Representational Scripting Effects on Group Performance

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Abstract: This study investigated the effects of a tool designed for supporting the online collaborative performance of learners carrying out complex learning tasks. Appropriate collaborative cognitive activities may be evoked by structuring the whole learning task into phases and providing congruent external representations for each stage (i.e., representational scripting). It was hypothesized that this combination would lead to increased individual learning and better results for the collaborative task. In groups, 47 secondary education students worked on a complex business-economics problem in four experimental conditions, namely one where groups received task-congruent representations for all stages and three where they received one of the representations for all three phases (task-incongruent). The results indicate that groups that received task-congruent representations in a phased order scored higher on the collaborative task, though this did not result in increased individual learning.

Introduction

Research on computer-supported collaborative learning (CSCL) has shown that computer technology can provide support (i.e., tools) for students collaboratively carrying out complex learning tasks. In such tasks, groups of students often solve a problem performing different kinds of activities in two dialogue ‘spaces’, namely a content space using cognitive activities for coping with the part-tasks / solution phases such as orienting to the problem (i.e., exploring the problem space), finding solutions and evaluating the solutions, and a relational space using communicative activities such as making knowledge and ideas explicit, creating shared understanding and negotiating multiple perspectives (Barron, 2003). Usually, the support consists of (1) externalizing knowledge and ideas through chat and representation tools to provide a solid basis for the negotiation of meaning (Fisher, Bruhn, Gräsel, & Mandl, 2002), (2) providing scaffolding opportunities through structuring the learning process via scripting modules and the representational guidance of a tool (Reiser, 2004, Suthers, 1998), and (3) offering offloading possibilities - by providing external memory (i.e., storing previous contributions and constructed external representations) and external information sources which leave more working memory left for the negotiation of meaning (e.g., Hollan, Hutchins, & Kirsh, 2000). Although we acknowledge the value of these studies, we question whether the full potential of computer technology can be reached by such an approach. Solely studying the effects of a tool aimed at supporting the whole learning task provides only one perspective on the problem, neglecting supporting the task demands and activities of part-tasks which may be so ontologically divergent that they need different tools to properly deal with them (de Jong et al., 1998). Furthermore, such an approach does not take combining and integrating the benefits of multiple tools into account. This may be especially detrimental when students are coping with all task demands and activities required for collaboratively carrying out complex learning tasks. First, students - typically non-experts - experience representational difficulties when carrying out such learning tasks (Chi, Glaser, & Rees, 1982). Students are often not able to create and apply suited problem representations which hinders them during problem solving. Second, grouping students does not spontaneously lead to discourse that is beneficial for learning (Dillenbourg, 1999). Due to the complexity of these learning tasks, students need to be supported in (1) performing the specific task demands and activities of the part-tasks in a proper sequence, (2) acquiring and applying well-suited problem representations for each part-task, and (3) combining different problem representations (Ploetzner, Fehse, Kneser, & Spada, 1999; Spector, 2008; van Merriënboer, Kester, & Paas, 2006). By combining the advantages of a scripting module together with a representation module - representational scripting - proper collaborative cognitive activities can be evoked.

