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Learning from Concept Mapping and Hypertext: An Eye Tracking Study

Franck Amadiou^{1*}, Ladislao Salmerón², Julien Cegarra³, Pierre-Vincent Paubel¹, Julie Lemarié¹ and Aline Chevalier¹

¹CLLE research institute, University of Toulouse, France // ²University of Valencia, Valencia, Spain // ³ISAE, University of Toulouse, France // amadiou@univ-tlse2.fr // ladislao.salmeron@valencia.edu // julien.cegarra@univ-jfc.fr // paubel@univ-tlse2.fr // lemarie@univ-tlse2.fr // aline.chevalier@univ-tlse2.fr

*Corresponding author

ABSTRACT

This study examined the effects of prior domain knowledge and learning sequences on learning with concept mapping and hypertext. Participants either made a concept map in a first step and then read the hypertext's contents combined with concept mapping (high activating condition), or they read the hypertext's contents first and then made a concept map and re-read the hypertext's contents (low activating condition). It was hypothesized that the low activating condition would support better learning of relations between concepts for low prior knowledge participants who would need information from hypertext first to efficiently build a map next. For high prior knowledge participants, it was expected that the high activating condition would increase prior knowledge activation that would improve learning by promoting germane cognitive load, or at least would help participants to cope with the cognitive demands of the learning task by reducing extraneous cognitive load. The results confirmed that the low activating condition fostered better learning of relations between the concepts than the high activating condition, regardless of the level of prior knowledge. However, concept mapping behaviors and eye movement data showed that prior knowledge reduced disorientation, improved navigation coherence, and supported better elaboration of semantic relations between the concepts before reading the texts.

Keywords

Concept mapping, Eye movements, Hypertext, Prior knowledge, Learning sequence

Introduction

Hypertexts are non-linear documents providing free access to different text sections by clicking on hyperlinks. Learning from hypertexts relies on comprehension processes that consist in establishing coherence between the consulted sections and constructing a mental representation of the overall semantic organization (Foltz, 1996). Selecting text sections by clicking on hyperlinks, maintaining coherent reading paths and extracting a structure of hypertext materials can be very demanding and imposes additional processes that could hamper the relevant processes of comprehension (Antonenko & Niederhauser, 2010; DeStefano & LeFevre, 2007; Niederhauser, Reynolds, Salmen, & Skolmoski, 2000). Pre-structured concept maps are relevant guiding tools for learners because they are explicit spatial overviews of the contents' semantic organization and may thus limit learners' disorientation (for a review see Amadiou & Salmerón, 2014).

While pre-structured concept maps limit some ineffective cognitive processes, they do not promote deep and active elaboration processes based on prior background knowledge. For instance, learners are less active and tend to navigate passively, respecting the structure imposed by the pre-structured map (Amadiou, van Gog, Paas, Tricot, & Mariné, 2009). Concept mapping can be seen as an alternative to pre-structured maps. Concept mapping requires that learners structure themselves a spatial overview of the semantic organization. Learners have to identify the main concepts from learning materials, and to organize them in a coherent manner by creating a spatial arrangement of concepts and links between the concepts to indicate the semantic relations. Coherence formation in learning from concept mapping is similar to coherence formation in learning from multiple representations, which requires the local structure of a single representation to be processed (intra-representational or local coherence formation) and to integrate the different representations (inter-representational or global coherence formation) to construct a deep understanding of the contents (Seufert, 2003). Global coherence formation is often considered as being an active learning task supporting elaboration (Karpicke & Blunt, 2011). Even though concept mapping is theoretically efficient for learning, empirical results are not clear cut (Hilbert & Renkl, 2009; Redford, Thiede, Wiley, & Griffin, 2012; Stull & Mayer, 2007) and the efficiency of this learning task seems to depend on several factors such as addition of heuristic examples (Hilbert & Renkl, 2009), or learners' perceptions toward concept mapping (Tseng, Chang, Lou, Tan & Chiu, 2012). Because concept mapping frequently implies both building of a map and reading of textual material and because learners have to manage these two tasks, the temporal organization of the learning sequence including mapping and reading merits being studied. Therefore, designing an instruction that imposes a

specific sequence, i.e., processing textual material first vs. constructing a concept map first, could lead to different learning performance. This point was investigated in the current study in a hypertext-learning environment. A second factor considered in the present study was prior domain knowledge that can support both concept mapping and hypertext reading. The study investigated the on-line processes underpinning concept mapping with a hypertext.

Cognitive requirements of concept mapping: extraneous or germane cognitive processing?

