Qualitative and Quantitative Information in Cognitive Group Awareness Tools: Impact on Collaborative Learning

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Abstract: A large body of research covers the positive impact of cognitive group awareness tools on collaborative learning processes. These tools provide learners with visualizations of relevant cognitive information on their learning partners, triggering the resolution of cognitive conflicts, improving accurate partner modeling and, associated therewith, implicitly guiding learners' activities instead of prescribing certain ways of behaving. Said visualizations can be differentiated by the type of awareness information they provide: qualitative or quantitative. We systematically compared the impact of both types of information on collaborative learning in an experimental study (*N* = 51). The results suggest that the availability of both qualitative and quantitative information can evoke cognitive conflicts that guide learners' communication behavior in a goal-oriented way. Furthermore, visualizations combining both types of information appear to facilitate accurate partner modeling.

Introduction

A large body of research covers the positive impact of cognitive group awareness tools on collaborative learning processes (cf. Janssen & Bodemer, 2013). Such tools support learners by providing them with relevant cognitive information on their teammates' knowledge (Janssen & Bodemer, 2013) and implicitly guiding them through the learning process, the latter meaning that the tools suggest certain ways of thinking, communicating and behaving instead of prescribing them (Bodemer, 2011). This enables the learners to (self-)regulate their learning with reference to learning mechanisms being central to collaborative learning, e.g., conflict and partner modeling (Dillenbourg, 1999). Although research on existing tools suggests a strong effect of such tools' visualizations on learning behavior and outcomes, the various types of visualized information, namely qualitative or quantitative information, have not been investigated separately so far. Thus, we aim to systematically investigate the impact of both types of visualizations on collaborative learning to better understand their degree of efficiency and get clues on how to design even better cognitive group awareness tools in the future.

Cognitive group awareness tools are characterized by its main function of transforming cognitive information, e.g., by categorizing or aggregating ratings on knowledge, and visualizing it (cf. Bodemer & Buder, 2006). In so doing, they differ in the types of cognitive information they provide: Some tools visualize *what* a learner knows about various concepts in comparison to another learner (e.g., Schnaubert & Bodemer, 2015; Dehler, Bodemer, Buder, & Hesse, 2011; Engelmann & Hesse, 2010), and other tools visualize *how much* the learning partner knows or rather combine both information in one knowledge representation (e.g., Erkens & Bodemer, 2015; Sangin, Molinari, Nüssli, & Dillenbourg, 2011). By focusing on the functions of the aforementioned cognitive group awareness tools, we can differentiate between qualitative and quantitative information. Qualitative cognitive information provides binary categories of knowledge distributed across concepts, i.e., whether or not knowledge on a specific concept is present. In contrast, quantitative information describes quantitative values that represent the extent of knowledge. Both can also be combined so that the learners can be aware of how much they know about each concept belonging to a topic. Such information can be visualized for one or several learning partner(s), usually including the learners themselves to simplify the comparison between teammates, allowing goal-oriented collaboration (Bromme, Hesse, & Spada, 2005).

Comparability between learning partners is an important factor in this context, since it is associated with relevant learning mechanisms such as partner modeling and conflict. The concept of conflict goes back to Piaget (1977) and is based on his idea that interactions with physical or social environments can lead to a disequilibrium. In the case of social environments contradicting the knowledge of a learner, intrapersonal (Piaget & Inhelder, 1969) or interpersonal cognitive conflicts (Doise & Mugny, 1984) might occur. Cognitive development is making progress when learners find cognitive balance through assimilation or accommodation (Piaget, 1977). Both types of cognitive conflict are regarded as important antecedents to individual learning (Buder, Schwind, Rudat, & Bodemer, 2015). Furthermore, it is assumed that learners maintain a model of their learning partners from which they can infer and internalize their knowledge (Dillenbourg, 1999). From a Vygotskian perspective, internalization of socially regulated and mediated knowledge is the motor of cognitive development taking place when a layperson interacts with a more capable partner (Tudge & Rogoff, 1989).