Representational Scripting

The tool scripts problem-solving behavior by explicating and sequencing different part-tasks in the problem-solving process with the goal of evoking the creation and application of specific problem representations. The tool’s scripting module structures the learning task by dividing it into a sequence of ontologically distinct problem-phases (i.e., problem orientation, problem solutions, solution evaluation) so that they can be foreseen with
representations congruent with the task demands and activities required for each phase (Duffy, Dueber, & Hawley, 1998; van Bruggen, Boshuizen, & Kirschner, 2003). In the problem orientation phase students should start by constructing a cognitive bridge between their initial mental model and the mental model to be created (Chi et al., 1982; Jonassen, 2003). This phase focuses on constructing a global problem representation, becoming aware of the problem itself and of the important concepts of the knowledge domain along with the constraints and criteria for solution and evaluation. For creating such a problem overview, a qualitative problem representation is more appropriate than a quantitative one (Jackson, Stratford, Krajcik, & Soloway, 1996; White, & Frederiksen, 1990). Qualitative representations provide an overview of the relevant concepts in the knowledge domain, supporting students in broadening the problem space. When the relationships are also quantitatively specified, as is often the case in business economics where these tools are being developed, students are more restricted in creating a suited problem representation because their attention is more focused on specific concepts and their mathematical relationship. This may be detrimental for problem solving because it hinders them in finding multiple solutions. The problem solutions phase aims at applying the underlying principles of the knowledge domain to produce concrete solutions. This phase is more structured and focuses on combining the concepts of the domain into principles and explicating causal relationships between the problem and the proposed solutions. This enables students to reason about the advantages and disadvantages of the proposed solutions. The main advantage of these activities is that the solutions come in a rather straightforward, often causal, way from this which makes the problem solving process more efficient and effective (Chi et al.) The problem representation remains qualitative, but contains - along with the central concepts of the problem - causal information that supports students in finding multiple solutions to the problem. During the solution evaluation phase it is more appropriate that students relate the solutions and their consequences with the purpose of negotiating their suitability. These discussions should enable them to reach a final and suitable problem solution. This part-task focuses on simulating the proposed solutions and gaining insight into their quantitative effects. It can only be understood if the students have a well developed qualitative understanding of the knowledge domain.

The representation module visualizes the knowledge domain by providing external representations (ERs) that influence cognitive behavior through their representational guidance (Cox, 1999; Suthers, 1998). Due to its ontology (i.e., objects, relations, and rules for combining them) each ER offers a restricted view of the domain making it easier to express certain aspects of that domain (Green, & Petre, 1996; van Bruggen et al., 2003). By matching the representational guidance of the ERs with the phase-related part-tasks, students’ understanding of the knowledge domain should gradually increase. However, an ER is seldom effective for all task demands and activities; a specific ER guides performance on a certain part-task (Cox, & Brna, 1995). Complex learning tasks require students to create different problem representations, which necessitates receiving multiple ERs that support them in creating these representations. Although it is important to distinguish the different phases and their required representations (Lesgold, 1998; Ploetzner et al., 1999), some studies indicate that combining multiple ERs requires extra cognitive activity which can be detrimental for learning. The extra cognitive burden hinders students in mastering all ERs and forces them to stick to just one ER and thereby one kind of reasoning (Boshuizen, & van de Wiel, 1998). The difficulties students encounter in combining multiple ERs are often due to (1) problems translating from and coordinating between different kinds of representations (Ainsworth, Bibby, & Wood, 2002), and (2) incongruence between representation and phase-specific (part-)task (Buckingham Shum, MacLean, Bellotti, & Hammond, 1997). Table 1 shows how the representational guidance of a specific ER matches with task demands and activities of a specific problem phase (i.e., scripting of the different ERs).

The representational guidance of an ER is determined by its ontology, which is specified through its constraints and salience (see Table 1). Constraints refers to what is expressed in the ER: the concepts and their interrelationships (i.e., specificity), and how accurately they are represented (i.e., their precision). Salience refers to the differences in expressiveness, caused by the different constraints, and which leads to the determination of the number and types of inferences that can be made. Less specific and less precise ERs have the advantage of having a high processability (Larkin, & Simon, 1987) making it easy to make many inferences from them (i.e., elaboration). Those ERs guide students in elaborating on the concepts of the knowledge domain and in relating them to the problem (Jonassen, 2003). Simple ERs, however, do not have much expressive power (Cox, 1999); the inferences cannot be very detailed. The order of an ER (White, & Frederiksen, 1990) determines in what way students can reason about the knowledge domain, determining the quality of the inferences. A zero order ER supports reasoning about the concepts and relating this reasoning to the problem in qualitative way. A first order ER is more expressive and supports reasoning about causal relationships and guides discussion about possible solutions. A second order ER is the most expressive and guides quantitative inference-making which should enable negotiation of suitability of the proposed solutions. When the representational guidance of the ER is congruent with the ontological demands of the part-task of a problem phase, students are supported in performing the required task demands and activities of
this phase. A mismatch, on the other hand, means that the ER is incongruent with the part-task. Reasons for this could be that the ER is too simple because it contains only global information, or too complex because students do not have enough prior domain knowledge to grasp and make use of the complexity of the ER.

