristics can make accessible to learners different information and relationships, induce different interpretations (or misinterpretations) of the presented information, and engage in different types (and levels) of processing that might result in learning performance differences. This refers to the concepts of representational effect (De Vries & Masclet, 2013) and representational guidance (Janssen, Erkens, Kirschner, & Kanselaar, 2010). Therefore, second generation researchers address how to select ERs so that they fit the cognitive demands of the task in relation with learners' prior knowledge, and also what kinds of scaffoldings to offer in order to help learners in their use of multiple external representations (e.g. Bodemer, Plötzner, Feuerlein, & Spada, 2004; Wu & Puntambekar, 2012; Sweller, Ayres, & Kalyuga, 2011). Results from these studies point out the difficulty for learners to coordinate and translate between MERs. The DeFT (Design, Function, Tasks) framework (Ainsworth, 2006) was proposed as a basis for developing tools and methods that support the learners' processes of relating and translating between MERs. These methods (integration, dynamic linking) are those that make the relations between MERs explicit, that help learners to identify similarities and differences between MERs as well as to match multiple elements belonging to different representations (van der Meij & de Jong, 2006).

CSCL research also focuses on the effect of external representations on collaborative learning processes and outcomes. In CSCL settings, MERs are "representations for mutual understanding", and provide "a shared and explicit ground for communication" (Ostwald, 1996 cited by Alpay, Giboin, & Dieng, 1998, p. 152). Schwartz (1995) showed that compared to individual representations, multiple learner generated representations tend to be more abstract as they bridge the learners' multiple perspectives and visually represent their mutual understanding. Suthers and Hundhausen (2003) investigated the effects of representational guidance during CSCL, and identified three roles for shared external representations (SERs). SERs refer here to notations (physically) shared and "manipulated by more than one person during a collaborative task" (Suthers, 2006, p. 1). The three roles of SERs are:

- negotiation/agreement role;
- deictic/referencing role;
- group awareness role.

First, individual actions carried out by one group member to build or modify SERs can be performed only with the agreement of the other group members, and SERs can serve as starting (focal) points for the negotiation of common meaning. Second, group members can use SERs as easy means to point or refer to ideas expressed during interaction, in order to establish a joint focus of attention on those ideas. Third, SERs can serve as external memory, and help the learning partners remember who said or did what during interaction. Suthers (2006) also investigated how SERs are used for knowledge construction, and developed a methodology for qualitatively analyzing transformations of SERs by multiple learners during interaction. Such transformations occur when one individual expresses a personal idea in the form of a change (e.g. adding, deleting, editing or linking objects) in the ER "shared with another individual who subsequently takes up this information and adds to, transforms or interprets it in a new way, again resulting in a change to the representation that may be taken up by the first individual" (p. 14). These transformations can be viewed as "an intersubjective cognitive process" (p. 14), and result in the "graphical co-construction of an interpretation" (p. 17). Fischer and Mandl (2005) studied the role of ERs on knowledge convergence in CSCL. They found that content-specific visualizations make more visible differences between co-learners in terms of points of view, encourage them to confront their conceptual positions in a more systematic way (conflict-oriented consensus building), and also facilitate convergence-related processes. Lund, Author, Séjourné and Baker (2007) focused on translation between external representations with different formats. They showed that asking co-learners to convert their debate in a chat (textual representation) into an argumentation graph (graphical representation), led them to deepen their conceptual understanding of the debate topic. Other CSCL research shows that working with MERs is not always beneficial to collaborative learning. According to van Bruggen, Boshuizen, and Kirschner (2003), coordination problems and misunderstandings can occur in situations where multiple agents with different perceptions of the problem to be solved have to deal with MERs. In multimedia and multi-representational collaborative learning environments, learners have to cope with a double complexity: the

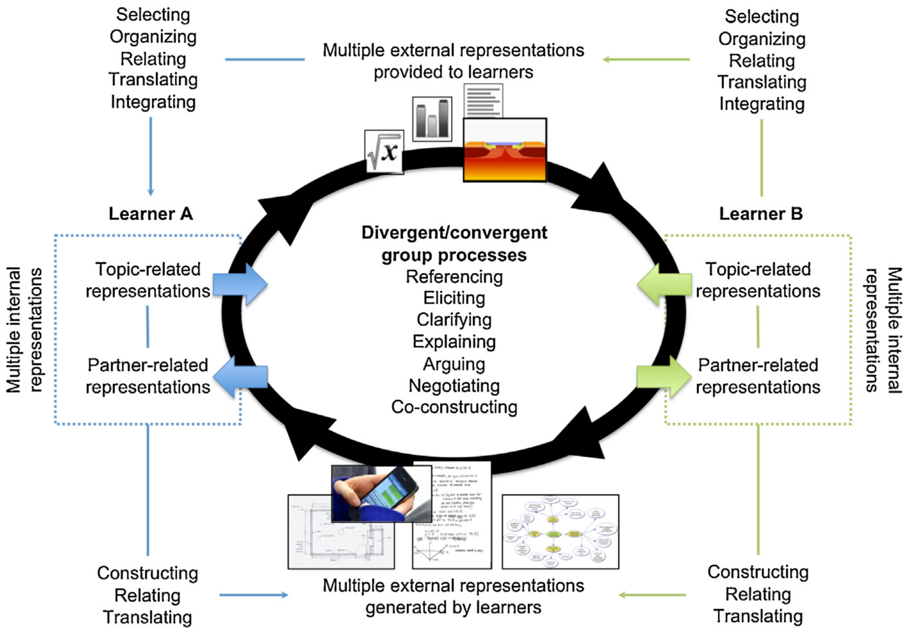

Fig. 2. The MUPEMURE (Multiple Perspectives on Multiple Representations) model
Adapted from Bodemer et al., 2011.

