Representational Scripting
for Carrying out
Complex Learning Tasks

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Representational Scripting
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Scripting middels Representaties
voor het Uitvoeren van
Complexe Leertaken
(met een samenvatting in het Nederlands)

Proefschrift

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1. General Introduction[1]

We don't need no education
We don't need no thought control
No dark sarcasm in the classroom
Teacher leave them kids alone
(*Another brick in the wall,* Pink Floyd, 1979)

Hearing or reading the first lines of this song might make educators and instructional designers wonder whether their educational practices are needed. The premise underlying this thesis is that there is no need for those worries as long as (1) learning tasks prepare learners (e.g., students or employees) to deal with the often rapidly changing demands of society and work and (2) learners' thoughts are guided properly instead of being controlled or, perhaps worse, uncontrolled when carrying out such tasks. Whereas the current importance of complex learning tasks (e.g., learning to solve complex problems) in the field of education is not questioned much, there is considerable debate on whether learners can be guided, and if so, what would be the best way. The thesis focuses on this debate by describing the difficulties associated with guiding learners' complex learning-task behavior and, thus, their performance, and suggests how these difficulties might be addressed. This chapter serves as an introduction to the studies reported on in the following chapters. First, I describe the nature, potential and pitfalls of carrying out complex learning tasks in education. Next, I introduce an instructional approach (i.e., representational scripting) as a possibly suitable way to guide learners carrying out complex learning tasks. Finally, I present the central research question of this thesis and provide an overview of the remaining chapters.

1.1 Complex Learning Tasks in Education

1.1.1 New pedagogical approaches to complex learning

The current interest in complex learning is often regarded as education's response to the rapidly changing demands of society and work. Complex learning is necessary to carry out activities endemic to modern society, such as complex tasks or problems which (1) cannot be described in full, (2) give no certainty about what the best solution is, and (3) require different perspectives on the problem and the problem-solving strategy for their solution (Jonassen, 2003; Kester, Kirschner, & Corbalan, 2007; Spector, 2008; Van Merriënboer & Kirschner, 2007). Learning to solve complex problems flexibly is thus an educational priority.

To this end, schools recently have incorporated new educational approaches such as inquiry learning, and (collaborative) problem-solving into their curricula (Hmelo-Silver, Duncan, & Chinn, 2007; P.A. Kirschner, Sweller, & Clark, 2006; Schmidt, Loyens, Van Gog, & Paas, 2007; Van Joolingen, De

[1] Based on Slof, B., Erkens, G., Kirschner, P. A., & Jaspers, J. G. M. (2010). Design and effects of representational scripting on group performance. *Educational Technology Research and Development, 58,* 589–608.

Jong, Lazonder, Savelsbergh, & Manlove, 2005). The constructivist theory of learning underlying these educational approaches advocates that learners be actively engaged in constructing their own knowledge to make it more meaningful. In current approaches, the emphasis lies on collaboratively or individually investigating authentic phenomena/problems (Kester & Paas, 2005; Loyens & Gijbels, 2008; Mergendoller, Maxwell, & Bellisimo, 2006). Inquiry-based learning approaches often focus on exploring (scientific) phenomena through such activities as (1) formulating hypotheses, (2) designing and conducting experiments, and (3) evaluating the obtained results by constructing evidence-based arguments (Hmelo-Silver *et al.*, 2007; Lazonder, Hagemans, & De Jong, 2010; Van Joolingen *et al.*; White, Shimoda, & Frederiksen, 2000). In problem-based learning approaches learners usually face a case-based problem for which a suitable solution must be formulated. Just as in inquiry-based learning, learners must carry out several phase-related activities, namely (1) problem-orientation; determining the core concepts and relating them to the problem, (2) problem-solution; proposing multiple solutions to the problem, and (3) solution-evaluation; determining the suitability of the solutions and coming to a definitive solution to the problem (Bigelow, 2004; Duffy, Dueber & Hawley, 1998; Jonassen, 2003; Lazakidou & Retalis, 2010; Van Bruggen, Boshuizen, & Kirschner, 2003).

Although these and other educational approaches - based on constructivist theories of learning - may differ in many ways, they all have a strong focus on authentic and complex learning tasks based on real-life tasks. The premise here is that carrying out such learning tasks may help learners to acquire new knowledge (e.g., concepts, methods, procedures), skills (e.g., collaboration, reasoning, self-regulation) and attitudes, integrate them, and facilitate the transfer of what is learned to new situations (Mergendoller *et al.*, 2006; Merrill, 2002; Van Merriënboer & Kirschner, 2007)

1.1.2 What are the pitfalls?

Whereas many studies advocate the potential of complex learning, others question whether it can effectively be employed as an educational approach. When learners carry out complex learning tasks without proper instructional support, they often experience difficulties leading to inefficient and ineffective learning (T. de Jong & Van Joolingen, 1998; P.A. Kirschner *et al.*, 2006; Mayer, 2004; Reiser, 2004). In contrast to expert problem-solvers, learners (i.e., non-experts) experience considerable difficulties in solving complex problems. That is, learners rely primarily on superficial features such as using objects referred to in the problem instead of the underlying principles of the knowledge domain (Chi, Glaser, & Reese, 1982; Corbalan, Kester, & Van Merriënboer, 2009; T. de Jong & Ferguson-Hessler, 1996; Jonassen, 2003; Kozma, 2003), and they employ weak problem-solving strategies such as working with a means-ends strategy towards a solution (Dufresne, Gerace, Thibodeau-Hardiman, & Mestre, 1992; Simon, Langley, & Bradshaw, 1981). Learners lack a well-developed understanding of the knowledge domain and consequently have problems creating and combining meaningful problem representations. This hinders learners in effectively and efficiently coping with their

problem-solving task because the ease with which a problem can be solved often depends on the quality of the available problem representations. Different problem representations initiate different kinds of operators which act to produce new information, supporting problem-solvers in reaching a solution to the problem (Chi *et al.*; Jonassen; Ploetzner, Fehse, Kneser, & Spada, 1999; Seufert, 2003).