Table 1: Congruence between external representations and task demands.

<table>
<thead>
<tr>
<th>Problem phase</th>
<th>ER</th>
<th>Representational guidance</th>
<th>Constraints</th>
<th>Order</th>
<th>Elaboration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem orientation</td>
<td>Conceptual</td>
<td>Low</td>
<td>Unrelated</td>
<td>Zero</td>
<td>Unstructured</td>
</tr>
<tr>
<td>Problem solutions</td>
<td>Causal</td>
<td>Middle</td>
<td>Causal</td>
<td>First</td>
<td>Quasi-structured</td>
</tr>
<tr>
<td>Solution evaluation</td>
<td>Simulation</td>
<td>High</td>
<td>Model</td>
<td>Second</td>
<td>Structured</td>
</tr>
</tbody>
</table>

Research Focus

This study focuses on how the design of a tool that scripts problem-solving behavior through providing ontological distinct external representations affects both individual and group performance on task performance and learning. Due to the presumed match between ERs and part-tasks, students’ conceptual understanding should gradually increase, making it easier for them to solve current and future problems in the knowledge domain.

Design and Expectations

Learning groups were required to solve a case-based problem in business-economics. All experimental groups had to collaboratively solve the problem in three problem phases. To this end, ERs and part-tasks were either matched or mismatched to the phase. In three mismatch conditions, groups received a different ER (i.e., conceptual, causal or simulation ER) which matched only one of the part-tasks (i.e., problem orientation, problem solutions, solution evaluation, respectively). Here, the scripting module structured the collaboration process in three phases, but only one of the ERs is available (phase-mismatch). In the fourth condition, groups receive all three ERs in a phased order receiving the ER most suited to each problem phase (i.e., there is a match between ERs and part-tasks for all phases). Groups in this condition receive the complete array of representations in the representation module of the tool. We hypothesize that the students in the match condition (H1) create a better developed conceptual understanding (i.e., learning gains) and (H2) will arrive at a better solution to the problem (i.e., task performance), because their knowledge has progressively evolved from qualitative to quantitative.

Method

Participants

Participants were students from one business-economics class from a secondary vocational education school in the Netherlands. The total sample consisted of 47 students (27 male, 20 female). The mean age of the students was 16.67 years ($SD = .80, Min = 15, Max = 18$). Students were randomly assigned to 15 triads and 1 dyad, which were equally divided between the four experimental conditions.

Learning task and materials

CSCL-environment: Virtual Collaborative Research Institute

Students collaborated in a CSCL environment called Virtual Collaborative Research Institute (VCRI, see Figure 1), a groupware application for supporting the collaborative performance of complex learning tasks, inquiry tasks and research projects (Jaspers, Broeken, & Erkens, 2005). For this study, six tools that are part of the VCRI were used and, except the Notes tool, shared among group members. The chat tool is used for enabling synchronous communication, supporting students in externalizing and discussing their ideas and knowledge. The chat history is stored automatically and can be re-read. Students can read the description of the learning task and the different part-tasks and other information sources (e.g., formula list) in the Assignment menu. The Co-writer is a shared text-processor supporting students in formulating and revising their answers to the part-tasks. The Notes tool is an individual notepad intended for cognitive offloading. It supports students in storing information and structuring their own knowledge and ideas before making them explicit. The Status bar displays which group members are logged into the system and which tool a group member is currently using. It is meant to support students in raising group members’ awareness.
Learning task and design of the tool

All groups worked on a complex business-economics problem in which they had to advise an entrepreneur about changing the business strategy in order to make the business more profitable (i.e., achieve a better company result). To provide a suitable advice, students had to perform three different part-tasks, namely (1) determine the main concepts responsible for the company’s results and relate them to the problem, (2) determine how certain interventions (i.e., changes of the business strategy) affect company results, and (3) compare these consequences and formulate a final advice based on this comparison. The scripting module divided the learning task into three phases (i.e., problem orientation, problem solutions, solution evaluation) each focused on one of the part-tasks. All groups were ‘forced’ to perform the part-tasks in a predefined order; they could only start with a new part-task after finishing the earlier phase. When group members agreed that a part-task was finished, they had to ‘close’ that phase in the assignment menu. This ‘opened’ a new phase, which had three consequences for the groups, namely they (1) received a new part-task (2) had to enter their new answers in a different window of the Co-writer and could not alter, but could still see, their prior answers, and (3) received a different ER (only in the fourth, matched, experimental condition). A description of the different phases for the fourth experimental conditions follows. All other experimental conditions received the part-tasks in the same order (i.e., scripting module), but did not receive different ERs in the representation module.