complexity of managing the interaction with their partner(s), and the complexity of generating, interpreting, relating and translating between MERs. In such settings, the collaboration load combined with the cognitive demands of processing multi-representational learning materials can lead to cognitive overload, which impairs learning (Dillenbourg & Bétrancourt, 2006; Schnotz, Böckheler, & Grzondziel, 1999). A "socio-cognitive" underwhelming effect can also be observed. The distribution of processing across co-learners associated to an "illusory feeling of understanding" sometimes induced by external representations, can lead learners to invest less cognitive and social effort (Sangin, Author, Dillenbourg, Rebetez, & Betrancourt, 2006).

1.2.1. *The MUPEMURE model*

Asking collaborative learners to generate and work with MERs can therefore be regarded as a demanding and challenging task. MUPEMURE (Bodemer et al., 2011; Author et al., 2011; Weinberger et al., 2011) is a model (see Fig. 2) based on the two strands of theory and research described above, i.e. learning from external representations and computer-supported collaborative learning. MUPEMURE investigates the role of collaborative learning activities in the context of learning with multiple representations in technology-enhanced learning environments. It also aims at identifying instructional approaches that can support collaborative learning with multiple representations.

In the MUPEMURE model, external representations are provided to or self-/co-constructed by learners. Provided external representations are processed and transformed into internal representations which can be in turn externalized through language, and also through the creation of different types of external representations. There is a reciprocal effect between representations and collaboration. The processes of interpreting, constructing and interacting with MERs are influenced by the quality of group processes, and methods used to foster productive interactions among learners are expected to positively impact learning from MERs. Simultaneously, the way learners interact with each other and with MERs is also affected and constrained by the type and quality of MERs. Carefully selecting and arranging MERs to convey multiple perspectives on a particular topic or as communication media for suggesting co-learners to confront their points of view should be regarded as an approach to foster CSCL

(Bodemer et al., 2011). Two approaches of instructional support are investigated in the MUPEMURE context, scripting and awareness. In the scripting approach (Weinberger et al., 2007), external scripts provide learners with instructions about how to collaborate and learn together. An example of collaboration script is the jigsaw that consists of distributing information to be acquired across the learning partners so as to create knowledge interdependence among them (Buchs & Butera, 2009; Author et al., 2008, 2009). In van Dijk, Gijlers and Weinberger (2013), a collaboration script was used to prompt elementary students to openly discuss, challenge and criticize their respective individual drawings on a learning topic. The awareness approach builds on technology-supported analysis of users' speech, actions and domain-specific knowledge, and on the idea of feeding that awareness information back to the users during computer-mediated interaction (Sangin et al., 2011). Bodemer (2011) proposed a CSCL environment in which learners needed to actively integrate algebraic and visual representations during learning statistics. An awareness tool was designed to facilitate the collaborative integration task by providing learners with information about the current state of integration of their learning partner.

1.3. Collaborative concept mapping

Concept mapping is a technique for the visualization of concepts and relations between concepts in the form of networks of nodes and links. It can be used as an instructional tool to enable individual learners to externalize their knowledge structures. Concept maps can be also built through collaboration. A collaborative concept map (CCM) is an external representation of a shared mental model (Johnson & O'Connor, 2008), that is, a collective knowledge structure co-constructed by a group of learners.

Concept mapping has potential when it comes to stimulate both individual and collaborative learning (Haugwitz, Nesbit, & Sandmann, 2010; Nesbit & Adesope, 2006; van Boxtel, van der linden, Roelofs, & Erkens, 2002; Van Gog, Kester, Nievelstein, Giesbers, & Paas, 2009). Asking individual learners to build a concept map of their knowledge can help them becoming aware of their own conceptions, and also of inconsistencies and gaps in their knowledge. This stimulates them to adjust, modify and reorganize their knowledge (metacognitive effect). The construction of a CCM leads co-learners to make their knowledge explicit to each other. This makes more visible similarities and differences in knowledge between learners, and encourages them to engage in knowledge negotiation and consensus building processes. Gao, Shen and Turner (2007) pointed out that some studies (e.g., Chiu, 2003) failed to prove a significant benefit of concept mapping in CSCL settings. These studies found, for example, that learners focused more on completing the task than on discussing concepts when building a CCM. Gao et al. (2007) therefore recommended the use of additional scaffolding and support in combination with the concept mapping technique to increase the probability of positive results. Engelmann and Hesse (2011) showed that learners benefit from the availability of the concept maps of their partners' individual knowledge during the construction of a CCM. The access to the partners' knowledge maps leads learners to discuss and process unshared information more deeply.