Problematic here is that acquiring a well-developed understanding of a domain without guidance is difficult if not impossible. In most domains, such an understanding consists of the availability of both qualitative and quantitative representations which enable the creation of meaningful problem representations and the ability to flexibly coordinate them (T. de Jong, Ainsworth, Dobson, Van der Hulst, Levonen *et al.*, 1998; Frederiksen & White, 2002; Kozma, 2003; Löhner, Van Joolingen, & Savelsbergh, 2003; Ploetzner *et al.*, 1999. *Qualitative representations* represent the concepts underlying a particular domain and the inference rules which interrelate them and, thus, give them meaning. *Quantitative representations* represent the formalism(s) underlying a particular domain to describe the definitions of and functional relationships between concepts, for example via algebraic equations in the domains of business-economics and mathematics. However, since human cognitive architecture can only process a limited amount of information in its working memory (Baddeley, 1992; Miller, 1956), learners can be easily overwhelmed by the number of interactive information elements that need to be processed simultaneously for acquiring such an understanding (Sweller, 1988; Trafton & Reiser, 1993; Tuovinen, & Sweller, 1999; Van Merriënboer & Kirschner, 2007). Although educators and instructional designers realize this and also that instructional support is required to guide learners' complex learning-task performance, they often lack clear guidelines for designing it. Consequently, current instructional approaches only accomplish this with varying degrees of success (Bera & Liu, 2006; Elen & Clarebout, 2007; Rikers, Van Gog, & Paas, 2008; Van Drie, Van Boxtel, Jaspers, & Kanselaar, 2005; Van Merriënboer & Kirschner). This seems especially true for approaches such as collaborative problem-solving and visualizing the content of the knowledge domain with representation tools.

Collaborative problem-solving

Generally it is assumed that collaboratively carrying out complex learning tasks such as solving complex problems is more efficient and effective than doing this individually (Johnson & Johnson, 2009; Laughlin, Carey, & Kerr, 2008; Okada & Simon, 1997; Rochelle & Teasley, 1995). Working in teams of learners might be more beneficial for learning because team memory is considered to be more effective than individual memory. Dividing the processing of the required information across the working memories of the team members might circumvent the cognitive difficulties individuals experience - caused by a limited working memory - when carrying out complex learning tasks (F.C. Kirschner, Paas, & Kirschner, 2009ab; Ohtsubo, 2005; Schellens & Valcke, 2005). In addition, due to its nature, collaborative problem-solving is also assumed to evoke a dynamic process of eliciting one's own prior knowledge,

discussing this with peers, and establishing and refining the teams' shared understanding of the problem and problem domain. Carrying out those activities might support teams and individuals in acquiring a well-developed understanding of the domain that can be applied to the problem at hand (Barron, 2003; Ding, 2009; Erkens, Jaspers, Prangsma, & Kanselaar, 2005; Hmelo-Silver *et al.*, 2007; Mercer, Littleton, & Wegerif, 2004; Van Blankenstein, Dolmans, Van der Vleuten, & Schmidt, in press; Van der Linden, Erkens, Schmidt, & Renshaw, 2000). Unfortunately, simply putting learners in a team and having them work together on a problem or a project is not always beneficial for learning (Barron; Brodbeck & Greitemeyer, 2000; Dillenbourg & Traum, 2006; Fischer, Bruhn, Gräsel, & Mandl, 2002; Kreijns, Kirschner, & Jochems, 2003; Van Boxtel, 2004). If teams of learners do not coordinate their collaboration process by carrying out communicative activities, such as (1) externalizing their knowledge and ideas, (2) creating a shared understanding of them and (3) negotiating their suitability, they hinder themselves from having in-depth meaningful discussions about the content of the domain (Akkermans, Van den Bossche, Admiraal, Gijselaers, Segers *et al.*, 2007; Clark & Brennan, 1991; Erkens *et al.*; Phielix, Prins, & Kirschner, 2010; Van Boxtel). Communicative difficulties may, for example, arise when team members:

- do not participate equally in the collaboration process,
- are not aware of each other's knowledge and ideas,
- are not aware of each other's attitudes, emotions, and moods.

Representational tools

Visualizing a domain's content with representational tools, by providing or having learners construct external representations, influences learners' cognitive behavior. Due to the ontology of the tool (i.e., its objects, relations, and rules for combining objects and relations) each tool provides a specific sort of representational guidance which makes certain concepts and/or interrelationships (e.g., conceptual, causal or mathematical) more salient than others. Using such tools makes it easier to express specific aspects of that domain (i.e., creating specific problem representations) and, thereby, influences learners' reasoning about it (Brna, Cox, & Good, 2001; Ertl, Kopp, & Mandl, 2008; Fischer *et al.*, 2002; Suthers, 2006; Tergan, 2005; Van Bruggen, Kirschner, & Jochems, 2002; Zhang, 1997). It is also advocated that embedding representational tools in collaborative settings, such as computer supported collaborative learning (CSCL) environments, may further stimulate the elaboration of these representations. Due to the environment's emphasis on dialogue and discussion, multiple perspectives on the domain may arise (De Simone, Schmid, & McEwan, 2001; Hmelo-Silver *et al.*, 2007; Janssen, Erkens, Kirschner, & Kanselaar, 2010; Wegerif, McClaren, Chamrada, Schreuer, Mansour *et al.*, 2010). Furthermore such tools could support teams of learners in creating a shared understanding of these different viewpoints and negotiating on them which would facilitate the problem-solving process even further (Dillenbourg & Traum, 2006; Suthers; Van Amelsvoort, Andriessen, & Kanselaar, 2007).

Although the educational benefits of representational tools are widely recognized, some studies report mixed or negative findings and, thus, question how learners' cognitive and communicative behavior (i.e., learner interaction) can best be guided (Bera & Liu, 2006; De Vries, 2003; P.A. Kirschner, Beers, Boshuizen & Gijselaers, 2008; Van Amelsvoort *et al.*, 2007; Van Bruggen *et al.*, 2003; Van Drie *et al.*, 2005). This inconsistency in the literature hinders educators and instructional designers in designing representational tools that foster learners' performance of complex learning tasks. A possible explanation might be that the interactivity between the tools' design, the characteristics of its users and the requirements of the learning task is not always properly taken into account (Elen & Clarebout, 2007; Marjanovic, 2007; Veerman, 2000). For a proper alignment, the tools' design has to be in line with the capabilities and intentions of its users. That is, the users have to possess the required prior knowledge and/or skills to use the tool properly and need to experience the tool as beneficial to carrying out their learning task. The tool also has to make clear to its users what they can and should do with it. Only then can learners use their prior knowledge and skills to make proper use of the tool and reach the intended learning goals (P.A. Kirschner, Martens, & Strijbos, 2004; Munneke, Andriessen, Kanselaar, & Kirschner, 2007; Van Amelsvoort *et al.*; Veldhuis-Diermanse, 2002).