The problem orientation phase focused on creating a global problem representation by asking students to explain what they thought the problem was, and describing what the most important concepts were for coming to an advice. During this phase, students received the conceptual ER (see Figure 2), which made two aspects salient, namely the core concepts and which concepts were related to each other. Students could, for example, see that the ‘company result’ is determined by the ‘total profit’ and the ‘efficiency result’. This should make it easier to create an overview of all relevant concepts (i.e., broadening the problem space), which supports students in finding multiple solutions to the problem in the following phase. The simplicity of the conceptual ER supports the creation of a global problem representation which can be elaborated on in subsequent problem phases that contain part-tasks that require the support of more expressive ERs, that is: casual and quantitative problem representations.
The problem solutions phase aimed at creating a scientific problem representation (i.e., explicating the underlying business-economics principles) by asking students to formulate several solutions to the problem. During this phase, students received the causal ER (see Figure 3), in which the causal relationships - visible through the arrows showing direction of the relationship between the concepts - were specified. The causal ER also contributed to increasing conceptual understanding by providing students with nine possible interventions (i.e., changes of the business strategy), each of which had a different effect on the company results. This should make it easier to explore the solution space and therefore should support students in finding multiple solutions to the problem. Students could, for example, see that receiving a rebate from a supplier affects the ‘variable part cost price’, which in turn affects the ‘cost price’. The conceptual ER is too simplistic for performing this part-task because the relations in that ER were not specified and the students did not receive any information about possible solutions. This means that they had to produce the advice themselves, without having sufficient conceptual understanding of the knowledge domain. The simulation ER used in the following phase has a quantitative character which supports testing the proposed advices, but is difficult to grasp without a properly developed qualitative understanding.
The *solution evaluation phase* aimed at increasing conceptual understanding with the aid of a quantitative problem representation. Students were asked to determine the financial consequences of their proposed solutions, and to formulate a final advice for the entrepreneur by negotiating the suitability of the solutions with each other. During this phase, students received a simulation ER which enabled them to manipulate some of the concepts by clicking on the arrows in the boxes. The results obtained through the simulations should facilitate determining and negotiating the suitability of their proposed solutions and coming to a final advice. Students could, for example, test how a supplier rebate (i.e., decrease of the total variable costs) affects the ‘cost price’ and how this in turn affects the ‘company result’. Only the simulation ER is capable of providing this kind of support, because the relationships between the concepts in this ER were specified as equations (i.e., weight of the relationship).

**Procedure**

In total, students devoted three, 70-minute lessons to the whole learning task during which each student worked on a separate computer in a computer room. Before the first lesson, students received information about the learning task and group composition. Furthermore, a pre-test (45 minutes) was administered to determine prior domain knowledge and relevant personal information (e.g., age, sex). Thereafter, students worked on the learning task in the computer room, whereby all actions and answers to the part-tasks were logged by the VCRI-program. During these lessons, the teacher was on stand-by for task-related questions and a researcher was present for technical support. After the final computer lesson, a post-test (45 minutes) was administered for determining the amount of domain knowledge of the students after the intervention.

**Measures**

**Learning gains**

Domain knowledge was measured with a pre-test (20 items, $\alpha = .60$) and a post-test (20 items, $\alpha = .65$). Based on work of Gagné, Wagner and Briggs (1992) a learning task analysis was conducted which resulted in 12 business-economics concepts. The concepts and their relationships can be understood conceptually (i.e., qualitative understanding of a concept), causally (i.e., qualitative understanding of the causal relationship between concepts), and mathematically (i.e., quantitative understanding of the relationships between concepts).