Author et al. (2008, 2009) carried out a study that focused on the effect of knowledge interdependence among learners in collaborative concept mapping. This study was part of a project that investigated the benefits of facilitating – through the use of awareness tools and scripts – the process of modeling the collaborative partner's knowledge. In this study, learners working in dyads were asked to create together a joint concept map to externally represent their shared understanding of a science topic (neurons). During the construction of the CCM, learners had access to the concept maps of both their own and partner's prior knowledge. The prior knowledge maps were constructed by learners themselves after having read a text in an individual phase. A jigsaw-type script was used to manipulate the level of mutual interdependence between learners by providing each of them with either identical or different but complementary learning resources. Two conditions were compared, a same/shared knowledge (SK) condition and a different/unshared knowledge (DK) condition. In the SK condition, both partners read the same text and therefore had shared prior knowledge (knowledge independence). In the DK condition, each partner read one of two complementary texts: they had unshared prior knowledge, and were thus dependent on each other for access to knowledge given in the text they had not read (knowledge interdependence). Two alternative hypotheses were formulated concerning the knowledge interdependence effect. On one hand, providing learners with same knowledge (SK condition) should encourage them to compare and confront their respective representations of the same information they received; it was demonstrated that confrontation of perspectives might have positive influence on learning. On the other hand, working on different but complementary information (DK condition) should stimulate learners to externalize and explain their knowledge to their partner. It would also encourage them to shift their focus from their own perspective to consider their partner's perspective, and an increase in perspective taking is seen as leading to a more positive collaborative learning experience (Buchs & Butera, 2009). Both partners' eye movements were recorded during collaboration. Eye-tracking methodology was used to investigate visual transactivity, that is, the degree to which learners visually referred to their partner's map while building the CCM. It was hypothesized an increase in visual transactivity in the condition of knowledge interdependence between learners. Individual learning performance was assessed after collaboration as well as the accuracy with which learners estimated their partner's outcome knowledge (mutual knowledge modeling accuracy). Results (Author et al., 2008, 2009) showed no difference in learning performance between the SK and DK conditions. There was also no significant effect of knowledge interdependence on visual transactivity. It was however found that participants with different knowledge:

- spent more time looking at their own map;
- made more eye movement transitions between their own and partner maps;
- were less able to accurately assess their partner's outcome knowledge, compared to participants with same knowledge.

Finally, it was observed that better learning performance was associated with lower fixation time on the own map and also a lower frequency of eye movement transitions between the own and partner maps. Overall, results suggested that the possibility for learners to inspect the concept map of their own knowledge and to visually translate between their own and partner's knowledge maps during collaboration could have a negative impact on learning. Moreover, results indicated that there was a higher need for participants of the different knowledge condition to look at their own knowledge map during interaction. They also seemed to experience more difficulties to translate between their own and partner's knowledge maps.

1.4. The present research

In the present paper, we present additional analysis of data from the study described above (Author et al., 2008, 2009). In the context of the MUPEMURE framework, we aim at better understanding how learners coordinate, combine and transform the concept maps of their respective prior knowledge (own and partner maps) into the collaborative concept map. We also examine to what extent the use of prior knowledge as well as the creation of new knowledge during collaborative concept mapping depend on the distribution of prior knowledge among co-learners (same/shared knowledge versus different/unshared knowledge).

In the present contribution, a temporal dimension is added to the previous analysis of co-learners' eye movements (dual eye-tracking data analysis) so as to investigate the dynamic process of co-constructing the joint map. Eye movement data is analyzed in two time periods, the first and second half of the collaborative concept mapping (CCP) session. According to models of collaborative learning (Cress & Kimmerle, 2008; Jorczak, 2011; Stahl, 2000), the first half should be characterized by externalization of prior knowledge and divergent processes by which co-learners compare and elaborate on their existing knowledge; one may expect that co-learners would pay more (visual) attention to both their own and their partner's prior knowledge maps during this first half period. Convergent processes would be more likely to occur in the second half of the CCP session, and co-learners should converge their attention mainly on the collaborative map during this period.

An analysis of individual and collaborative maps is also performed in order to assess learning effectiveness in collaborative concept mapping. We consider together two levels of learning effectiveness measures (see Khamesan & Hammond, 2004): the group level and the interaction between individual and group levels. At the individual–group interaction level, we analyze the individual-to-group transfer with a focus on the transfer of elements (concepts and links) shared by both individual maps (own and partner maps) into the collaborative map. At the group level, we examine both group achievement and group creativity. Regarding the effect of prior knowledge distribution among co-learners, we should observe a greater focus of (visual) attention on the prior knowledge maps and also a higher transfer from prior knowledge maps to the collaborative map in the condition where participants had different/unshared rather than same/shared prior knowledge. Moreover, individual-to-group transfer would concern mainly elements shared by both prior knowledge maps in the condition of same/shared prior knowledge between learners. Finally, no differences in terms of both group achievement and group creativity would occur between the two conditions since previous findings indicated that they did not differ in terms of collaborative learning outcomes.