Cognitive group awareness tools aim to facilitate the comparison between learning partners by visualizing or highlighting conflicts between them and making conflictual situations more salient (Bodemer, 2011). From a Piagetian perspective, comparative visualizations draw one's attention to knowledge gaps triggering intrapersonal conflicts or to contradicting knowledge that appears to trigger interpersonal conflicts—both of which need to be resolved. Intrapersonal conflicts can support collaborative learning, since knowing about shared and unshared knowledge resources triggers discussions about topics, with which only one learner in a group is familiar (Schittekatte & Van Hiel, 1996). Dehler and colleagues (2011) further found that the visualization of binary qualitative information on topical knowledge (present or not) guides the communication between learning partners. Learners who were aware that they did not comprehend a text paragraph, independent of the learning partner's knowledge of the paragraph, asked more questions than learners with visualized knowledge on the topic. When deficits of partners were visualized, learners also gave more explanations, irrespective of whether a learner knew something about the topic or not (Dehler et al., 2011). Thus, the group awareness tool used in this study guided learning behavior in so far as learners asked their partners for help or offered their help to ignorant peers. Furthermore, Sangin and colleagues (2011) showed that visualized differences of knowledge can guide students not only in their behavior, but also improve their learning outcomes. Discovering gaps in their knowledge through the comparison of quantity of knowledge (percentage) per learning module (providing peers' prior knowledge in a collaborative concept mapping phase) motivated students to converge to their partner's better knowledge status as the students achieved better learning outcomes than unaware learners after the collaboration. Since the different tools mentioned previously have used qualitative information (Dehler et al., 2011) or combined qualitative with quantitative information (Sangin et al., 2011), we assume that the availability of both types of information can increase the number of content-related questions and explanations (including an explorative investigation of possible interaction effects).

Hypothesis 1: Learners supported by qualitative and/or quantitative cognitive information ask more questions than learners without such support.

Hypothesis 2: Learners supported by qualitative and/or quantitative cognitive information explain more than learners without such support.

Concerning partner modeling, the relevance of reducing the effort for grounding processes in collaborative learning was highlighted (Bodemer, 2011). Bodemer (2011) found that learners with group awareness support spent less time for grounding and modeling processes and were more involved in meaningful discussions than those without support. Sangin and colleagues (2011) further confirmed that the aforementioned increase of learning outcome depends on the positive impact of partner modeling. With the visualization of objective cues on their peers' prior knowledge, learners became more accurate in estimating their partner's knowledge, and this accuracy predicted higher learning outcomes (Sangin et al., 2011). Since the latter tool provides qualitative and quantitative awareness information, or rather more comprehensive information than the other visualizations, this leads us finally to the following assumption:

Hypothesis 3a: Learners supported by a combination of qualitative and quantitative information estimate their partners' knowledge more accurately than learners with availability to solely qualitative information.

Hypothesis 3b: Learners supported by a combination of qualitative and quantitative information estimate their partners' knowledge more accurately than learners with availability to solely quantitative information.

Methods

We conducted an empirical study to investigate the impact of different types of awareness information on learning behavior. After an individual phase of text reading to learn about biogas plants, students were asked to communicate with a bogus learning partner, of whose non genuine nature they were not aware. Therefore, the learning environment offered the participants to write down questions and/or explanations. During this 'collaboration', the learners were supported (or not) by a knowledge profile that allowed them to compare their self-assessed knowledge on eight concepts about biogas plants with their partner's knowledge. The respective bogus partners' knowledge was assigned by an algorithm aiming to cover all possible knowledge combinations with random values. As seen in Figure 1, we offered four different versions of visualizations: (1) no profile (qual-/quan-), (2) a profile displaying the qualitative information *what* concepts both know about or not (qual+/quan-), (3) one displaying the quantitative information *how much* learners know on biogas plants in total (qual-/qual+), and (4) another displaying a combination of qualitative and quantitative information on *how much* learners know *about each concept* (qual+/quan+). A list of concepts was available in each condition.