Concept mapping may not be as efficient for learning as expected (e.g., Redford, Thiede, Wiley, & Griffin, 2012) and may even turn the learner away from learning (Stull & Mayer, 2007). Indeed, Stull and Mayer (2007) showed that concept mapping could impair content integration in contrast to studying already completed concept maps. The activity of constructing concept maps may induce extraneous processing, leaving less resources in working memory for essential processing. Different levels of cognitive requirements may be considered in concept mapping. Chang, Sung and Chen (2001) showed that filling in blank nodes and links in an incomplete concept map provided better learning than constructing an entire concept map. Gurlitt and Renkl (2008) also observed that, for high school students, creating and labeling links was more challenging and detrimental for learning than only labeling links. In another study, Gurlitt and Renkl (2009) found that when concept mapping was very demanding (i.e., creating links between concepts instead of just tagging already created links), learners performed worse in post-test measures of learning. These results argue for Cognitive Load Theory (Sweller, Ayres, & Kalyuga, 2011) considering that instructional design should avoid additional and ineffective cognitive processes (i.e., extraneous cognitive load) with regards to limited working memory resources.

Nevertheless, concept mapping might also contribute to active learning by fostering deep processing. In this line, the model of generative processes of comprehension (Wittrock, 1989), considers that relational processes (i.e., inferring relations between parts of a text and between text and prior knowledge) support deeper comprehension and learning. For instance, Bodemer, Plötzner, Feuerlein and Spada (2004) showed that learners who had to actively integrate different representations in a multimedia document by dragging and dropping the representations outperformed learners who received pre-integrated representations. As it contributes directly to the construction of meaning, relational processing required by concept mapping could be considered as belonging to the germane cognitive load. Learners who are able to produce elaborate concept maps would be engaged in germane cognitive processing as shown by Hilbert and Renkl (2008) who observed that learners who had good knowledge integration scores constructed more coherent concept maps. Moreover, Ponce and Mayer (2014) showed that filling in a graphic organizer close to a concept map led learners to conduct integrative strategies in their reading of a text.

In sum, instructional design would impose extraneous cognitive load if it makes relational processing difficult to run, or promote germane cognitive load if it makes it as a desirable difficulty (Bjork & Bjork, 2011). Leading learners to generate themselves connections between information parts may support germane cognitive load when learner's prior knowledge level is appropriate.

Prior domain knowledge in concept mapping and hypertext reading

Prior domain knowledge plays a major role in the construction of meaning in comprehension (Kintsch, 1998) and learning (Sweller et al., 2011). Prior knowledge seems to contribute to process challenge imposed by concept mapping. Students with a high level of background knowledge can construct concept maps faster (Amadiou, Tricot, & Mariné, 2009) or more interconnected maps (Dogusoy-Taylan & Cagiltay, 2014). Actually, concept mapping can contribute to the activation of prior knowledge (Gurlitt & Renkl, 2008, 2009). Gurlitt and Renkl (2008) studied how different concept mapping tasks could activate prior knowledge before learning from a hypertext. Their results initially showed that concept mapping could be a relevant knowledge activation task that orients the processes in the following hypertext reading task (i.e., more focused and less explorative approach). As argued by the authors, concept mapping can contribute to activate prior knowledge and to help learners to identify what they already know and what they do not yet know. Next, they showed that inducing a low-coherent prior knowledge activation, consisting in the elaboration of high demanding concept mapping (i.e., creating and labeling links) was more advantageous for high prior knowledge learners. By contrast, a high-coherent prior knowledge activation that consisted in the elaboration of low demanding concept mapping (i.e., only labeling provided links) was more advantageous for low prior knowledge learners. Their findings are consistent with the idea that the mere existence of

background knowledge does not warrant those facilitative effects and that students need to be engaged in the task to activate their prior knowledge to contribute to germane cognitive load (for similar arguments in research on text and hypertext comprehension see Salmerón, Kintsch, & Cañas, 2006; Kintsch & Kintsch, 1995; McNamara, Kintsch, Songer, & Kintsch, 1996).

Text reading and concept mapping: which learning sequence?

Because concept mapping is often combined with a reading task, the type of complementarity between text reading and concept mapping (i.e., learning sequence) is an issue for designing effective learning instructions. In a recent study (Amadiou, Cegarra, Salmerón, Lemarié, Chevalier, & Paubel, 2013), it was observed that learners who spontaneously read several hypertext nodes before starting building the map tended to better comprehend the hypertext than learners who started earlier building the map. The study conducted by Hilbert and Renkl (2008) showed that a concept-mapping task after a reading task contributes to learning. However, building a concept map before reading texts may also have a positive effect on learning as shown by the study of Gurlitt and Renkl (2008). In line with this result, Bonestroo and De Jong (2012) showed that asking learners to create their own plan (i.e., organizing a sequence of concepts) before learning from a hypertext supported better knowledge acquisition of the concepts' structure. No previous studies to our knowledge have compared what learning sequence (i.e., reading-before or mapping-before) is the most beneficial for learning. Therefore, further investigations into the effects of learning sequence and into the conditions of its efficiency are needed.