2. Method

2.1. Participants and design

Participants were 60 first year students (mean age 20.5 ± 3.6 years, 49 men, 11 women) from the Swiss Federal Institute of Technology (Lausanne). Participation was voluntary and was rewarded with 30 Swiss Francs after the experiment. An open question was used to assess participants' background knowledge of the topic to be studied (neurons) so as to include only those with low prior knowledge. Participants were randomly grouped into 30 dyads. Members of the dyads did not know each other prior to the study. Dyads were randomly assigned to one of the two conditions, the "shared/same knowledge" (SK) condition (16 dyads) and the "unshared/different knowledge" (DK) condition (16 dyads).

2.2. Material and procedure

The members of each dyad were seated in two different rooms and were placed in front of computers equipped with Tobii™ 1750 eye-trackers. A computer-based setup was designed to automate the procedure and the recording of data. As described in Table 1, each session lasted 80 minutes and consisted of 5 phases: prior knowledge assessment; individual learning (text reading); individual concept mapping; collaborative concept mapping; outcome assessment (individual learning performance and knowledge modeling accuracy).

In the individual learning phase, both members of each dyad read the same text (original text) in the SK condition while each dyad member read one of two complementary texts in the DK condition, the electric and ionic texts. The original text provided two interconnected pieces of information: one about electrical processes in neurons, the other about chemical processes. The electric and ionic texts were derived from the original text. Each of them provided only one piece of information (either about electrical processes or about chemical processes), and the amount of information common to both texts was relatively small (around 20%). CmapTools was used as software for computer-based concept mapping, and participants were provided with a video tutorial of how to create concept maps using this software in the individual concept mapping session. In the collaborative concept mapping

Table 1
Phases of the experimental session.

Phase	Mode	Duration	Description
1	Individual	5 min	Writing down everything they know about neurons
2	Individual	15 min	Reading a text to learn about neurons
3	Individual	10 min	Creating a concept map to represent what they have learnt from reading the text (CmapTools)
4	Collaborative	20 min	Discussing the topic of neurons, and creating a joint concept map to represent their shared understanding (CmapTools and TeamSpeak)
5	Individual	15 min	Completing 2 posttests designed to evaluate students' (1) learning outcomes, and (2) ability to accurately estimate their own and partner's outcome knowledge (knowledge modeling accuracy)

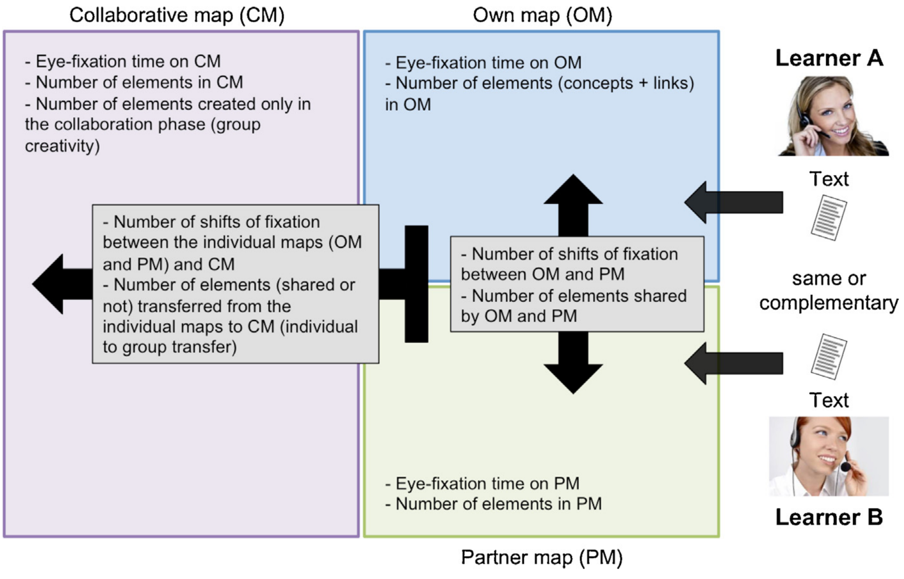

Fig. 3. Spatial distribution of the individual (own/OM and partner/PM maps) and collaborative (CM) maps on the shared screen during collaboration and dependent variables used.

session, the dyad members shared the same screen. The screen was divided into 2 main areas: one for the co-construction of the collaborative map (CM) on the left side, and one for the display of individual maps on the right side. Participants could see the concept map of their own knowledge (OM) at the top right side of the screen and the concept map of their partner's knowledge (PM) at the bottom right side (see Figs. 3 and 4). They could voice with each other using a microphone headset and an audio conferencing application (TeamSpeak) while building the joint map. After collaboration, participants answered 18 questions used to assess what they have individually learned about neurons (see Author et al., 2008, 2009).

2.3. Variables

We investigated how learners inspected each concept map (own, partner and collaborative maps) and how their visual attention moved from one map to another one. Eye movement data was divided into two sets that correspond to two periods: the first and second half of the collaborative concept mapping (CCM) session. As shown in Fig. 3, two types of eye movement measures were used (see Author et al., 2008):

- the ratio of fixation time spent in each map;
- the number of shifts of fixation (eye movement transitions) between both individual maps (own and partner maps) and between individual and collaborative maps.