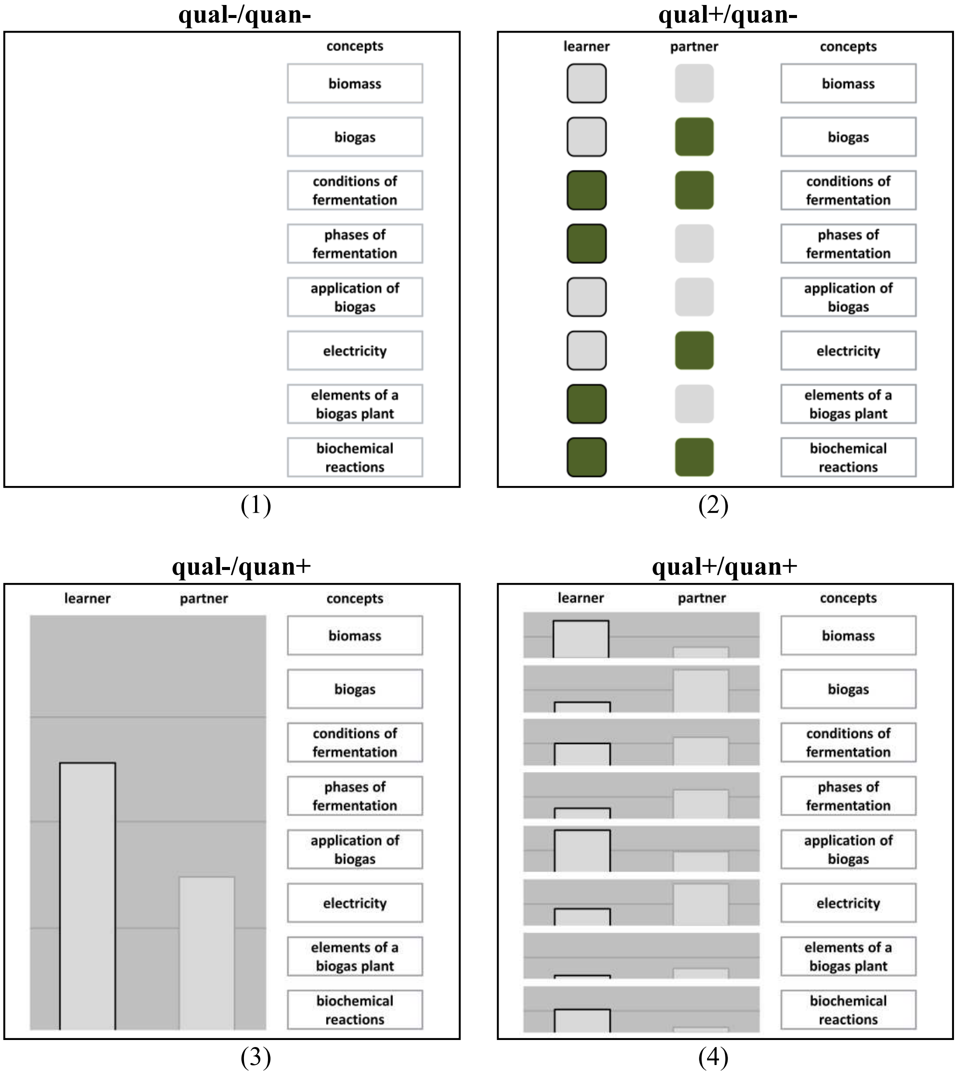

Figure 1. Awareness conditions: no information (1); qualitative information on present (dark boxes) and missing (light boxes) knowledge (2); quantitative information as bar chart (3); combination of both (4).

Sample and design

The sample consisted of 51 persons, mainly university students, 18 to 30 years old (M = 23.18, SD = 3.06). The participants were randomly assigned to one of the four experimental conditions in a 2x2 factorial design. As you can see from Figure 1, we varied the graphical knowledge representation concerning its qualitative dimension (no visualization of qualitative information vs. visualization of qualitative information) and its quantitative information (no visualization of quantitative information vs. visualization of quantitative information). As dependent variables, we captured the number of questions (hypothesis 1), explanations (hypothesis 2), and accurate estimations concerning the partner modeling distance (hypothesis 3). All three variables are further described in the next section.

Instruments and dependent variables

Number of questions and explanations

The visualization of a concept list in all conditions enabled us to assign learners' contributions to the respective concepts. The learning environment allowed subjects to select a concept and to choose between "Would you like to ask a question?" or "Would you like to give an explanation?". Depending on the selection, a text window prompted the participant to either formulate a question or an explanation on the concept and to save the text afterwards. Figure 2 illustrates the choice to ask a question (featured by a dark background) and shows the input window with a learner's question. Participants could decide to contribute either a question or an explanation, both, or none at all for each concept. Subsequent to this bogus collaboration, we counted the numbers of questions (DV in hypothesis 1) and explanations (DV in hypothesis 2) per person.