Overview of the present experiment and hypotheses

In the current study, the concept-mapping task consisted in spatially organizing the concepts on screen and in creating and labeling links between provided concepts. Two factors were investigated in the present study: the learning sequence including concept mapping and hypertext consultation (level of prior knowledge activation) and the learners' prior domain knowledge. Two learning sequences were compared: a mapping-before condition considered as a condition of high activation of prior knowledge (i.e., in a first step, learners had to build a concept map with no access to the texts sections of the hypertext, and in a second step, learners could read the text sections and continue building the concept map) and a reading-before condition considered as a condition of lesser activation of prior knowledge (i.e., in a first step, learners had to read all text sections, and in a second step, they could reread the text sections and start building a concept map). Additionally, an originality of the current study concerns the use of eye-tracking to examine online processes during concept mapping (see also Dogusoy-Taylan & Cagiltay, 2014; Ponce & Mayer, 2014). Specifically, eye-tracking was used to assess two cognitive activities. First, students' level of attention to the core concepts on the map was assessed by examining eye fixations (Lai et al., 2013). Dogusoy-Taylan and Cagiltay (2014) found, by using verbal protocols, that novices did not mention an initial strategy during the early steps of concept mapping, suggesting that they were less able to analyze the situation and to plan their map construction. As high prior knowledge individuals fixate on more areas that are relevant for the task (Cook, Wiebe, & Carter, 2008; Gegenfurtner, Lehtinen, & Säljö, 2011), the current study investigated the attention driven by prior knowledge by measuring the attention distribution on core concepts that reflects top-down processes. Second, the level of relational processing was assessed by measuring eye transitions between information sources (O'Keefe, Letourneau, Homer, Schwartz, & Plass, 2014; Ponce & Mayer, 2014). Yang, Chang, Chien, Chien and Tseng (2013) conducted analyses of saccade paths during multimedia learning and observed that high prior knowledge students conducted more inter-AOI (area of interest) scanning between multiple representations (i.e., saccade paths between the text and picture zones), indicating better integration of the different representations. The current study examined the learners' inter-AOI scanning (i.e., transitions between concepts on the map).

It was hypothesized that low prior knowledge learners would benefit more from a low activating condition (i.e., reading-before sequence) than a high activating condition (i.e., mapping-before sequence). In contrast to a mapping-before condition, a reading-before condition provides relevant information from texts to learners early in the learning process, to build a rather coherent text representation. This representation should guide their following concept mapping activity by supporting global coherence formation. Therefore, for low prior knowledge participants a low activating condition should promote better learning of the relations between concepts (Hypothesis 1a), should limit extraneous cognitive load (Hypothesis 1b), should lead to more coherent navigation (Hypothesis 1c), should guide

attention on the most relevant map concepts (Hypothesis 1d) and should facilitate the processing of relevant relations between concepts (Hypothesis 1e).

As far as high prior knowledge learners are concerned, it was expected that building a concept map before reading a hypertext could promote a more intense activation of their prior knowledge (i.e., high activating condition). To structure a concept map before reading a hypertext, learners have to elaborate relations between provided concepts by mobilizing their background knowledge. In contrast, a reading-before task (i.e., low activating condition) should promote less activation of prior knowledge and lead learners to build a map more from text contents than from their prior knowledge. Therefore, it was hypothesized that high prior knowledge learners either benefit from a high activating condition or reach equivalent learning performance under both learning conditions because they are able to cope with concept-mapping early in learning (Hypothesis 2a). In a high activating condition, their cognitive load should be higher than in a low activating condition, but associated with better learning of relations between concepts (i.e., germane cognitive load) (Hypothesis 2b). Because more top-down processes should be activated in this condition, their navigation should be more coherent (Hypothesis 2c), they should pay more attention to the most relevant concepts on the map (Hypothesis 2d) and they should perform more relevant transitions between concepts (Hypothesis 2e).

Method

Participants

Seventy-five undergraduate psychology students volunteered to participate in the study (82.66 % of female participants; mean age = 19.31 years, $SD = 2.66$). Each participant received a purchase voucher of 15 euros for her/his participation at the end of the study. For the analyses, 10 participants were removed from the sample because of eye movement issues (unreliable calibration, loss of signal over the task). Hence, analyses were conducted on 65 participants.

Materials

Learning materials

A hypertext dealing with the greenhouse effect was designed. It consisted of twelve hypertext nodes corresponding to the main concepts (for a total of 635 words). A main page gathered together the twelve concepts, each being presented in a specific box. The concepts were linearly displayed on screen in an alphabetic order to avoid a coherent reading sequence. Participants could create the map on this main page by moving the concepts, drawing and labeling links between them (see Figure 1 for an example of concept map built by a participant). A label could be added to each created link by selecting one of 5 terms (i.e., belongs to, contributes to, emits, absorbs, reflects). Double-clicking on a link deleted it. Clicking on a concept opened the text dealing with this concept. The text appeared in full screen. A link below the text led back to the main page displaying the concept map where a new concept (or the same concept) could be opened. Therefore, participants could not simultaneously view the map and the texts on-screen. The participants were free to view the hypertext nodes several times and in any order.