Besides this, the tools' design needs to be suited to supporting its users in carrying out the task demands and activities endemic to the learning task. Since representational tools guide learners in visualizing and discussing specific representations of the domain, educators and instructional designers should realize that such tools are only appropriate for carrying out specific task demands and activities (Ainsworth, 2006; Bodemer & Faust, 2006; Cox, 1999; Mayer, 1990; Schnotz & Kürschner, 2008). Although the presence and availability of a representational tool can support learners in carrying a specific learning task, this may be inappropriate for supporting learners' complex learning-task performance as a whole. Important here is the fact that such learning tasks are usually composed of different phase-related part-tasks, such as problem-orientation, problem-solution and solution-evaluation (Duffy, Dueber, & Hawley, 1998; Van Bruggen *et al.,* 2003). Carrying out each part-task requires a different perspective of the domain and, thus, a tool with specific representational guidance. Combining multiple representations of the domain is, however, problematic for learners. They often encounter difficulties in translating information from and coordinating between different representations (Bodemer & Faust; T. de Jong *et al.*, 1998; Kozma, 2003; Vekiri, 2002). Learners, for example, might not understand or know:

- which parts of the domain are or can be represented,
- the relationship between the representations and the task or problem,
- how to select, use or construct appropriate representations,
- how and why different kinds of representations should be interrelated.

Without proper alignment between the design and use of the tool and the demands of the part-tasks learners might experience at least two difficulties

when using such tools (Suthers, 2006; Van Bruggen *et al.*, 2003). First, *part-task related difficulties* may arise when learners do not have a realistic idea of the concepts and relationships they must use and how they should relate them to the problem. Due to this, learners experience difficulties in constructing and interpreting their representations and, thus, in acquiring a well-developed understanding of the domain (Bodemer & Faust, 2006; Brna, Cox, & Good, 2001; Liu *et al.*, 2010). Second, learners in CSCL-environments often use multiple tools (e.g., chat tools, representational tools) in a non-sequential way which complicates tracking each others' knowledge, ideas, and actions (Dillenbourg & Traum, 2006; Mühlpfordt & Stahl, 2007; Van Amelsvoort *et al.*, 2007). When learners are unable to interpret conveyed messages properly and relate them to each other, they are hindered in carrying out their communicative activities (i.e., coordinating their collaboration process; see Andriessen, Baker, Suthers, 2003; Barron, 2003; Erkens *et al.*, 2005). When learners experience *communicative difficulties*, this hinders them from elaborating on and discussing the content of the domain meaningfully. Whether learners can have such discussions depends on how easily they can refer and relate their contributions to those of others (Reinhard, Hesse, Hron, & Picard, 1997; Suthers, Girardeau, & Hundhausen, 2003; Van Boxtel & Veerman, 2001). This 'deictic referencing' is hard when the design of the representational tool is incongruent with the demands and activities of a learning task (Suthers *et al.*; Van Bruggen *et al.*)

To make learners' problem-solving processes more efficient and effective, it might prove beneficial to provide support aimed at gradually increasing their level of expertise, for example by mimicking the processes of experts, so that learners are supported in acquiring and applying a well-developed understanding of the domain in question (Dufresne *et al.*, 1992; Frederiksen & White, 2002; Ploetzner *et al.*, 1999; Quintana, Reiser, Davis, Krajcik, Fretz *et al.*, 2004; Van Merriënboer & Kirschner, 2007). To do this effectively, one must avoid or neutralize the difficulties learners encounter when combining multiple representations, namely (1) problems translating from and coordinating between different kinds of representations (Ainsworth, 2006; Bodemer & Faust, 2006; T. de Jong *et al.*, 1998), (2) incongruence between representations and part-task related activities (Schnotz & Kürschner, 2008; Van Bruggen *et al.*, 2003; Vekiri, 2002) and (3) limitations and duration of working memory capacity (Miller, 1956; Sweller, 1988; Van Merriënboer & Kirschner). To address this, the research reported on in this thesis introduces an instructional approach - representational scripting - as a possible solution and examines the effects of its different variants; providing or constructing part-task congruent representations.

1.2 Representational Scripting

1.2.1 Design principles

Integrating scripting with the availability of multiple representational tools (i.e., *representational scripting*) sequences the different part-task demands, makes them explicit and tailors the congruency of the tools' representational

guidance to the part-task demands. *Representational tools* are meant to support learners in gradually acquiring a well-developed understanding of the knowledge domain in which the complex learning task is situated. To this end, representational tools facilitate visualizing of the domain both qualitatively and quantitatively. *Qualitative representations* stimulate reasoning about the concepts, their underlying causal principles, and the circumstance under which those principles can legitimately be applied, enabling problem-solvers to define the problem effectively and propose multiple solutions. *Quantitative representations* stimulate reasoning about the concepts and their mathematical relationships (e.g., algorithms), enabling learners to evaluate the effects of proposed solutions and, thus, to come to a definitive solution. *Scripting* is employed to ensure proper alignment of the tool, its use, and the part-task demands (Dillenbourg, 2002; Kobbe, Weinberger, Dillenbourg, Harrer, Hämäläinen *et al.*, 2007; Weinberger, Ertl, Fischer, & Mandl, 2005). According to Dillenbourg, a script is "a set of instructions regarding how the team members should interact, how they should collaborate and how they should solve the problem" (p. 64). Such scripting entails the segmentation of a complex problem in distinct phases with distinct purposes for each phase of the problem-solving process (Beers, Boshuizen, Kirschner, & Gijselaers, 2005; Dillenbourg; O'Donnell & Dansereau, 1992). The script structures the complex learning task by dividing it into a sequence of ontologically distinct problem phases (i.e., problem-orientation, problem-solution, solution-evaluation) so that they can be foreseen with representational tools congruent with the part-task demands and activities required for each phase (Duffy *et al.*, 1998; Van Bruggen *et al.*, 2003).

In the *problem-orientation phase*, learners need to create a cognitive bridge between their initial mental model and the mental model to be created (Chi *et al.*, 1982; Jonassen, 2003). This phase involves a part-task focused on creating a global problem representation, becoming aware of both the problem and the important concepts of the knowledge domain, and becoming aware of the constraints and criteria for solution and evaluation (e.g., this concept should affect that concept and that is something that will help to achieve this goal). To create the problem overview and thus broaden the problem space, a qualitative problem representation containing the relevant concepts is more appropriate than a quantitative one. The *problem-solution phase* follows the orientation phase and is where learners apply the underlying causal principles of the knowledge domain to produce concrete solutions. The part-task in this phase is more structured than in the previous phase and focuses on combining the concepts of the domain into principles and making explicit causal relationships between the problem and proposed solutions (e.g., if this concept increases, then that concept decreases). Here learners could create a number of possible solutions and then reason about the advantages and disadvantages of each. The main advantage of doing this is that the solutions come in a relatively straightforward, often causal, way which makes the completion process more efficient and effective (e.g., Jonassen & Ionas, 2008). The problem representation remains qualitative, but contains - along with the central

concepts of the problem - causal information which supports learners in finding multiple solutions to the problem. Finally, in the *solution-evaluation phase* it is more appropriate that learners relate the arrived at solutions to their consequences so as to determine their suitability. This should enable learners to reach a definitive and appropriate problem solution. This part-task focuses on gaining insight into the quantitative effects (e.g., increasing this concept doubles that concept, but also increases it to a level that is unrealistic) of the proposed solutions and into comparing the suitability of various solutions for solving the problem.