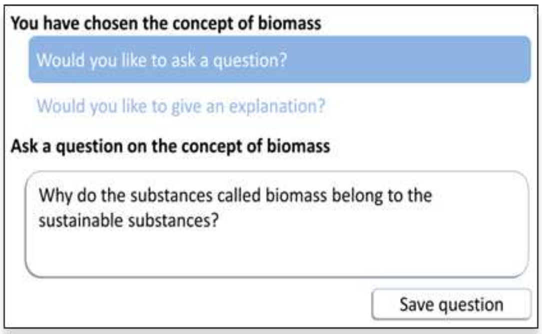

Figure 2. Learner's view when asking a question.

Estimations of knowledge, visualization of constellations, and calculation of distances
Learners' estimations of own knowledge were needed for two reasons: (1) for the visualization of the learners' 'real' knowledge about biogas-related concepts as a first component of their knowledge profile, and (2) as a basis to apply the algorithm that generates values to complement said profile with the visualization of the bogus learning partner's knowledge (if required by the test condition). Concerning (1), the learners had to rate their own degree of knowledge (with regard to their assumed competence to explain it to a learning partner) prior to the bogus collaboration via a six-point scale (reaching from 1 = 0% knowledge to 6 = 100%, to be rated separately for each out of eights concepts about biogas plants). To visualize the qual-/quan+ profiles, we created a total of all values given and visualized it in one aggregated bar chart per profile. The qual+/quan- profiles were realized by classifying the values from 0 to 40% as 'no knowledge given' of a concept and the values from 60 to 100% as 'knowledge given'; the former minor knowledge status was visualized as a light grey box and the latter major knowledge status as a darker green box. To create the qual+/quan+ profiles, we finally visualized each value by a bar chart for each concept. Referring to (2), we designed the algorithm to build on the values described before. The algorithm generated additional random values within a reasonable range that were included into the visualizations, taking into account that in both qual+ conditions each type of knowledge combinations should ideally occur in equal numbers. Furthermore, the learners were asked to additionally estimate their partner's knowledge after the collaboration. Therefore, they had to rate on a six-point scale reaching from 1 (0% knowledge) to 6 (100% knowledge) how much knowledge they award their partner concerning each concept about biogas plants. These estimations of bogus partner's knowledge were needed for the calculation of the partner modeling accuracy. Therefore, the values were compared to the visualized knowledge of the partner in order to determine the distance between both (DV in hypothesis 3).

Procedure
The experimental study was conducted in our research laboratory under controlled conditions. Each participant worked on the learning environment on a single computer. After welcoming and declaration of consent, we informed the participants that they have to read and memorize a learning text and collaborate with another participant in a computer-supported scenario. Then, we invited them to start the experiment and fill out a demographics questionnaire querying their age, sex, and level of education. Having completed these questions, the subjects were given 15 minutes to read the learning material on biogas plants Following this learning phase, they were requested to estimate their own knowledge on each given subtopic of biogas plants, just as it was described in the last chapter. The subsequent bogus collaboration took ten minutes. In this phase, the knowledge profile of the respective condition was presented to the participants (cf. Figure 1), and they could make their contributions in the form of questions or explanations (cf. Figure 2). Finally, they estimated their bogus partner's knowledge. A graphical overview of the whole procedure can be found in Figure 3.

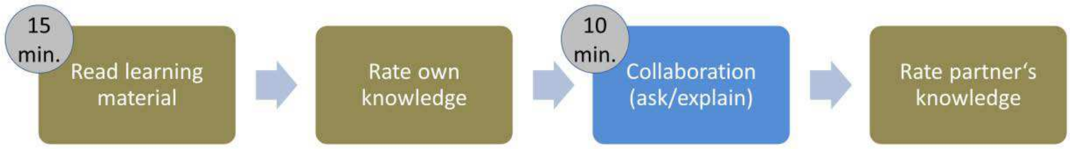

Figure 3. Graphical overview of the experiment's procedure.