Two prior knowledge activation conditions reflected by learning sequences were designed. For the high activating condition, during the first step of learning, participants were instructed to build a concept map from the boxes displayed on screen. The texts dealing with the concepts were not available during the first step. In the low activating condition, the participants were instructed to read all the texts, at least once each text, by clicking on the boxes organized in alphabetical order to access the corresponding text. They could neither move the concepts nor draw links between the concepts. When participants judged they had finished their map in the high activating condition, or had read enough the texts in the low activating condition, they were allowed to start the second learning step. During this second step, participants in the high activating condition could access to the texts by clicking on the links in the boxes (see Figure 1) and could still change their concept map, while participants in the low activating condition could build the map by moving the boxes and drawing links between them and could reread the texts. Participants were free to stop their learning for each step; nonetheless a time limitation of 30 minutes was imposed for each step (limitation assessed from preliminary tests).

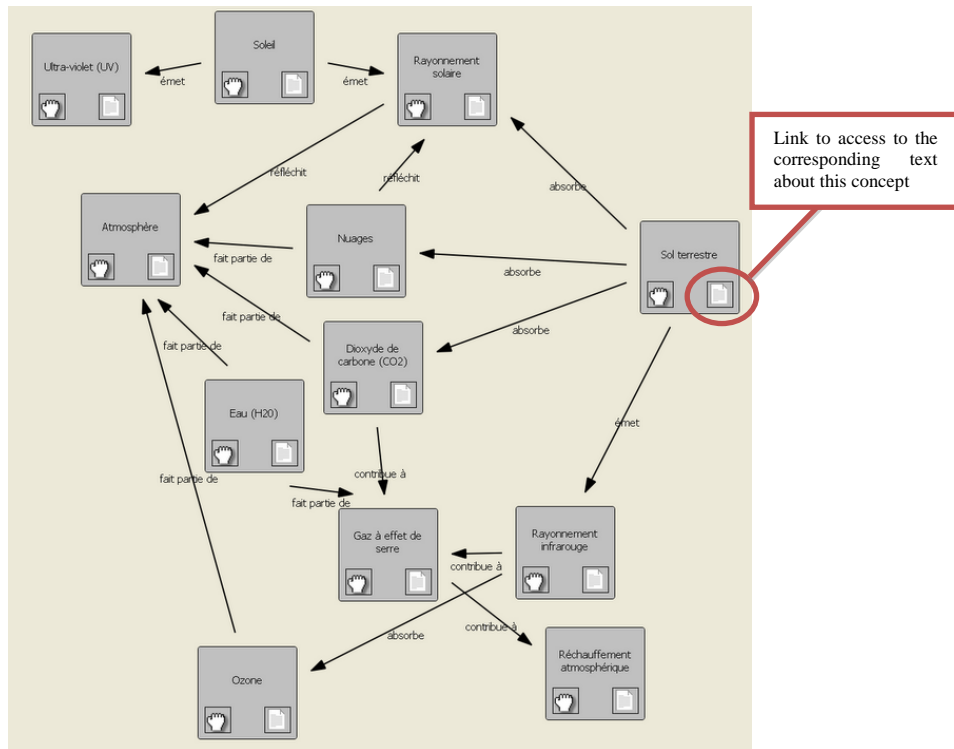


Figure 1. Example of a concept map built by a participant

Prior domain knowledge

According to the distinction between domain knowledge and topic knowledge (i.e., knowledge specific to the hypertext contents) proposed by Alexander, Kulikowich and Schulze (1994), prior domain knowledge was general knowledge about the subject matter, that is to say, knowledge of principles in physics and biology that are relevant to understand the greenhouse effect mechanism and climate change. An example of a question concerning the principle of absorption and emission of energy by objects is: “In physics, which principle is true?” Choices: (a) A physical object cannot absorb or emit energy, (b) A physical object can absorb energy without reemitting it, (c) A physical object can absorb and reemit energy (correct answer), (d) I do not know. Thirteen multiple-choice questions were used and validated by a physics teacher who taught the greenhouse effect. Each question had four possible choices including the answer “I do not know” to limit random answers. Each correct answer was awarded one point ($\alpha = .61$).

Measures of cognitive load

To measure the overall cognitive load, a scale was used (Paas, 1992): “The mental effort that you invested to study the mechanism of the greenhouse effect was.” “Mental effort is the aspect of cognitive load that refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task; thus, it can be considered to reflect the actual cognitive load” (Paas, Tuovinen, Tabbers, & van Gerven, 2003, p. 64). In addition, to assess extraneous cognitive load linked to navigation, learners’ feelings of disorientation were measured by adaptation of a set of scales developed by Ahuja and Webster (2001). The scales were modified according to the material of the study: (a) “your difficulty knowing which text you had to view next was:”, (b) “your difficulty knowing where you were in the instructional document was:” and (c) “your difficulty finding information that you had previously read was:” ($\alpha = .76$). In both scales, a 7-point rating scale (1 = “Very low”, 7 = “Very high”) was used.