**Task performance**

The quality of the collaborative product was used as an indicator of task performance. To measure the effect of condition on group performance, an assessment form for each unit of the learning task was developed. All 41 items were coded as: 0, 1 or 2, whereby a ‘2’ was coded when the answer given was of high quality (e.g., was more suitable). In total, groups could maximally score 82 points on the quality of the collaborative product. Table 2 shows the description and the reliability (Cronbach’s alpha) for each unit of analysis.
Table 2: Items and reliability for the collaborative product (N = 13).

<table>
<thead>
<tr>
<th>Unit</th>
<th>Description</th>
<th>Items</th>
<th>α</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Suitability</td>
<td>Whether the group’s answers were suited to the different part-tasks.</td>
<td>9</td>
<td>.81</td>
</tr>
<tr>
<td>2. Elaboration</td>
<td>Number of different business-economics concepts or financial consequences</td>
<td>9</td>
<td>.56</td>
</tr>
<tr>
<td></td>
<td>incorporated in the answers to the different part-tasks.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Justification</td>
<td>Whether the groups justified their answers to the different part-tasks.</td>
<td>9</td>
<td>.71</td>
</tr>
<tr>
<td>4. Correctness</td>
<td>Whether the groups used the business-economics concepts and their</td>
<td>9</td>
<td>.68</td>
</tr>
<tr>
<td></td>
<td>interrelationships correctly in their answers to the different part-tasks.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Continuity</td>
<td>Whether the groups made proper use of the answers from a prior problem phase.</td>
<td>2</td>
<td>.67</td>
</tr>
<tr>
<td>6. Quality advice</td>
<td>Whether the groups gave a proper final advice.</td>
<td>3</td>
<td>.76</td>
</tr>
<tr>
<td></td>
<td>- Number of business-economics concepts incorporated in the advice.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Number of financial consequences incorporated in the advice.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Whether the final answer conformed to the guidelines provided.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Total</td>
<td>Overall score on the collaborative product.</td>
<td>41</td>
<td>.92</td>
</tr>
</tbody>
</table>

Exclusion of groups from further analysis

From the 16 groups participating in the study, three (1 dyad and 2 triads) were excluded from the analyses because the group members did not participate in all lessons and scored unexplainably lower on the post-test. Task performance score of these groups was also unexplainably lower than for the other groups. We assume that this was not caused by the design of the experiment because the excluded groups came from different conditions.

Results

Learning gains

The overall mean score on the pre-test was 12.19 (SD = 2.12; max = 20). The overall mean on the post-test score was 12.58 (SD = 2.71; max = 20). The t-test showed that the overall post-test score of 31 students (not all 39 students were present when the pre- and/or post-test were administered) was not significantly higher than the overall pre-test score (t(31) = 12.58, p > .05). There was, thus, no increase in learning. One way ANOVA showed no significant difference between the conditions on the pre-test score (F(3, 27) = 2.09, p > .05). This means that students did not differ in the amount of prior knowledge and there was, therefore, no need to correct for this variable. Table 3 shows the overall and condition means and standard deviations on the pre-test and post-test scores.

Of the total variance on post-test score 59% could be explained by the variance on group level. This means that working in groups accounts for more variance on individual post-test scores than individual characteristics of the group members (e.g., age, sex). For this reason, multilevel analysis was used for determining the effect of condition on post-test score (Kenny, Kashy, & Cook, 2006). Analysis showed that students in the conceptual condition scored significantly lower than those in the other conditions (β = -2.94, p = .01; two-sided), and (2) there was a trend that students in the causal condition scored significantly higher than the students in the other conditions (β = 1.52, p = .07; two-sided). The model fit the data (χ²(3) = 14.34, p = .00) and could, therefore, be used to account for the differences in variance on the post-test score.

These results are not completely in line with our first hypothesis. Students in the match condition only scored higher on the post-test in comparison to students in the conceptual condition. Furthermore, on average, students in the causal condition had the highest score on the post-test.

Table 3: Means and standard deviations of pre-test and post-test scores for conditions (N = 31).