The method we used to compute the fixation time ratio was the same for each half of the CCM session, and can be described as follows. The eye-tracker error was taken into account by adding a tolerance zone of 10 pixels around each map area. We then summed the fixation durations for each map separately and also for all fixations disregarding their position. This gave us a total fixation time and one fixation time for each map. Using these values, we computed a ratio of fixation time spent in each map according to the whole fixation time.

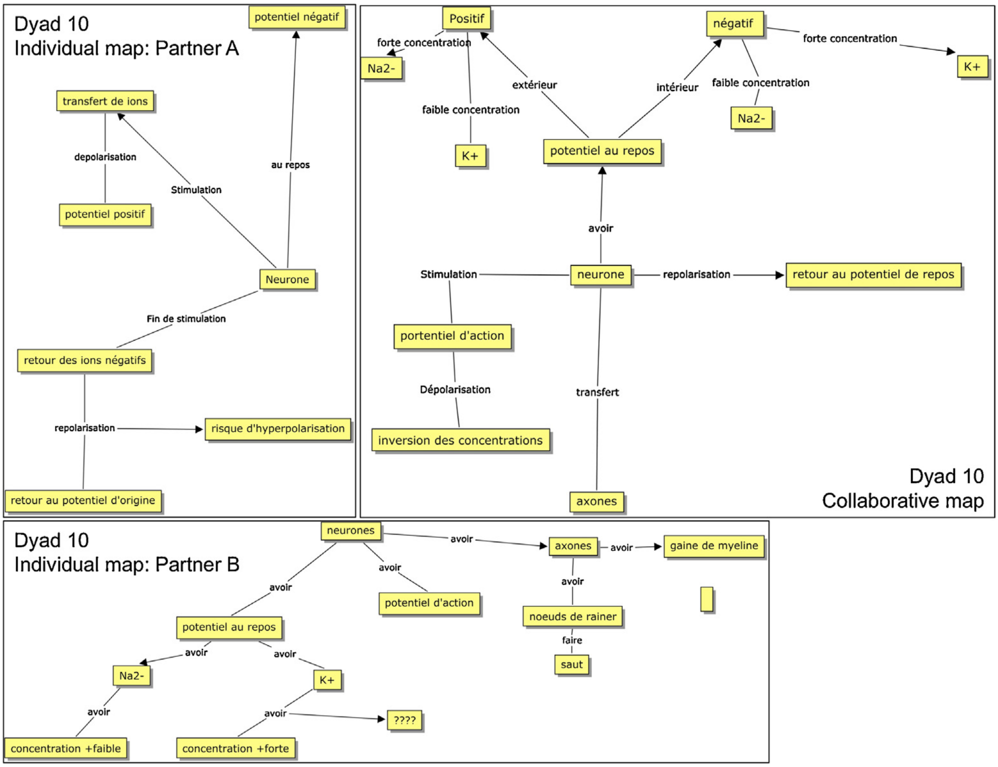

Fig. 4. Examples of individual and collaborative maps (dyad 10 in the different knowledge condition).

We also examined how learners used individual map elements to create the collaborative map. We used 6 concept map measures (see Fig. 3), some of them developed by Khamesan and Hammond (2004):

- the total number of elements (i.e. concepts as well as links between concepts) in the individual maps (individual achievement);
- the number of elements shared by both individual maps (overlapping of individual maps);
- the total number of elements in the collaborative map (group achievement);
- the number of new elements in the collaborative map that were not in both individual maps and were created only during the collaboration session (group creativity);
- the total number of transferred elements from individual maps to the collaborative map (individual-to-group transfer);
- the number of elements shared by both individual maps and transferred to the collaborative map (individual-to-group transfer of shared elements).

We also analyzed the correlation of eye movement and concept map measures with individual learning performance. The unit of analysis was the individual for variables, such as fixation time on concept map, shifts of fixation between maps, the number of individual map elements, and individual elements transferred to the collaborative map. The group was the unit of analysis for elements shared by individual maps, (new) elements in the collaborative map, and shared individual map elements transferred to the collaborative map. Due to technical issues concerning the recording of eye movement data (missing data, poor quality, problems in synchronization of both partners' eye movements, etc.), some dyads had to be removed from the initial database (60 participants). Results reported here concerned 28 participants, 14 participants (7 dyads) per condition. Finally, an alpha level of 0.05 was chosen as criterion for statistical significance.

3. Results

3.1. Eye movement analysis

The ratio of fixation time spent on the collaborative map (M = 0.55, SD = 0.18) was almost 1.5 higher than the ratio of fixation time spent on both individual maps (M = 0.38, SD = 0.17, that is, M = 0.18, SD = 0.11 for the own map and M = 0.20, SD = 0.10 for the partner map) in the first half of the CCM session. Participants spent the majority of time looking at the collaborative map in the second half. The ratio of fixation time spent on the collaborative map increased to reach a value of 0.81 (SD = 0.13) whereas the ratio of fixation time spent on both individual maps decreased more than half (M = 0.13, SD = 0.11, that is, M = 0.07, SD = 0.06 for the own map and M = 0.06, SD = 0.06 for the partner map). Results also showed that participants divided their attention equally between their own and partner maps in both halves of the CCM session.