Processing of concept mapping

Attention and relational inter-AOI scanning. The areas of interest (AOI) were the boxes representing the concepts on the mapping page. Two indices from eye-tracking data were calculated: (1) Attention to core concepts was calculated as the number of fixations on the core concepts (i.e., the concepts the most directly implicated in the greenhouse mechanism: Solar Radiation, Infrared Radiation, Ground, Greenhouse Gases including the concepts of Ozone, CO₂ and Water) divided by the number of fixations on all the map concepts (the number of fixations was divided by the number of words on the concept boxes to control word variability between the different concept boxes); (2) Relational inter-AOI scanning was calculated as the number of times eyes moved between concepts linked in the experts' map (i.e., high-related pairs of concepts), divided by the number of times eyes moved between any concepts in the map. Thus, the index ranged from 0 to 1. This index indicated the degree to which students focused on the relationships between important map concepts, among all potential relationships between concepts on the map. Values closer to 1 indicated that the majority of visual transitions were relevant. In sum, we interpreted this index as a measure of relational deep-processing of the relations between important map concepts.

Interconnectivity and quality of the concept maps

The concept maps built by participants were taken as a measure of the quality of the mental model they elaborated. Two indices were calculated: (1) Number of links drawn between the concepts, indicating to what extent participants established connections between concepts; and (2) Relevance of the links. To calculate a relevance index, the map built by participants was compared to that produced by two high-school teachers in biology and physics. An expert's concept map was produced, including all the links created by both experts. The relevant links created by participants corresponded to the links shared with the experts' map. A relevance index of each participant's map was calculated by dividing the number of drawn links similar to the experts' map by all drawn links.

Navigation coherence

An index of navigation coherence was calculated as the number of navigation transitions between texts corresponding to a link of the experts' map divided by the number of total navigation transitions (Amadiou, Tricot, & Mariné, 2010).

Knowledge gain

A pre-test and a post-test were used to calculate knowledge gain scores. To limit recognition of the questions by participants, the order of questions between the pre-test and the post-test was changed and five days were allowed to elapse between tests. Two types of knowledge were considered: (a) microstructural level (i.e., knowledge of explicit details specific to a concept mentioned within text sections) and (b) macrostructural level (i.e., knowledge of relations between concepts). The two types of knowledge were measured by multiple-choice questions (five choices per question including the answer "I do not know" to limit random answers) that are considered as relevant question formats to assess the mental model (Ozuru, Best, Bell, Witherspoon, & McNamara, 2007). Eight items measured the microstructural level ($\alpha = .46$ for the pre-test & $\alpha = .60$ for the post-test) and sixteen items measured the macrostructural level ($\alpha = .68$ for the pre-test & $\alpha = .71$ for the post-test).

Apparatus

Gaze data were recorded using an SMI RED 250 binocular eye tracker (SMI, Teltow, Germany). The sampling rate was set to 60Hz. This eye tracker has a spatial accuracy greater than 0.5°, and a 0.03° tracking resolution. A chin rest was used to maintain distance and to avoid large head movements. Eye movements for each participant were calibrated using five fixation points. A DELL 22" monitor with a refresh rate of 75 Hz and a resolution of 1680x1050 pixels was used. All fixations on areas of interest (i.e., concepts on the map) were detected using the SMI BeGaze default dispersion-based algorithm (set to 100 pixels and minimum duration of 80 msec).

Procedure

During an initial session (approx. 40 minutes), participants performed the prior domain knowledge test followed by the pre-test specific to the greenhouse effect topic. They were then instructed how to use the program to open the texts from the concepts displayed on screen and how to construct a concept map by using the mouse. Thus, they practiced with the concept-mapping program to avoid unfamiliarity problems with the task and the functions of the program.

During the second session (approx. 50 minutes) conducted several days later, students performed the experimental task while their eye movements were recorded. Before starting each step, eye calibration was set up. They were randomly assigned to one of the learning conditions: high activating condition or low activating condition.

They were told that there were two learning steps and that they had to learn the greenhouse effect mechanisms to answer subsequent questions. In the high activating condition (i.e., mapping-before task), they were instructed to build a concept map from the provided concepts without texts to represent the greenhouse effect mechanism and were told that they would gain access to the texts and that they would be allowed to modify their map in the second step. In the low activating condition (i.e., reading-before task), participants were told they had to read the texts in the first step and, for the second step, that they would have to build a concept map and could access to the texts again. After that, they rated their mental effort (i.e., overall cognitive load) and perceived disorientation and performed the post-test questions.