<table>
<thead>
<tr>
<th>Unit</th>
<th>Condition</th>
<th>Conceptual (n = 12)</th>
<th>Causal (n = 6)</th>
<th>Simulation (n = 6)</th>
<th>Match (n = 7)</th>
<th>Overall (n = 31)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>Pre-test</td>
<td>13.11</td>
<td>1.45</td>
<td>12.44</td>
<td>2.65</td>
<td>10.50</td>
<td>2.07</td>
</tr>
<tr>
<td>Post-test</td>
<td>10.00</td>
<td>2.59</td>
<td>14.55</td>
<td>1.74</td>
<td>13.20</td>
<td>2.05</td>
</tr>
</tbody>
</table>

Task performance

One way MANOVA on the total score on the collaborative product showed a significant difference for condition (F(3, 9) = 1.99, p = .04; one-sided; Pillai’s Trace = 2.00; partial eta squared = .67). Bonferroni post hoc analyses showed that groups in the match condition scored significantly higher than groups in both the conceptual (p = .02; one-sided; d = 2.28) and the simulation condition (p = .05; one sided; d = 1.90). Differences between other
conditions were not significant. Table 4 shows the overall and condition means and standard deviations of the scores on the collaborative product.

When the results for the dependent variables were considered separately, condition effects were found for suitability ($F(3, 9) = 4.49$, $p = .02$; one-sided), elaboration ($F(3, 9) = 3.13$, $p = .04$; one-sided) and correctness ($F(3, 9) = 4.25$, $p = .02$; one-sided). The mean scores indicated that there were several significant differences between conditions. First, groups in the match condition scored significantly higher on suitability than groups in both the conceptual ($p = .03$; one sided; $d = 3.61$) and the simulation condition ($p = .05$; one sided; $d = 3.28$). Second, groups in the match condition scored significantly higher on elaboration than groups in the conceptual condition ($p = .04$; one sided; $d = 1.57$). Third, groups in the match condition scored significantly higher on correctness than groups in the conceptual condition ($p = .03$; one sided; $d = 2.13$) and a trend was found in comparison to the groups in the simulation condition ($p = .07$; one sided; $d = 1.85$).

These results confirmed our second hypothesis, namely that groups that received a matching ER for each part-task scored higher on task performance (i.e., the collaborative product).

Table 4: Means and standard deviations of the collaborative product scores for conditions ($N = 13$).

<table>
<thead>
<tr>
<th>Unit</th>
<th>Conceptual $(n = 4)$</th>
<th>Causal $(n = 3)$</th>
<th>Simulation $(n = 3)$</th>
<th>Match $(n = 3)$</th>
<th>Overall $(N = 13)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
</tr>
<tr>
<td>Suitability (max 18)</td>
<td>10.75</td>
<td>1.50</td>
<td>13.67</td>
<td>1.52</td>
<td>11.33</td>
</tr>
<tr>
<td>Elaboration (max 18)</td>
<td>3.75</td>
<td>2.06</td>
<td>6.67</td>
<td>2.08</td>
<td>6.00</td>
</tr>
<tr>
<td>Justification (max 18)</td>
<td>3.25</td>
<td>2.06</td>
<td>4.67</td>
<td>3.06</td>
<td>3.00</td>
</tr>
<tr>
<td>Correctness (max 18)</td>
<td>4.50</td>
<td>1.29</td>
<td>6.33</td>
<td>3.77</td>
<td>5.33</td>
</tr>
<tr>
<td>Continuity (max 4)</td>
<td>2.00</td>
<td>1.41</td>
<td>2.00</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Final answer (max 6)</td>
<td>2.50</td>
<td>0.58</td>
<td>3.67</td>
<td>0.58</td>
<td>3.33</td>
</tr>
<tr>
<td>Total score (max 82)</td>
<td>26.75</td>
<td>4.17</td>
<td>37.00</td>
<td>7.00</td>
<td>31.00</td>
</tr>
</tbody>
</table>