The *congruency of representational guidance* provided by a tool can be determined and, thus, matched to the task demands by specifying the ontology of the tool into its *expressiveness* and *processability* (see Table 1.1). *Expressiveness* refers to which concepts and interrelationships can be represented (i.e., tool specificity) and how accurately this is done (i.e., tool precision). *Processability* refers to differences in processing the ontological information caused by variations in expressiveness and determines the number and quality of inferences that can be made. Less expressive (i.e., less specific and less precise) ontologies have the advantage of being highly processable (Larkin & Simon, 1987) making it easy to draw many inferences (i.e., elaboration). Such ontologies guide learners in elaborating on the concepts of the domain and in relating them to the problem (e.g., Jonassen, 2003). These ontologies, however, do not have much expressive power (Cox, 1999); the inferences made from them are neither specific nor precise. The *order* of an ontology (Frederiksen & White, 2002) determines the quality of the inferences that can be made (i.e., kind of reasoning used). A *zero order* ontology supports reasoning about concepts and relating this reasoning to the problem in qualitative terms. It is highly processable, but not very expressive. A *first order* ontology is more expressive - specific and precise - which supports reasoning about causal relationships and guides discussion and/or thinking about possible solutions. A *second order* ontology is the most expressive guide and supports quantitative inference-making thus enabling negotiation and/or determination of the suitability of the proposed solutions.

Table 1.1
Ontology and Guidance Specifications for a Representational Tool

Ontology				Representational guidance
Expressiveness		Processability		
Specificity	Precision	Elaboration	Order	
Low	Conceptual	Unstructured	Zero	Qualitative conceptual inference-making
Medium	Causal Relations	Quasi-structured	First	Qualitative causal inference-making
High	Mathematical relations	Fully Structured	Second	Quantitative inference-making

1.2.2 Active and passive representational scripting

Although both types of representational scripting (i.e., active and passive) are intended to foster complex learning-task performance, there are differences in how and why they could accomplish this. Before discussing their differences, it should be noted that both types integrate scripting with the availability of multiple representational tools. By doing so, they both sequence and make the different part-task demands explicit and tailor the congruency of the tools' representational guidance to the part-task demands of the complex problem. The types, however, differ in the manner in which the representational tools facilitate learners in *visualizing* the content of the domain. That is, the tools either provide or enable the construction of domain-specific representations and might, therefore, affect learning-task performance differently (Cox, 1999; Nesbit & Adesope, 2006; Reimann, 1999; Stull & Mayer, 2007; Van Amelsvoort *et al.*, 2007; Vekiri, 2002).

Passive representational scripting facilitates learners in visualizing the content of the domain through *providing* them with part-task congruent expert representations of the domain. This guides learners' cognitive behavior and, thus, learning-task performance since evident information (e.g., concepts and their interrelationships) and inference rules can be directly read off and applied to the task at hand (Ainsworth, 2006; Cox, 1999; Larkin & Simon, 1987; O'Donnell, Dansereau, & Hall, 2002; Stull & Mayer, 2007; Tergan, 2005; Van Bruggen *et al.*, 2002, Zhang, 1997). Additionally, the provided representations can serve as a memory aid that supports learners in storing, retrieving and referring to important information. (Löhner *et al.*, 2003; Reimann, 1999; Van Bruggen *et al.*; Zhang). When employed in collaborative settings (e.g., CSCL-environments) shared representations can support learners in interpreting the conveyed messages and relating them to each other (Clark & Brennan, 1991; Cox). Inspecting representations that are constructed by others is, however, not always beneficial for learning (De Simone *et al.*, 2001; Greeno & Hall, 1997; Hilbert & Renkl, 2008; Lee & Nelson, 2005; Van Amelsvoort *et al.*, 2007) since this may:

- lead to superficial processing of provided information when learners are unable to interpret the overview properly or fail to fit it in with their existing understanding,
- hinder learners in generating new ideas, knowledge and approaches and applying them when carrying out the task at hand.

Active representational scripting facilitates learners in visualizing the content of the domain by enabling the *construction* of part-task congruent representations. This is advocated to increase learners' involvement in their learning process which often results in deeper and more meaningful learning (Ainsworth, 2006 Cox, 1999; Kollöffel, Eysink, & De Jong, 2010; Lee & Nelson, 2005; Liu *et al.*, 2010; Shaw, 2010; Stern, Aprea & Ebner, 2003; Van Meter & Garner, 2005). That is, it can foster understanding and/or task performance since learners are more stimulated to carry out cognitive and meta-cognitive activities such as (1) selecting relevant information, (2) organizing information into coherent structures, (3) relating information to prior understanding, (4) determining

knowledge and comprehension gaps, and (5) generating new ideas, questions and plans (De Simone *et al.* 2001; Hilbert & Renkl, 2008; Shaw; Stull & Mayer, 2007). When employed in collaborative settings (e.g., CSCL-environments) actively constructing and adjusting a shared representation may foster learning even more since it can evoke more elaborate (i.e., more content-related interaction) and meaningful (i.e. management of their collaboration process) discussions about the content of the domain (Erkens *et al.*, 2005; Fischer *et al.*, 2002; Löhner *et al.*, 2003; Mühlpfordt & Stahl, 2007; Munneke *et al.*, 2007; Van Amelsvoort *et al.*, 2007). Other studies, however, showed no effects, mixed or even negative effects concerning learning when learners where facilitated to construct their own representations (Reader & Hammond, 1994; Scheiter, Gerjets, & Catrambone, 2006; Stull & Mayer; Suthers *et al.*, 2003; Van Drie *et al.*, 2005). There seem to be at least three reasons that might account for these contrasting findings. First, learners might perceive constructing the representation as an additional task demand instead of as support. When this is the case, after the concepts are interrelated in the representation, learners pay no further attention to the representation and, therefore, do not apply it to complete their learning task (De Simone *et al.*; Suthers *et al.*; Van Amelsvoort *et al.*). Second, even if a tool's ontology is congruent with the part-task at hand, learners are still facilitated in constructing a variety of representations. This may become problematic if representations are incorrect (e.g., misconceptions) or inaccurate (Cox & Brna, 1995; Lim, 2001; Van Meter & Garner; Veerman, 2000). Finally, constructing representations that are beneficial for learning requires learners to focus simultaneously on the content of the domain, the task at hand and the mechanics of how to construct the representation. It can be, therefore, a rather cognitively demanding activity for learners. If these demands become too high (i.e., go beyond the capacity of the learners' working memory) it is likely that learners will not benefit from constructing the representation (Leutner, Leopold, & Sumfleth, 2009; Stull & Mayer; Sweller, 2005; Zhang, 1997). This especially applies when learners construct a representation in teams instead of individually. The already challenging task becomes even more demanding when learners also have to (1) ensure that their team members understand the adjustment of the shared representations and (2) negotiate on the suitability of the adjustment (Cox; F.C. Kirschner *et al.*, 2009ab; Van Bruggen *et al.*, 2002).