Findings

For answering the question of how awareness information affects learning behavior, we observed the impact of qualitative and quantitative cognitive information on the number of contributions to a bogus communication and on the modeling of the learning partner. Two-factorial ANOVAs were used to investigate each single hypothesis, with qualitative information (no visualization of qualitative information vs visualization of qualitative information) and quantitative dimension (no visualization of quantitative information vs visualization of quantitative information) as between-subject factors. All effects are reported as significant at $p < .05$.

Impact of awareness information on the number of questions (hypothesis 1)

We hypothesized that learners supported by the visualization of qualitative information ask more about subject matters than learners without qualitative information. To test this, we observed the number of total questions per person as dependent variable. This total included solely complete sentences, since we excluded contributions of less than three words from the calculation. There was a significant main effect of available qualitative information (qual+/quan- and qual+/quan+) on the number of questions, $F(1, 47) = 4.12$, $p = .048$, $\eta_p^2 = .081$. Regarding the assumption that quantitative group awareness triggers questions, there was also a significant main effect of quantitative information (qual-+/quan+ and qual+/quan+) on the number of questions, $F(1, 47) = 4.64$, $p = .036$, $\eta_p^2 = .090$. Finally, there was no interaction effect of qualitative and quantitative information on the number of questions, $F(1, 47) = 0.29$, $p = .590$, $\eta_p^2 = .006$. Table 1 shows the related descriptive statistics.

Table 1: Number of average questions in each condition.

awareness information	qual- ($n = 26$)		qual+ ($n = 25$)		both ($N = 51$)	
	M	*SD*	*M*	*SD*	*M*	*SD*
quan- ($n = 26$)	2.15	2.34	3.08	1.80	2.62	2.09
quan+ ($n = 25$)	3.15	2.54	4.75	2.09	3.95	2.43
both ($N = 51$)	2.65	2.45	3.88	2.09	3.25	2.34

Since we wanted to identify which visualization of knowledge results in the most questions, we further used a two-factorial repeated measure ANOVA with visualized qualitative information only (qual+/quan- vs. qual+/quan+) as between subject factor and knowledge constellation as within-subject factor ((1) learner's deficit with partner's knowledge vs. (2) same knowledge (both have deficit or both have knowledge) vs. (3) partner's deficit with learners knowledge). As dependent variable, we observed the number of questions in each of said knowledge constellations divided by the total number of occurrences of this constellation per person (which was varying between subjects due to their self-assessment).

There was a significant main effect of knowledge constellation on the percentage of questions asked in each category, $F(2, 34) = 12.11$, $p < .001$, $\eta_p^2 = .416$. The pairwise comparison for the main effect of knowledge constellation indicates a significant difference ($p < .05$) between levels 1 and 2 (learner's deficit and same knowledge) and 1 and 3 (learner's deficit and partner's deficit) but not between levels 2 and 3 (same knowledge and partner's deficit). In 72.8% ($SD = 29.6\%$) of cases in which the comparison to their bogus collaboration partner enclosed missing knowledge, learners asked a question on the belonging concept. In contrast, only in 49.9% ($SD = 37.8\%$) of cases with same knowledge, and in 28% ($SD = 34.7\%$) of cases with better expertise than the partner triggered questions. This seems to indicate that learners asked a question if they recognized own missing knowledge compared to partner's knowledge. Furthermore, there was a significant effect of the knowledge profile on the weighted number of questions asked in each of the three categories of knowledge constellation, $F(1, 17) = 6.63$, $p = .020$, $\eta_p^2 = .281$. As you can see from Figure 4, the combination of qualitative and quantitative information appears to outperform solely qualitative cognitive information. Finally, there was no significant interaction effect of knowledge constellation and qualitative information on the weighted number of questions, $F(2, 34) = 0.83$, $p = .447$, $\eta_p^2 = .046$.