**Conclusion and Discussion**

This study shows that structuring a complex problem-solving task into ontologically distinct part-tasks (i.e., phases) and providing the part-tasks with congruent representations leads to better problem solutions (i.e., task performance). The match condition outperformed both the conceptual and the simulation condition, the answers were more suited for a specific part-task, contained more business-economics concepts and financial consequences, and were more often correct. These results mostly confirmed our expectation and are in line with those of Ploetzner et al. (1999), who also stress the importance of sequencing and interrelating qualitative and quantitative aspects of the knowledge domain during collaborative problem solving. No differences were found between the match and the causal condition. Apparently the causal representation provided more support than both the conceptual and the simulation representation did, but in combination these three representations resulted in a higher score on task performance. Furthermore, it was expected that gradually shifting from a conceptual to a simulation representation would also result in higher individual scores on the post-test (i.e., learning gains). Students in the conceptual condition were indeed outperformed by the students in the other conditions. However, in contrast to our expectation, students in the causal condition also scored better on the post-test than students in both the simulation and the match condition.

It appears that providing only a conceptual or a mathematical perspective does not support students in applying and acquiring domain knowledge. Students in both the causal and the match condition were supported, but remarkably no significant differences were found between these two conditions. Although the causal representation also provides one perspective, students in this condition outperformed students in the match condition on individual learning gains, but were outperformed by the match condition on group task performance. In our opinion, there seem to be four explanations that might account for this result. First, there could be an underestimation of the importance of causal reasoning (Jonassen, & Ionas, 2008). The causal representation provides all relevant concepts and their causal interrelationships. It provides multiple qualitative perspectives on the domain which are also comprehensible for the students. Combining the causal representation with both the conceptual and the simulation representation could be detrimental for individual learning because of the difficulty in integrating the different perspectives on the domain (Ainsworth, Bibby, & Wood, 2002). Second, the design of the tool was primarily aimed at supporting students in applying domain knowledge in order to come to better and richer solutions. According to Kirschner, Sweller, and Clark (2006), solving complex problems is an instructional method based on the epistemological content (i.e., methods and processes) instead of the pedagogical content (i.e., acquiring knowledge) of a knowledge
domain. Such a learning experience, therefore, mainly focuses on the application of knowledge (i.e., task performance) and due to the required cognitive activity may hinder students in acquiring a well-developed understanding of the knowledge domain (i.e., learning). In this respect, students in the causal condition were less supported in task completion which might have supported them in acquiring more domain knowledge. Third, the post-test only measured the acquired conceptual understanding of the knowledge domain. It did, therefore, not enable students in the match condition to fully demonstrate their gained understanding of the knowledge domain. The difference between the design of the post-test and the nature of the collaborative task performance was perhaps less apparent for students in the causal condition. This could have made the post-test more suited for them in comparison to students in the match condition. Fourth, collaboration requires interaction in both the content space and the relational space from all group members. If the whole group is not able to cope with these activities, the collaboration process could have detrimental effects on group performance (Barron, 2003). We are currently analyzing the log files (i.e., dialogue-protocols) to determine what students talked about (i.e., content space) and how students managed their collaboration (i.e., relational space). These analyses should provide insight into the collaboration process and how it was affected by the design of the tool.

The results of this study have several limitations. First, the effects of the tool on group performance were based on only 13 groups. Second, this study was conducted in the field of business-economics. Although there are many other domains (e.g., science, physics, planning) in which qualitative and quantitative problem representations are required, the effect of a tool depends on the characteristics of the problem and the involved knowledge domain(s). Third, condition effects were found for task performance and learning gains, but when one inspects the standard deviations it appears that there are also differences between groups within the conditions. The present results of this study are solely focused on the question whether a difference in characteristics of a tool affects task performance and individual learning. Further analyses will be focused on why these differences occurred.

In sum, structuring the online collaborative performance of complex learning tasks into ontologically distinct part-tasks and providing congruent representations for each part-task (i.e., representational scripting) seems to broaden the perspective on designing CSCL-environments. It provides opportunities for combining the advantages of multiple tools in order to offer more suited support for the online collaborative performance of complex learning tasks. The design of the tool resulted in higher scores on group task performance in comparison to both the conceptual and simulation condition and also in more individual learning gains in comparison to the conceptual condition. At this stage, the reasons for the lack of significant differences between the causal and the match condition remain unclear. Keeping this lack and the limitations into mind, additional research into the effects of tools should be carried out to investigate the results and the collaboration process for multiple problems and in a diversity of knowledge domains.

**References**


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