Results

In order to test the effects of independent variables, prior knowledge activation (high activating vs. low activating) and prior knowledge, multiple regression analyses with interaction terms were conducted on each dependent variable. The independent variables were entered simultaneously into the regression model before entering the interaction term. Prior knowledge was entered as z-standardized variables. The level of prior domain knowledge was similar across conditions (for the low activating condition, $M = 6.94$, $Min = 2$, $Max = 12$, $SD = 2.23$, for the high activating condition, $M = 7.12$, $Min = 3$, $Max = 12$, $SD = 2.48$), $t(63) = 0.31$, $p = .76$. The learning condition was entered as a contrast-coded dummy variable.

First, the analyses of students' learning performance and cognitive load measures are reported. Then, the analyses of learning processes including navigation and concept mapping processing are described.

Learning performance and cognitive load

Descriptive data of the knowledge gains and cognitive load measures are presented in Table 1.

Table 1. Gain of knowledge and cognitive load measures

		Learning condition			
		High activating condition (Mapping-before task)		Low activating condition (Reading-before task)	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Gain of knowledge	Microstructure scores (max = 8)	1.73	1.38	2.28	1.75
	Macrostructure scores (max = 16)	4.48	3.22	6.63	2.81
Cognitive load measures	Mental effort ratings (from 1 to 7)	4.91	0.91	5.09	0.86
	Disorientation ratings (from 1 to 7)	3.94	1.11	4.07	1.25

Knowledge gains

Multiple regression analyses with the knowledge gain scores indicated no effect for the microstructure scores, $R_{\text{corr}}^2 = .01$, $F(3, 61) = 0.73$, $p = .540$, though there was an effect for the macrostructure scores, $R_{\text{corr}}^2 = .09$, $F(3, 61) = 3.02$,

$p = .037$. A main effect of condition was observed, $t(61) = 2.87, p < .006, \Delta R^2 = .117$. Participants in the low activating condition outperformed participants in the high activating condition. There was no effect of prior knowledge, $t(61) = 1.01, p = .316$, and contrary to predictions, there was no interaction effect, $t(61) = 0.30, p = .763$. Thus, the reading-before task entailed better learning of the relations between the concepts, regardless of the level of prior knowledge.

Cognitive load: Perceived disorientation and overall cognitive load

The multiple regression analyses conducted on the perceived disorientation ratings showed a significant model, $R_{\text{corr}}^2 = .10, F(3, 61) = 3.38, p = .024$. Only prior domain knowledge had an effect, $t(61) = -3.13, p < .003, \Delta R^2 = .138$. The more prior domain knowledge participants had, the less disorientated they felt in the hypertext. There were no other effects (all $p > .10$). By contrast, the multiple regression analysis of mental effort ratings reflecting the overall cognitive load did not indicate any effect, $R_{\text{corr}}^2 = -.03, F(3, 61) = 0.37, p = .78$.

Analyses of learning processes: Navigation, quality of maps and eye movements

Descriptive data of the navigation and concept mapping measures are presented in Table 2.

Table 2. Navigation, concept mapping and eye movements' data

	Learning condition							
	High activating condition (Mapping-before task)				Low activating condition (Reading-before task)			
	Step 1		Step 2		Step 1		Step 2	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Rate of navigation coherence	-	-	.33	.12	.22	.07	.27	.12
Number of drawn links in the concept maps built by participants	11.45	2.20	15.27	3.35	-	-	12.75	2.17
Rate of relevant links in the concept maps built by participants	.45	.16	.66	.13	-	-	.70	.13
Rate of eye fixations on the core concepts	.38	.06	.41	.07	.44	.14	.38	.05
Rate of relational inter-AOI scanning	.34	.07	.43	.07	.26	.13	.43	.04

Navigation coherence

A multiple regression model indicated effects on navigation coherence for the second learning step (it was not possible to run the analysis on step 1 because participants in the high activating condition didn't have to navigate), $R_{\text{corr}}^2 = .14, F(3, 61) = 4.48, p = .007$. There was a main positive effect of prior knowledge, $t(61) = 2.85, p = .006, \Delta R^2 = .109$. This result confirmed that high prior domain knowledge facilitated the selection of the next text to read according to its semantic proximity to the previously read text. Navigation coherence tended to be higher in the high activating condition than in the low activating condition, $t(61) = -1.85, p = .070, \Delta R^2 = .046$. Finally, there was no interaction, $t(61) = -0.90, p = .372$.

Interconnectivity and quality of concept maps

The examination of the drawn links on the participants' maps at the end of the first learning step (only participants from the high activating condition could be considered) did not show any effect of prior knowledge, $R_{\text{corr}}^2 = .00, F(1, 31) = 0.91, p = .342$. However, the model was significant for the second step (including participants from both

conditions), $R_{\text{corr}}^2 = .21$, $F(3, 61) = 6.77$, $p = .001$. High prior knowledge facilitated the construction of more interconnected maps, $t(61) = 2.48$, $p = .016$, and the maps built in the high activating condition were more interconnected than in the low activating condition, $t(61) = -3.62$, $p = .001$. No interaction was observed, $t(61) = -.32$, $p = .749$.