Impact of awareness information on the number of explanations (hypothesis 2)

We tested the assumption that learners supported by a profile with qualitative information explain more about subject matters than learners without access to qualitative information by investigating the number of total explanations as dependent variable. This total included solely complete sentences again. There was a significant main effect of qualitative information on the number of explanations, $F(1, 47) = 4.44$, $p = .041$, $\eta_p^2 = .086$. Regarding the further assumption that the presence of quantitative information also triggers explanations, there was no significant main effect of the quantitative dimension on the number of explanations, $F(1, 47) = 3.45$, $p = .069$, $\eta_p^2 = .068$. Furthermore, there was no interaction effect between qualitative and quantitative

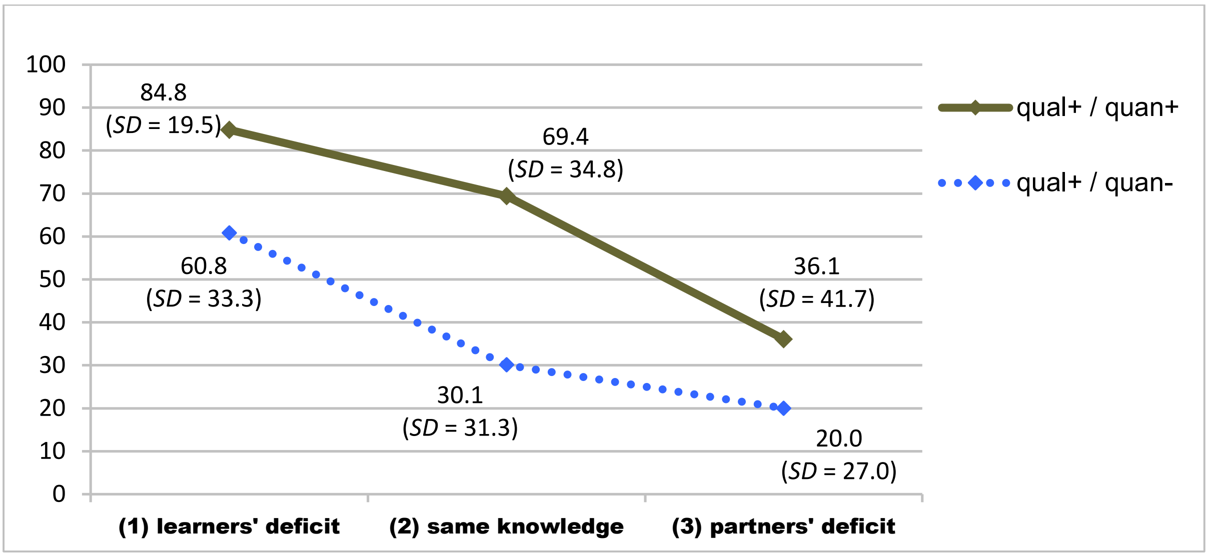

Figure 4. Percentage of questions asked per knowledge constellation weighted by the total number of occurrences of this constellation per person.

information on the number of questions, $F(1, 47) = .85$, $p = .179$, $\eta_p^2 = .038$. Table 2 shows the descriptive statistics, disclosing that, in contrast to our first assumption, most explanations were given, if no qualitative information was available.

Table 2: Number of average explanations in each condition.

awareness information	qual- ($n = 26$)		qual+ ($n = 25$)		both ($N = 51$)	
	M	*SD*	*M*	*SD*	*M*	*SD*
quan- ($n = 26$)	4.61	1.45	3.00	1.35	3.81	1.60
quan+ ($n = 25$)	4.85	1.67	4.50	2.11	4.68	1.86
both ($N = 51$)	4.73	1.54	3.72	1.88	4.24	1.77

Impact of awareness information on partner modeling (hypothesis 3)

We used independent *t*-tests to test the assumption that learners supported by a combination of qualitative and quantitative information estimate their learning partners' knowledge more accurately than learners with visualizations of either qualitative or quantitative information. This derogation from the main research design was required to separately compare (a) both qual+ conditions (qual+/quan- vs. qual+/quan+) with each other, and (b) both quan+ conditions (qual-/quan+ vs. qual+/quan+). The control group (qual-/quan-) was excluded from both calculations, since there was no partner information available in this condition. To observe the accuracy of partner modeling as dependent variable, we calculated the distance between the sums of estimated partner's knowledge (which were additionally divided by 8 in the case of the quan+ conditions) and algorithm-generated values visualized in the knowledge profile. The smaller the value, the better was the accuracy.