As shown in Table 2, in the first half of the CCM session, participants with same prior knowledge (SK condition) spent less time consulting their own map and more time consulting their collaborative map compared to participants with different prior knowledge (DK condition), $F(1, 26) = 25.26$, $p < .01$, $\eta^2 = .49$ and $F(1, 26) = 5.18$, $p = .03$, $\eta^2 = .17$, respectively. There was no significant difference between both conditions with respect to ratio of fixation time spent on the partner map ($F < 1$). Results also indicated that more fixation time was spent on the partner map than on the own map in the SK condition, whereas the reverse pattern occurred in the DK condition, $F(1, 26) = 19.60$, $p < .01$, $\eta^2 = .43$. No significant differences in terms of ratio of fixation time spent on the three concept maps were found between both conditions in the second half of the CCM session ($F < 1$).

Table 3 displays the number of shifts of fixation (hereafter called transitions) between:

Table 2
Means and standard deviations for the ratio of fixation time on each concept map (OM = own map; PM = partner map; CM = collaborative map) in the first and second half of the collaborative concept mapping (CCM) session, and in the SK (same knowledge) and DK (different knowledge) conditions.

	First half of the CCM session				Second half of the CCM session			
	SK		DK		SK		DK	
	M	SD	M	SD	M	SD	M	SD
OM	.11	.06	.26	.09	.06	.07	.07	.06
PM	.20	.12	.19	.08	.07	.06	.05	.05
CM	.62	.18	.48	.15	.80	.15	.81	.12

The sum of the three ratios (OM, PM, CM) in each mean column does not add up to the value of 1.0 (it is equal to .93) due to fixations outside these three areas of interest.

Table 3
Means and standard deviations for the number of shifts of fixation between (a) both individual maps (OM-PM; OM = own map and PM = partner map), (b) the own and collaborative maps (OM-CM; CM = collaborative map), and (c) the partner and collaborative maps (PM-CM) in the first and second half of the collaborative concept mapping (CCM) session, and in the SK (same knowledge) and DK (different knowledge) conditions.

	First half of the CCM session				Second half of the CCM session			
	SK		DK		SK		DK	
	M	SD	M	SD	M	SD	M	SD
OM-PM	17.43	14.15	47.07	26.21	7.43	11.76	5.86	4.18
OM-CM	33.71	27.73	80.21	60.37	23.50	23.10	38.64	18.67
PM-CM	38.00	29.47	37.50	18.32	23.86	23.79	22.07	26.10

- the own and partner maps;
- the own and collaborative maps;
- the partner and collaborative maps in the first and second half of the CCM session.

Overall, the number of transitions between the own and partner maps (M = 19.45, SD = 14.16) was lower than:

- the number of transitions between the own and collaborative maps (M = 44.02, SD = 33.22; $t(27) = 4.36$, $p < .01$);
- the number of transitions between the partner and collaborative maps (M = 30.36, SD = 21.75; $t(27) = 2.79$, $p < .01$).

Moreover, participants made more transitions between their own and collaborative maps than between their partner and collaborative maps (M = 30.36, SD = 25.21), $t(27) = 2.24$, $p = .03$. Finally, the number of concept map transitions significantly decreased from the first to the second half of the CCM session:

- from M = 32.25 (SD = 25.59) to M = 6.64 (SD = 8.70) for the own-partner transitions ($t(27) = 3.12$, $p < .01$);
- from M = 56.96 (SD = 51.82) to M = 31.07 (SD = 51.82) for the own-collaborative transitions ($t(27) = 3.61$, $p < .01$);
- from M = 37.75 (SD = 24.08) to M = 22.96 (SD = 24.52) for the partner-collaborative transitions ($t(27) = 5.28$, $p < .01$).

This decrease was also higher for the own-collaborative ($d = 25.89$) and own-partner ($d = 26.61$) transitions than for the partner-collaborative transitions ($d = 14.79$).

In the first half of the CCM session, the number of transitions between the own and partner maps was significantly higher in the DK condition than in the SK condition, $F(1, 26) = 13.90$, $p < .01$, $\eta^2 = .35$. The same pattern was observed for the number of transitions between the own and collaborative maps [DK condition > SK condition; $F(1, 26) = 6.86$, $p = 02$, $\eta^2 = .21$]. No significant difference occurred between both conditions with respect to the number of transitions between the partner and collaborative maps ($F < 1$). In the second half of the CCM session, the difference in the number of own-collaborative transitions between both conditions (DK condition > SK condition) was marginally significant, $F(1, 26) = 3.64$, $p = 07$, $\eta^2 = .12$. No other significant differences (in terms of the number of concept map transitions) were observed between conditions ($F < 1$).

Table 4
Means and standard deviations for the six concept map measures in the SK (same knowledge) and DK (different knowledge) conditions.