Next, regarding the relevance of the maps, the initial map drawn in step 1 was analyzed first (only the high activating condition was concerned). Regression analyses revealed that prior knowledge led to a higher proportion of relevant links, $R_{\text{corr}}^2 = .15$, $t(1, 31) = 2.56$, $p = .016$. Second, the analyses of the final maps constructed in step 2 (including both conditions) did not show any significant model, $R_{\text{corr}}^2 = .01$, $F(3, 61) = 1.11$, $p = .353$.

Attention to core concepts

The rate of fixations on core concepts was analyzed. In the first step the model was significant, $R_{\text{corr}}^2 = 0.08$, $F(3, 61) = 2.89$, $p = .043$. Attention to core concepts was higher in the low activating condition than in the high activating condition, $t(61) = 2.38$, $p = .021$, $\Delta R^2 = .081$. There was no effect of prior knowledge, $t(61) = 0.49$, $p = .623$, nor interaction, $t(61) = -1.62$, $p = .110$. No effect for the second step was observed, $R_{\text{corr}}^2 = 0.02$, $F(3, 61) = 1.36$, $p = .264$.

Relational inter-AOI scanning

For the first learning step, the analysis of the ratio of relational inter-AOI scanning revealed a significant model, $R_{\text{corr}}^2 = .15$, $F(3, 61) = 4.66$, $p = .005$. The ratio was significantly higher in the high activating condition than in the low activating condition, $t(61) = -3.01$, $p = .004$, $\Delta R^2 = .121$. Prior knowledge did not have any effect, $t(61) = .85$, $p = .398$. However the interaction tended to be significant, $t(61) = -1.89$, $p = .064$, $\Delta R^2 = .047$. Relational inter-AOI scanning increased with prior knowledge in the high activating condition, $R_{\text{corr}}^2 = .22$, $F(1, 31) = 9.95$, $p = .004$, but not in the low activating condition, $R_{\text{corr}}^2 = -.02$, $F(1, 30) = 0.31$, $p = .579$. For the second learning step, the analysis did not show any effect, $R_{\text{corr}}^2 = -.05$, $F(3, 61) = 0.01$, $p = .99$.

Discussion

This study investigated the effects of students' prior domain knowledge and the level of prior knowledge activation induced by the learning sequence (i.e., reading-before task for the low activating condition vs. mapping-before task for the high activating condition) on learning with concept mapping from a hypertext. The results showed that the gain of the macrostructural level was higher when participants started by reading the hypertext than with concept mapping (Hypothesis 1a). Contrary to hypothesis 2a, this effect occurred whatever the level of prior knowledge. Microstructural level gains did not differ between the two learning conditions. This concurs with previous findings showing that concept mapping impacts global coherence formation and deep processing of material rather than retention (Stull & Mayer, 2007). To shed light on these unexpected results, we will next discuss how students' prior knowledge influenced their concept mapping, as evidenced by building and eye-movement data.

Students' prior knowledge and concept map processing

Eye data analyses indicated that the low activating condition led both high and low prior knowledge learners to distribute more attention to the core concepts during the first learning step (Hypothesis 1d) but not to pay more attention to the most relevant relations between concepts during mapping (Hypothesis 1e). Moreover, contrary to expectations, for the low prior knowledge learners, the low activating condition did not reduce the overall cognitive load (hypothesis 1b) and did not improve navigation (Hypothesis 1c). Concerning the high activating condition, the results indicated that building a map before reading a hypertext yielded more interconnected maps, regardless of the level of prior knowledge, but did not lead to higher map quality.

As far as high prior knowledge learners are concerned, the results showed that the low activating condition entailed better learning than the high activating condition as mentioned above (Hypothesis 2a). In addition, contrary to

expectations, for the high prior knowledge learners, the high activating condition did not support better navigation (Hypothesis 2c), or more attention paid to the core concepts (Hypothesis 2d), or more relational processes (Hypothesis 2e) during learning phase 2. Nevertheless, the study yielded interesting findings on the positive effects of prior knowledge on navigation and concept map processing. First, prior knowledge reduced extraneous cognitive load linked to navigation (i.e., disorientation ratings) and supported more coherent navigation corroborating previous findings (Amadiou et al., 2010). Second, prior knowledge supported the building of more interconnected maps as observed by Dogusoy-Taylan and Cagiltay (2014). These two results confirmed that prior knowledge contributed to more relational processing between the concepts. However, the clearest effects of prior knowledge on concept mapping were observed during the first learning step. In the high activating condition, prior knowledge led learners to build more coherent maps (i.e., better rate of relevant links between concepts). The examination of eye transitions between the concepts on the map confirmed that more attention was allocated to the most relevant relations between concepts. The results pertaining to the role of knowledge activation played by a mapping task before reading are consistent with previous findings (Bonestroo & De Jong, 2012; Gurlitt & Renkl, 2008). However, after text introduction, the effects of prior knowledge on the attention paid to the most relevant relations between concepts on the map vanished, showing no effect of knowledge activation on hypertext processing.