Whereas both types of representational scripting have their own benefits, they also have their specific pitfalls. Thus far, it remains to be seen how and why providing and constructing part-task congruent representations affects complex learning-task performance.

1.2.3 Carrying out complex business-economics tasks in teams

In the research reported on in this thesis, learners collaborated on solving a case-based business-economics problem. They had to advise an entrepreneur on changing business strategy to increase profits (i.e., company result). Learning-task analysis was conducted to gain insight into the part-tasks and their required domain-specific perspectives (Anderson & Krathwohl, 2001; Gagné, Briggs, & Wagner, 1992). Based on these insights, the sequence and demands of the part-tasks were specified and part-task congruent representational tools were developed (see Table 1.2).

Table 1.2
Congruence between the Active/Passive Representational Tool and Phase-related Part-task Demands

Problem phase	Task demands	Representational tool	Representational guidance
Problem-orientation	Determining core concepts and relating them to the problem	Conceptual	Visualizing concepts and their conceptual relationships
Problem-solution	Proposing multiple solutions to the problem	Causal	Visualizing causal relationships between the concepts and the possible solutions
Solution-evaluation	Determining suitability of the solutions and coming to a definitive solution to the problem	Simulation	Visualizing mathematical relationships between the concepts and enabling manipulation of their values

In the *problem-orientation phase* teams of learners have to explain what they think the problem is and describe what the most important factors are for solving it. Learner interaction should, thus, be guided towards determining the core concepts needed to carry out this part-task and to discussing how these concepts are qualitatively related. The design of the representational tool should facilitate teams in creating and discussing a global qualitative problem representation by guiding them in relating the relevant concepts. Figure 1.1 shows an expert representation of the concepts and their conceptual interrelationships involved in this domain. The conceptual representational tool facilitates visualization of the concepts and their interrelationships. Determining and relating the concepts that teams may regard as beneficial for solving the problem helps them become more familiar with those concepts and broadens their problem space. Teams using this conceptual tool could see, for example, that 'company result' is explicitly related to 'total profit' and 'efficiency result'. This should guide teams in elaborating (i.e., causal or mathematical details) on the relationships in the following two problem phases, making it easier for them to find multiple solutions to the problem and to evaluate their effects.

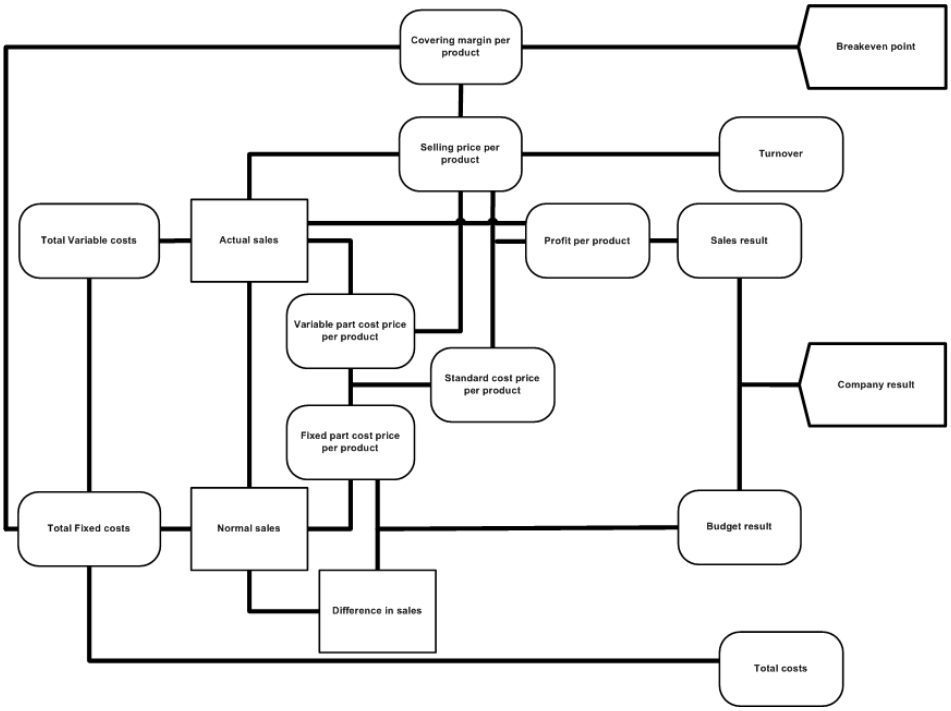

Figure 1.1 Experts' conceptual representation of the domain (translated from Dutch).

In the *problem-solution phase* teams of learners have to formulate several changes in business strategy (i.e., interventions) and clarify how they might solve the problem (i.e., problem-solution) by describing their effects on the outcome (i.e., company result). Learner interaction should, thus, be guided towards formulating multiple interventions and discussing how each of these interventions affects the selected core concepts by further specifying the relationships between the concepts and proposed interventions. The representational tool should facilitate creation and discussion of a causal problem representation by relating concepts to each other and to possible interventions. Figure 1.2 shows an expert representation of the concepts, the possible interventions and their causal interrelationships involved in this domain. The causal representational tool facilitates visualization of the concepts, interventions and their interrelationships. Determining relevant concepts and interventions and causally relating them supports the effective exploration of the solution space and, thus, finding multiple solutions to the problem. Teams receiving the causal representational tool could see that an intervention such as a 'promotion campaign' (e.g., placing an advertisement in a newspaper) explicitly affects 'actual sales', which in turn affects 'total profit'. Representing the interrelationships only conceptually, as in the first problem phase, is not expressive enough for this part-task since the relationships need to be further specified and teams need additional information about the possible

solutions. If this is not the case, then teams are forced to come up with a solution (i.e., the advice) themselves without sufficiently understanding the underlying qualitative principles governing the domain.