	SK		DK	
	M	SD	M	SD
Individual achievement (1)	31.36	7.30	28.57	7.70
Overlapping of individual maps (2)	4.71	1.50	2.43	1.99
Group achievement (3)	45.71	13.07	53.43	16.12
Group creativity (4)	23.14	8.45	29.29	13.24
Individual-to-group transfer (5)	9.29	6.23	11.36	7.84
Individual-to-group transfer of shared elements (6)	3.71	1.48	1.43	1.27

(1): number of elements (concepts + links) in individual maps; (2): number of elements shared by both individual maps; (3): number of elements in the collaborative map; (4): number of elements that were not in both individual maps and that were created only in the collaboration session; (5): number of elements transferred from individual maps to the collaborative map; (6): number of elements shared by both individual maps and transferred to the collaborative map.

3.2. Concept map analysis

The means and standard deviations for the six concept map measures are presented in Table 4. Participants of the SK condition did not differ from participants of the DK condition with respect to individual achievement ($F < 1$). The overlapping of individual maps was significantly higher in the condition in which participants had same prior knowledge than in the condition in which participants had different prior knowledge, $F(1, 13) = 5.91$, $p = .03$, $\eta^2 = .33$.

Achievement was higher at the group level: the collaborative map contained a significantly greater number of elements (M = 49.57, SD = 14.66) compared to individual maps (M = 29.96, SD = 6.41), $F(1, 13) = 35.60$, $p < .01$, $\eta^2 = .75$. The number of new elements in the collaborative map (M = 26.21, SD = 11.14) was also significantly higher than the total number of elements transferred (M = 10.32, SD = 5.66) from individual maps to the collaborative map, $F(1, 13) = 19.30$, $p < .01$, $\eta^2 = .62$; in other words, the collaborative map was more the product of group creativity than of individual-to-group transfer. Results showed no significant differences between both conditions with respect to:

- group achievement ($F < 1$);
- group creativity ($F(1, 13) = 1.07$, $p = .32$, $\eta^2 = .08$);
- individual-to-group transfer ($F < 1$).

However, individual-to-group transfer of shared elements was significantly greater in the SK condition than in the DK condition, $F(1, 26) = 9.41$, $p < .01$, $\eta^2 = .48$.

3.3. Analysis of correlation between eye movement and concept map measures

In the first half of the CCM session, individual learning performance was negatively correlated with the ratio of fixation time spent on the own map ($r = -0.43$, $p = .02$) and also with the number of shifts of fixation between the own and partner maps ($r = -0.47$, $p = .01$). There were no significant correlations between eye movement measures and learning performance in the second half. We also did not find significant correlations between concept map measures and learning performance.

In the first half of the CCM session, individual-to-group transfer of shared elements was negatively correlated with:

- the ratio of fixation time spent on the own map ($r = -0.73$, $p < .01$);
- the number of transitions between the own and partner maps ($r = -0.52$, $p = .05$).

In the second half, the more participants spent time consulting their partner map and also transitioned between their own and partner maps, the more they transferred shared elements from individual maps to collaborative map (time on the partner map: $r = 0.75$, $p = .002$; shared elements transferred: $r = 0.59$, $p = .03$).

4. Discussion and conclusion

In this study, the first goal was to investigate how collaborative learners coordinated their own and partner's prior knowledge maps to build together a collaborative map. The main results showed that learners looked at the prior knowledge maps mainly in the first half of the CCM session, and gave the same amount of attention to their own map as to their partner's map. They also transitioned more between one individual map and the collaborative map than between both individual maps. It is noteworthy that eye movement transitions between the own and collaborative maps occurred more often compared to eye movement transitions between the partner and collaborative maps. According to models of collaborative learning, learners' eye movement behavior during the first half of the interaction can be interpreted as reflecting initial externalization and divergent processes through which learners express their personal understanding, mutually compare their knowledge, and engage in the process of modeling each other.

The strategy when looking at the prior knowledge maps was also to identify individual map elements that could be relevant for building the collaborative map, such as elements shared by the own and partner maps. Shared elements could serve as anchor points for discussion and elaboration, and could also be directly transferred to the collaborative map. Results regarding correlations with the individual-to-group transfer of shared elements showed that the difficulty in constructing a common ground of knowledge during the first half of the collaboration was reflected in a tendency for learners to remain focused on their own map, and also to shift their attention more often between their own and partner's maps.

Furthermore, the first half of the collaboration was characterized by a significant relationship between the way learners visually navigated across the prior knowledge maps and learning outcomes. This is in line with the hypothesis that group learning is predicted mainly by the quality of processes during the divergent phase (Jorczak, 2011). Results showed that individual learning performance decreased when learners spent more time looking at their own map, and also when they switched more frequently between their own and partner maps. Higher fixation time on the own map could be therefore associated with a difficulty for learners to express their knowledge to their partner (they would need to be helped by their own map to do that) or to find concept map elements in common with their partner's map. An increase in the number of transitions between the own and partner maps would also reflect coordination and negotiation problems. Learning partners would experience difficulties in comparing their respective maps, coordinating between them, elaborating on each other's concept map elements, and reaching agreement on elements to remove or include in the collaborative map. Such difficulties should be even more pronounced when differences were considerable between the own and partner maps. These results suggest therefore that efficient divergence can arise mainly when co-learners are able to "decentrate" from their own understanding and knowledge, as well as able to become aware of similarities and differences between their own knowledge and their partner's knowledge.