Concerning hypothesis 3a, participants supported by the combination of qualitative and quantitative information ($M = 1.33$, $SD = 0.65$) estimated their partners more accurately than participants with solely qualitative information ($M = 1.62$, $SD = 0.89$). However, this difference was not statistically significant $t(15) = 0.50$, $p = .621$, $r = .13$ (hypothesis 3a). Regarding hypothesis 3b, participants with available qualitative and quantitative information differed significantly from participants with support of quantitative information,

$t(23) = 2.83$, $p = .010$, $r = .51$. Learners estimated their partners more accurately if both types of information were available ($M = .48$, $SD = 0.32$) than without the combined visualization ($M = 1.34$, $SD = 1.01$).

Conclusions and implications

We conducted this empirical study to systematically investigate the impact of visualizations of qualitative and quantitative cognitive information on collaborative learning. Both types of information are systematically gathered and made available by cognitive group awareness tools, allowing learners for comparing to others, shaping learning mechanisms, and facilitating the control and (self-)regulation of their learning. Our assumption that the visualization of both qualitative and quantitative information moves learners to ask more questions in general was confirmed. With an additional exploration of the two conditions offering qualitative information, we further showed that visualizations supporting the awareness of one's own deficit (and partner's knowledge) had a significantly higher impact on questioning behavior than visualizations of the same or (binary / discrete) visualizations of more knowledge than the partner. Furthermore, we could show that this effect was significantly stronger if learners were supported by the combination of qualitative and quantitative information. This only partially confirms the results of Dehler and colleagues (2011), since they found that the awareness of one's knowledge gaps (independent of partner's knowledge) is sufficient to trigger questions, meaning that visualized gaps encouraged learners to ask partners for help. Our results indicate that besides the awareness of own gaps the concurrent awareness of the partner being knowledgeable about the concept might be relevant to shape the questioning behavior. Indeed, the bogus scenario requires some caution regarding the interpretation so that further research is needed in order to clarify the question what specific role is played by qualitative and quantitative information.

Concerning the number of explanations, it could have been expected that the visualization of partner deficits guides learners to give more explanations (Dehler et al., 2011). In contrast to the assumption that learners supported by qualitative information explain more than learners without such support, we could find that especially the absence of qualitative information significantly increased the number of explanations. Even available quantitative information seemed to lead to more explanations, if they were presented without additional qualitative information. One explanation as to why learners give fewer explanations with increasing level of informational detail might be that they can better choose relevant cases and interact in a more goal-oriented way. Furthermore, another learning mechanism central to collaborative learning could be of relevance, namely (self-)explanation (cf. Dillenbourg, 1999). The absence of information may drive learners to remember the learning text by paraphrasing it in the text windows provided during the collaboration phase of the study. However, further research is needed here to investigate this concern more deeply, not least because of the artificial scenario without a real learning partner.

Finally, we investigated whether learners supported by a visualization that combines qualitative and quantitative information estimate their partners' knowledge more accurately than learners with availability of single cognitive information. It is suggested by a large body of research that the absence of cognitive information results in matching own knowledge with estimations of partner (cf. Sangin et al., 2011). Small accuracy values in our study indicated that the estimations of learners were largely based on the visualizations presented to them. Although especially the availability of combined qualitative and quantitative information appeared to be useful in this context, it needs to be clarified, if the presentation of qualitative information is sufficient to support partner modeling. Taking cognitive load (cf. van Merriënboer & Sweller, 2005) into account, it might be that visualizations combining qualitative and quantitative information are associated with additional mental effort.

Overall, we can derive from these results that qualitative and quantitative information visualized by cognitive group awareness tools is suitable to elicit a desired collaborative learning behavior. It is often mentioned that prescribing collaborative activities might carry the risk of demotivating the learners (Hesse, 2007). Group awareness tools offer an opportunity to satisfy the resulting need for implicit guidance and learners' empowerment associated therewith. Tracing back to Piaget's approach, it is recommended to use knowledge profiles that combine qualitative and quantitative information where the intention is to make learners aware of cognitive conflicts that elicit a meaningful exchange between them. The same applies to the support of partner modeling which is needed in a Vygotskian sense to maintain an accurate model of the learning partners and optimize internalization processes.