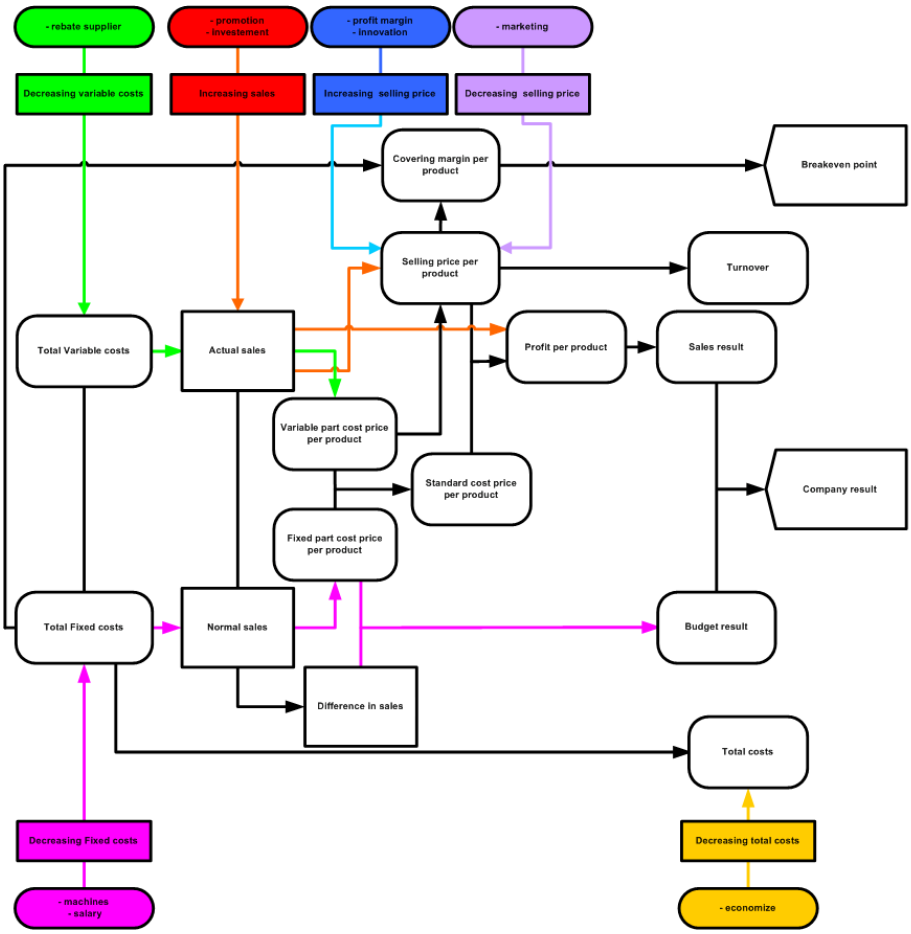

Figure 1.2 Experts' causal representation of the domain (translated from Dutch).

Finally, in the *solution-evaluation phase* teams of learners have to determine the financial consequences of their proposed interventions and formulate definitive advice for the entrepreneur by discussing the suitability of the different interventions. Learner interaction should, thus, be guided towards determining and comparing the financial consequences by discussing the mathematical relationships between the selected concepts. The representational tool must thus facilitate creating and discussing a quantitative problem representation by specifying the relationships as algebraic equations. Figure 1.3 shows an expert representation of the concepts and their mathematical interrelationships involved in this domain. The simulation representational tool facilitates visualization of the concepts and their mathematical relationships. Determining

relevant concepts and specifying the interrelationships as algebraic equations supports learners in evaluating the effects of their proposed interventions and, thus, in coming to a suitable advice. Teams receiving the simulation representational tool could, for example, simulate how an intervention such as a 'promotion campaign' affects 'actual sales' and whether this affects 'total profit'. By entering and adjusting values (i.e., increasing or decreasing), the values of the other related concepts are automatically computed. Since such quantitative representations can only be properly understood and applied when learners have a well-developed qualitative understanding of the domain, this kind of support is only appropriate for carrying out this type of part-task.

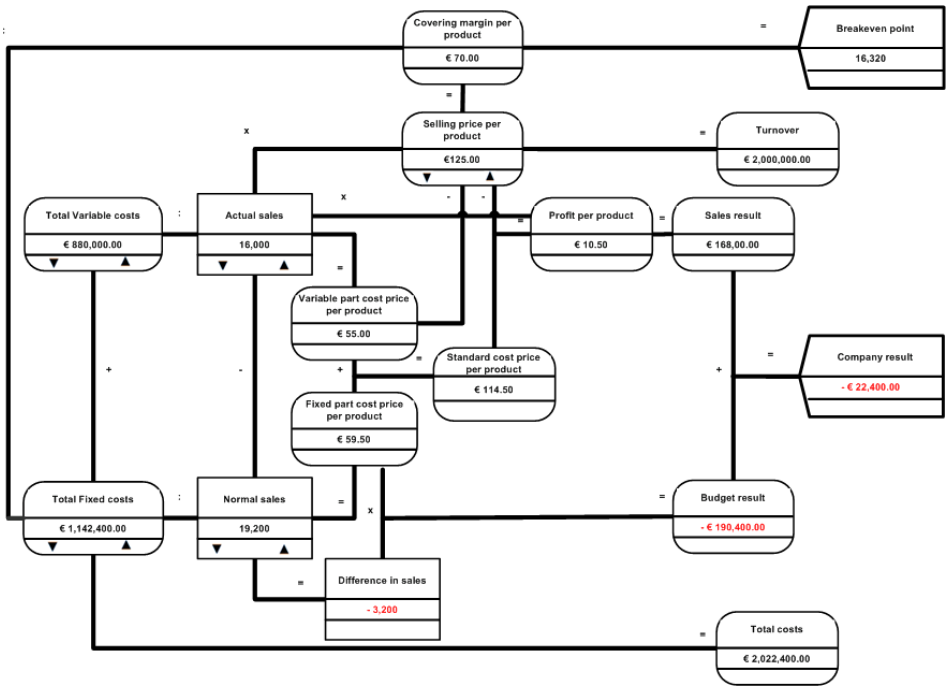

Figure 1.3 Experts' mathematical representation of the domain (translated from Dutch).

Learner interaction in the concent and the relational space

Guiding teams of learners in visualizing and discussing the content of the domain in a task-appropriate manner should actively engage them in the process of making sense of the domain in question by articulating and discussing multiple perspectives on the problem and of the problem-solving strategy (Hmelo-Silver *et al.*, 2007; Jonassen, 2003; Ploetzner *et al.*, 1999). Representational scripting (i.e., active and passive) employed in collaborative settings is intended to evoke learner interaction in two dialogical spaces (e.g., Barron, 2003), namely the content space (i.e., carrying out part-task-related activities) and the relational space (i.e., carrying out communicative activities).

In the *content space* learners carry out part-task related activities that enable them to acquire a well-developed understanding of the domain and to apply this during their problem-solving process. To this end, the representational scripting stimulates learners to carry out *cognitive activities* such as (1) discussing the goal of the problem-solving task or part-tasks, (2) discussing and selecting concepts, principles, and procedures in the domain, and (3) formulating and revising their decisions (Jonassen, 2003; Vermunt, 1996). Learners may also be induced to employ a proper problem-solving strategy and reflect on its suitability through carrying out *meta-cognitive activities* (F. de Jong, Kollöffel, Van der Meijden, Kleine Staarman, & Janssen, 2005; Hmelo-Silver, Chernobilsky, & Jordan, 2008; Molenaar, Van Boxtel, & Sleegers, in press; Moos & Azevedo, 2008; Vermunt). This requires that learners discuss (1) how they should approach the problem (i.e., planning), (2) whether they have finished the part-tasks on time (i.e., monitoring), and (3) how suitable their approach was (i.e., evaluation or reflection).