The second half of the CCM session was characterized by a decrease in transitions between maps, and also by a convergence of co-learners' attention on the collaborative map. According to collaborative learning models, co-learners' eye movement behavior during the second half of the interaction can be interpreted as reflecting convergent processes. Results showed that the individual-to-group transfer of shared individual map elements increased with the time spent looking at the partner map, and also with the number of transitions between the own and partner maps in the second half of the collaboration. In this convergent phase, the attentional shifts between prior knowledge maps would reflect the strategy to find common elements that had been previously unused and were however relevant to the final version of the collaborative map. Interestingly, such convergent processes would be related to the need to maintain the focus of attention on the partner's map. The partner's map would serve as an anchor point for the search of elements common to both prior knowledge maps, and the individual-to-group transfer of shared elements would require a mutual agreement between both learners. Finally, results showed that compared to individual maps, the collaborative map obtained at the end of collaboration was more elaborate demonstrating a greater number of concepts and links between concepts. It was also more the result of group creativity than of transfer of individual concept map elements. This can be related to what it has been found in previous research (Schwartz, 1995) regarding multiple learner generated representations; such representations are more than the "sum" of the individual representations based on which they are developed.

In line with the second goal of the present study, we found an effect of the distribution of prior knowledge among dyad members (same/shared prior knowledge versus different/unshared prior knowledge) on eye movement behavior across the three concept maps, but only in the first half of the collaboration, that is, during the initial externalization and divergent phases. The main results showed that learners focused more on their partner's map than on their own map in the same/shared prior knowledge condition whereas the reverse was observed in the different/unshared prior knowledge condition. Participants with same knowledge also spent more time looking at the collaborative map than those with different knowledge. Finally, there were more transitions between:

- the own and partner maps;
- the own and collaborative maps in the different/unshared prior knowledge condition.

Concept map analysis did not show any effect of prior knowledge distribution among co-learners on learning effectiveness in collaborative concept mapping (group achievement, group creativity and individual-to-group transfer). The only difference observed between both conditions was that the individual-to-group transfer of shared elements was higher in the shared prior knowledge condition than in the unshared prior knowledge condition. This could simply be due to the fact that the number of elements shared by the own- and partner maps was greater for co-learners who received identical prior knowledge.

To sum up, these results reveal that the distribution of prior knowledge among co-learners influenced collaborative learning processes mainly in the divergent phase. When learners have different/unshared prior knowledge, they were more likely to stick to their own perspective and less inclined to take into account their partner's perspective. This suggests that the processes of partner modeling and perspective taking – processes recognized as playing an important role in collaborative learning – would not benefit from working on different prior knowledge. This is not consistent with previous research that demonstrated more positive interactions and more investment in knowledge sharing in the condition where co-learners received different learning resources prior to collaboration (Buchs & Butera, 2009). Our results rather show that possessing unshared prior knowledge would force each learner to act as an expert and to take control/responsibility for the piece of knowledge (s)he had received; this would have led them to work together in a less collaborative way. In the condition where learners had shared prior knowledge, the strategy seems to be quite different. It would consist of identifying elements common to the own and partner's knowledge maps in order to then quickly focus on the collaborative map. Shared individual map elements would serve as an immediate frame of reference to start building the joint map. This result can, therefore, be interpreted as a tendency for collaborative learners to move fairly quickly towards a convergent regime in the first half of the collaboration when they possess shared prior knowledge. Such a strategy is viewed as not necessarily leading to learning when it is not associated with sufficient divergence (Jorczak, 2011).

To conclude, the main limitation of the present study was in the relatively small number of dyads used in the analysis due to technical issues concerning the recording of eye movements. There would be also the need to complement the dual eye-tracking and concept map analyses by examining verbal interaction data. Despite these limitations, this study offers results that are meaningful for better understanding the collaborative mechanisms involved in the coordination of external representations of individual knowledge in a computer-supported collaborative concept mapping task. Within the MUPEMURE framework (Bodemer et al., 2011; Author et al., 2011; Weinberger et al., 2011), these findings have implications for supporting CSCL. They suggest a need for scripts and group awareness tools mainly in the first half of the collaboration; such tools should be designed to support divergent processes and should take into consideration the distribution of prior knowledge within groups of learners. For example, these tools should encourage learners with different prior knowledge to move from their own perspective to their partner's perspective, and learners with similar prior knowledge to go against the tendency to too quickly work in a convergent regime.

Disclosure of interest

The author declares that she has no competing interest.

Acknowledgement

I gratefully acknowledge my MUPEMURE colleagues with whom I have worked on collaborative learning with multiple external representations: Armin Weinberger, Nikol Rummel, Daniel Bodemer, and Manu Kapur (a STELLAR Theme Team). I would like also to thank my colleagues with whom I have worked on the SNSF (# 105513-106940) “Mutual Modeling” project: Mirweis Sangin, Marc-Antoine Nüssli, and Pierre Dillenbourg.

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