References

Bodemer, D. (2011). Tacit guidance for collaborative multimedia learning. *Computers in Human Behavior*, *27*(3), 1079–1086. http://doi.org/10.1016/j.chb.2010.05.016

Bodemer, D., & Buder, J. (2006). Supporting Collaborative Learning with Augmented Group Awareness Tools, *3*(2), 123–139. http://doi.org/10.1007/s11412-008-9037-5

Bromme, R., Hesse, F. W., & Spada, H. (2005). Barriers, Biases and Opportunities of Communication and Cooperation with Computers: Introduction and Overview. In R. Bromme, F. W. Hesse, & H. Spada (Eds.), *Barriers and Biases in Computer-Mediated Knowledge Communication* (Vol. 5, pp. 1–14). New York: Springer-Verlag. http://www.springerlink.com/index/10.1007/0-387-24319-4_1

Buder, J., Schwind, C., Rudat, A., & Bodemer, D. (2015). Selective reading of large online forum discussions: The impact of rating visualizations on navigation and learning. *Computers in Human Behavior*, *44*, 191–201. http://doi.org/10.1016/j.chb.2014.11.043

Dehler, J., Bodemer, D., Buder, J., & Hesse, F. W. (2009). Providing group knowledge awareness in computer-supported collaborative learning: Insights into learning mechanisms. *Research and Practice in Technology Enhanced Learning : RPTEL*, *4*(2), 111–132.

Dehler, J., Bodemer, D., Buder, J., & Hesse, F. W. (2011). Guiding knowledge communication in CSCL via group knowledge awareness. *Computers in Human Behavior*, *27*(3), 1068–1078. http://doi.org/10. 1016/ j.chb.2010.05.018

Dillenbourg, P. (1999). What do you mean by "collaborative learning"? In P. Dillenbourg (Ed.), *Collaborative-learning: Cognitive and Computational Approaches* (pp. 1–19). Oxford, UK: Elsevier.

Doise, W., & Mugny, G. (1984). *The Social Development of the Intellect*. Amsterdam: Pergamon Press.

Erkens, M., & Bodemer, D. (2015). Potentials of Text Mining based Technologies for Improving Cognitive Group Awareness. In O. Lindwall, P. Häkkinen, T. Koschmann, P. Tchounikine, & S. Ludvigsen (Eds.), *Exploring the Material Conditions of Learning: The Computer Supported Collaborative Learning (CSCL) Conference 2015* (Vol. 2). Gothenburg, Sweden.

Hesse, F. (2007). Being told to do something or just being aware of something? An alternative approach to scripting in CSCL. In F. Fischer, I. Kollar, H. Mandl, & J. Haake (Eds.), *Scripting computer-supported communication of knowledge-cognitive, computational and educational perspectives* (pp. 91–98). New York: Springer.

Janssen, J., & Bodemer, D. (2013). Coordinated Computer-Supported Collaborative Learning: Awareness and Awareness Tools. *Educational Psychologist*, *48*(1), 40–55. http://doi.org/10.1080/00461520.2012. 749153

Piaget, J. (1977). *The development of thought: equilibration of cognitive structures*. Viking Press.

Piaget, J., & Inhelder, B. (2008). *The Psychology Of The Child*. Basic Books.

Sangin, M., Molinari, G., Nüssli, M.-A., & Dillenbourg, P. (2011). Facilitating peer knowledge modeling: Effects of a knowledge awareness tool on collaborative learning outcomes and processes. *Computers in Human Behavior*, *27*(3), 1059–1067. http://doi.org/10.1016/j.chb.2010.05.032

Schittekatte, M., & Van Hiel, A. (1996). Effects of partially shared information and awareness of unshared information on information sampling. *Small Group Research*, *27*, 431–449. http://doi.org/10.1177/ 1046496496273006

Schnaubert, L., & Bodemer, D. (2015). Subjective Validity Ratings to Support Shared Knowledge Construction in CSCL. In O. Lindwall, P. Häkkinen, T. Koschmann, P. Tchounikine, & S. Ludvigsen (Eds.), *Exploring the Material Conditions of Learning: The Computer Supported Collaborative Learning (CSCL) Conference 2015* (Vol. 2). Gothenburg, Sweden.

Tudge, J., & Rogoff, B. (1989). Peer influences on Cognitive Development: Piagetian and Vygotskian Perspectives. In M. H. Bornstein & J. S. Bruner (Eds.), *Interactiion in Human Development*. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive Load Theory and Complex Learning: Recent Developments and Future Directions. *Educational Psychology Review*, *17*(2), 147–177. http://doi.org/10.1007/s10648-005-3951-0