In the *relational space* learners carry out communicative activities enabling them to have meaningful discussions in the content space (Barron, 2003; Kreijns *et al.*, 2003). To this end, representational tools may support learners in coordinating their collaboration process by carrying out communicative activities (Clark & Brennan, 1991; Hmelo-silver *et al.*, 2008; Reiser, 2004). Three important communicative activities are (1) focusing, (2) checking, and (3) argumentation (see Erkens *et al.*, 2005). That is, learners have to make their own knowledge and ideas explicit to other team members. When these are made explicit, learners must maintain a shared topic of discourse (i.e., achieve a common *focus*) and repair that focus if they notice any divergence. Also, understanding and relating the relevance of individual messages may be difficult when learners are discussing different topics simultaneously. Therefore, learners should coordinate their topic of discourse by focusing (Dillenbourg & Traum, 2006; Erkens *et al.*). Since not all concepts, principles, and procedures are relevant to carrying out a specific part-task, learners must also maintain the coherence and consistency of their shared understanding by *checking* (Van der Linden, Erkens, Schmidt, & Renshaw, 2000; Veerman, 2000). Furthermore, learners must come to an agreement about relevant concepts, principles and procedures. Through *argumentation* they can try to change their team members' viewpoints to arrive at the best way of carrying out a part-task or at a definition of concepts acceptable to all. In this argumentation process, they try to convince others by elaborating on their own point of view and by explaining, justifying and accounting for their viewpoints (Andriessen *et al.*, 2003; Erkens *et al.*).

1.3 Research Questions and Thesis Overview

The general theme in this thesis is whether visualizing the content of the domain in a part-task congruent manner (i.e., representational scripting) fosters complex learning-task performance. To address this, two types of the representational scripting were developed: (1) passive representational scripting (i.e., providing expert representations of the domain) and (2) active representational scripting (i.e., constructing domain-specific representations), and their effects were examined. The general research question of this thesis is, therefore, specified as follows:

> *How and why does visualizing domain content in a part-task congruent manner affect the collaboration process and complex learning-task performance in teams and individual learning?*

The research questions derived from the general question are:

1. What are the effects of *passive representational scripting* on the collaboration process and complex learning-task performance in teams and on individual learning?
2. What are the effects of *active representational scripting* on the collaboration process and complex learning-task performance in teams and on individual learning?
3. What are the effects of *constructing qualitative and quantitative domain specific representations* on the collaboration process and complex learning-task performance in teams and on individual learning?

The studies were each aimed at answering a specific research question. Study 1 (Chapter 2) addresses the first question by examining the effects of providing part-task congruent representations. Study 2 (Chapter 3) addresses the second question by examining the effects of constructing part-task congruent representations. Study 3 (Chapter 4) addresses the third question by examining the effects of constructing qualitative and quantitative representations of the domain.

All studies in this thesis involved participants aged 15 to 18 years from business-economics classes in secondary education schools in the Netherlands. In each study classmates were randomly assigned to teams of learners (i.e., triads, see Laughlin *et al.*, 2008; Schellens & Valcke, 2006). The teams had to solve a complex business-economics problem in a CSCL-environment called the Virtual Collaborative Research Institute (VCRI, see Chapters 2-4). Data were collected on *learning results* (i.e., the complex learning-task performance and learning results for both teams and individuals) and the *learning process* (i.e., constructed representations and learner interaction).

This thesis concludes with a general discussion of the results obtained from the three studies, their limitations, and suggestions for future research in Chapter 5.

2. Guiding Teams' Online Complex Learning-task Behavior through Representational Scripting[2]

Abstract
This study investigated the effects of passive representational scripting on teams' performance of a complex business-economics problem. The scripting structured the learning task into three part-tasks, namely (1) determining core concepts and relating them to the problem, (2) proposing multiple solutions to the problem, and (3) coming to a definitive solution to the problem. Each provided representation (i.e., conceptual, causal, or simulation) was suited for carrying out a specific part-task. It was hypothesized that providing part-task congruent support would guide learner interaction towards better learning-task performance. Teams of learners in four experimental conditions had to carry out the part-tasks in a predefined order, but differed in the representation(s) they received. In three non-matched conditions, teams only received one of the representations and were, thus, only supported in carrying out one of the part-tasks. In the matched condition, teams received all three representations in the specified order (i.e., passive representational scripting). The results indicate that teams in the matched condition had more elaborated discussions about the content of the knowledge domain (i.e., concepts, solutions and relations) and were better able to share and to negotiate about their knowledge. As a consequence, these teams performed better on the learning task. However, no differences concerning the learning process and learning results were obtained when comparing teams in the matched condition to teams receiving only a causal representation of the domain for all part-tasks.

Keywords: Complex Learning Tasks, Computer Supported Collaborative Learning, External Representations, Learner Interaction, Representational Scripting

[2] Based on Slof, B., Erkens, G., Kirschner, P. A., Jaspers, J. G. M., & Janssen, J. (2010). Guiding students' online complex learning-task behavior through representational scripting. *Computers in Human Behavior, 26,* 927–939.

2.1 Introduction

Collaboratively performing complex learning task such as solving complex problems is often regarded as an effective pedagogical method beneficial for both team and individual learning (Hmelo-Silver, Duncan, & Chinn, 2007). The premise underlying this approach is that through a dynamic process of eliciting one's own knowledge, discussing this with peers, and establishing and refining the teams' shared understanding of the knowledge domain, learners acquire new knowledge and skills and process them more deeply (Erkens, Jaspers, Prangsma, & Kanselaar, 2005; Mercer, Littleton, & Wegerif, 2004). Unfortunately, simply putting learners in a team and having them work together on a problem or a project is not always beneficial for learning (P.A. Kirschner, Beers, Boshuizen, & Gijselaers, 2008; Kreijns, Kirschner, & Jochems, 2003). To address this inconsistency, educators and instructional designers need to design learning situations that aim at evoking a specific kind of interaction enabling teams of learners to properly carry out their complex learning task (Kester, Kirschner, & Corbalan, 2007; Weinberger, Ertl, Fischer, & Mandl, 2005).