Knowledge activation and learning from concept mapping

Although the high activating condition supported prior knowledge activation during the first step, it did not favor learning for learners with high prior knowledge. Two main reasons can explain the lack of interaction. First of all, prior knowledge activation might also have occurred in the low activating condition. In this condition, learners read the texts in a non-coherent order because they were organized alphabetically. This could have concurred with prior knowledge activation by requesting strong inferential activity between texts to understand relations between them (i.e., the concepts) as shown in hypertexts (Amadiou et al., 2010) or text comprehension (McNamara et al., 1996). This explanation is supported by the results obtained on navigation, indicating that prior knowledge supported inferential activity in both conditions, as can be interpreted by their high levels of coherent navigation. The second reason that could explain the positive effect of the low activating condition on learning for both levels of prior knowledge concerns the function of the concept mapping task after reading the texts. During the first step, learners may have developed a rich text representation from the texts (i.e., text base, Kintsch, 1998) and may have sketched some interrelationships between concepts. The posterior concept-mapping task may have helped them to reflect on these relationships, which may in turn have boosted students' inferential knowledge. Besides, reading the texts before could have help learners to plan their concept mapping. Indeed, Hilbert and Renkl (2008) found that a good planning predicted better performance in concept mapping.

In sum, the low activating condition could also have promoted inferential processing supporting better comprehension of relations between concepts (i.e., global coherence formation), but contrary to the high activating condition, the inferences drawn by learners would be more accurate or less ambiguous because they were conducted on the basis of both prior knowledge and text material. The texts fulfilled the function of aids by providing information about relations between the concepts that could have facilitated global coherence formation (Seufert & Brünken, 2006). Participants in the high activating condition may have kept in their mental representation incorrect relationships built during phase 1, even after reading the texts in phase 2, as indicated by a higher number of links on their maps. A potential means of testing this idea in future research would be to provide corrective feedback on the constructed maps before proceeding to the reading of the texts.

Limitations and future research

A potential limitation of the study is the knowledge background of participants. The lack of interaction of the learning conditions with prior knowledge may be due to the level of the participants who were psychology undergraduates with some notions of biology. Further studies should be conducted on students with more prior knowledge of the study materials. In line with this point, the use of a concept mapping task to activate students' knowledge should be used with caution, or at least be restricted to the creation and labeling of links, as found in previous studies (Gurlitt & Renkl, 2008). Therefore, different levels of cognitive demands linked to concept mapping should be examined by comparing free concept mapping and guided concept mapping (e.g., labeling provided links). Another interpretation explaining that high prior knowledge learners benefited from the low activating condition is

that students may be more used, and probably may feel more confident with an activity that involves first reading a text and after doing something with it, such as writing a summary, answering questions, or building a concept map. A long-term study including several practice sessions with hypertext concept mapping may shed light on this point.

Although the current study provided a picture of the online processes engaged in concept mapping, questions remain over how each learning step contributed to learning. Thus, it would be informative to examine how comprehension and cognitive load evolves throughout a learning task involving text reading, concept mapping and both. Moreover, although the study showed that the low activating condition improved comprehension of the relations between concepts, the cognitive load measure results failed to prove that building a concept map before reading texts entailed more cognitive load. The lack of difference in disorientation ratings might be explained by the fact that the navigation task across the texts was quite similar between both learning conditions. Concerning the single retrospective cognitive load rating, as well as for the measures of comprehension, introducing intermediate measures of cognitive load after each learning step should provide information about the dynamic of cognitive demands over learning and should lead to different results than a single retrospective rating (Van Gog, Kirschner, Kester, & Paas, 2012). Investigations of the three types of cognitive load assessed by measures designed by Leppink, Paas, van der Vleuten, van Gog and van Merriënboer (2013) could help disentangle the different types of cognitive load. Moreover, to disentangle the types of cognitive processing consuming working memory resources linked to text reading and concept mapping, a dual task paradigm, using concurrent verbal and spatial tasks, could be used in future studies, as well as dual-task methods measuring executive control processes, such as the rhythm method recently tested by Park and Brünken (2015). The rhythm method provides an indicator for executive control by including inhibition processes and thereby may be considered as a good method of measure navigation through a hypertext. Besides, this continuous measure allows the assessment of fluctuations in cognitive load and cognitive load peaks.

In this study, the use of different online and offline methods to investigate relational processing engaged in a concept-mapping task in hypertext provided fruitful results. Relational processes to plan and build a concept map were captured, by eye movements (relational inter-AOI scanning) (Ponce & Mayer, 2014), the maps constructed by learners (number and relevance of drawn links in the concept map), along with the navigation paths (coherence of the transitions between node texts). While we obtained a complete picture of a complex learning task, future studies may include additional methods (e.g., verbal protocols, electroencephalography) to contribute to the investigation of learning.

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