Research on Computer Supported Collaborative Learning (CSCL) has shown that proper use of representational tools or negotiation scripts can beneficially affect interaction by stimulating learners to externalize and discuss knowledge and ideas (Fischer, Bruhn, Gräsel, & Mandl, 2002; P.A. Kirschner *et al.*, 2008; O'Donnell, Dansereau, & Hall, 2002; Suthers, 2006). However, whereas these studies show promising results, other research questions if and how representational tools can best guide interaction when collaboratively carrying out a complex learning task (Bera & Liu, 2006; Elen & Clarebout, 2007; Marjanovic, 2007; Van Drie, Van Boxtel, Jaspers, & Kanselaar, 2005). The sole presence or availability of such a tool does not in itself affect learning. The nature of the interaction depends on the interrelationship between the types of interaction that the tool is intended to support, the way the chosen tool is used by the learners, and the characteristics of the users themselves. Important here is whether the design of the tool is in line with the learners' capabilities and their intentions. That is, learners have to possess the required prior knowledge and/or skills to use the tool properly and need to experience the tool as being beneficial for carrying out their learning task. Furthermore, the tool has to make clear to its users what they can and should do with it. Only then can learners use their prior knowledge and skills to make proper use of the tool and reach the intended learning goals (P.A. Kirschner, Martens, & Strijbos, 2004; Veldhuis-Diermanse, 2002). Also important is the fact that complex learning tasks are usually composed of fundamentally different part-tasks, each of which requires a different perspective on the knowledge domain (Van Bruggen, Boshuizen, & Kirschner, 2003). The part-tasks were: (1) determining core concepts and relating them to the problem (i.e., problem-orientation), (2) proposing multiple solutions to the problem (i.e., problem-solution), and (3) determining suitability of the solutions and coming to a definitive solution to the problem (i.e., solution-evaluation). Carrying out these different cognitive part-task demands should be supported by different tools. The guidance that a

representational tool gives to learners carrying out a complex learning task, therefore, needs to match the demands of the different part-tasks; otherwise this will lead to communication problems and decreased learning-task performance (Slof, Erkens, Kirschner, & Jaspers, 2010; Van Bruggen *et al.*, 2003).

Recently, *scripting* has been advanced (Dillenbourg, 2002; Weinberger *et al.*, 2005) as a way to ensure the alignment between tool, tool use and learning goals in collaborative learning. According to Dillenbourg a script is "a set of instructions regarding to how the team members should interact, how they should collaborate and how they should solve the problem" (p. 64). Scripting complex learning-task performance with representational tools sequences and makes the different part-task demands explicit so that they can be provided with congruent content-related guidance by the tools. By doing so, a kind of interaction beneficial for the complex learning-task performance can be evoked.

2.2 Theoretical Background

2.2.1 Collaboratively solving a complex problem

Solving a complex problem is frequently regarded as a sequenced phased process (i.e., problem-orientation, problem-solution, and solution-evaluation) in which each phase has its own specific purpose and where each phase requires a specific kind of interaction (Ploetzner, Fehse, Kneser, & Spada, 1999; Van Bruggen *et al.*, 2003).

In the *problem-orientation phase*, learners orient themselves to the problem by creating a cognitive bridge between their initial mental model of the knowledge domain and the mental model that needs to be created (Chi, 1997; Jonassen, 2003). This phase involves carrying out a part-task which focuses on creating a global qualitative problem representation. This representation makes learners aware of the (1) problem itself, (2) important concepts in the knowledge domain, and (3) constraints and criteria for solution of the problem and evaluation of the solution (e.g., concept A should affect concept B and this will help achieve the goal). In the *problem-solution phase*, learners must find one or more possible problem solutions. This part-task is more structured than the one in the previous phase and focuses on combining concepts in the knowledge domain into qualitative principles and making the causal relationships between the problem to be solved and the proposed solutions explicit (e.g., if concept A is increased, then concept B decreases). Here learners might formulate several solutions and make clear how they solve the problem (i.e., problem-solution) by describing how they will affect the outcomes (i.e., company result). During the third and last phase, the *solution-evaluation phase*, learners evaluate the solutions so as to choose the best one. Learners need to relate the solutions with their consequences in order to determine suitability, enabling them to reach a definitive and suitable problem solution. This part-task focuses on evaluating the proposed solutions (e.g., making calculations) and gaining insight into their quantitative or qualitative effects and criteria (e.g., increasing concept A doubles concept B, increasing it to an unrealistic level).

Successfully solving complex problems entails learners actively engaging in a process of making sense of the knowledge domain in question by articulating and discussing multiple perspectives on the problem and the problem-solving strategy (Hmelo-Silver *et al.*, 2007; Jonassen, 2003; Ploetzner *et al.*, 1999). Properly carrying out a collaborative problem-solving task requires that learners interact in two different dialogical spaces (e.g., Barron, 2003), namely the content space (i.e., carrying out part-task related activities) and the relational space (i.e., carrying out communicative activities).

Content space

In the content space, learners are required to carry out *part-task related activities* that enable them to properly discuss the content of the knowledge domain in question. Learner interaction in the content space should be aimed at acquiring a proper understanding of the knowledge domain. This requires learners to carry out *cognitive activities* such as (1) discussing the goal of the problem-solving task/part-tasks, (2) discussing and choosing concepts, principles, and procedures in the knowledge domain, and (3) formulating and revising their decisions (Jonassen, 2003; Vermunt, 1996). Furthermore, learners need to employ a proper problem-solving strategy and reflect on its suitability through carrying out *meta-cognitive activities* (F. de Jong, Kollöffel, Van der Meijden, Kleine Staarman, & Janssen, 2005; Lazonder & Rouet, 2008; Narciss, Proske, & Koerndle, 2007; Vermunt). This means that learners must discuss (1) how they should approach the problem (i.e., plan), (2) whether they have finished the part-tasks on time (i.e., monitor), and (3) the suitability of their approach (i.e., evaluate). Carrying out these cognitive and meta-cognitive activities should enable learners to acquire multiple perspectives on the problem and their problem-solving strategy. However, where expert problem-solvers experience no difficulties in carrying out these kinds of activities, learners (i.e., non-experts) do. When solving problems, learners rely primarily on surface features such as using objects referred to in the problem instead of the underlying principles of the knowledge domain (Corbalan, Kester, & Van Merriënboer, 2009), and employ weak problem-solving strategies such as working via a means-ends strategy towards a solution (Simon, Langley, & Bradshaw, 1981). An important reason for this is that learners lack a well developed understanding of the knowledge domain and as a consequence have problems creating and combining meaningful problem representations. This hinders learners in effectively and efficiently coping with their problem-solving task because the ease with which a problem can be solved often depends on the quality of the available problem representations (Ploetzner *et al.*, 1999; Seufert, 2003). Different problem representations initiate different kinds of operators which act to produce new information supporting problem solvers in reaching a solution to the problem (Chi, 1997; Jonassen, 2003). To this end, it would be beneficial if suitable representations were provided and combined in a part-task appropriate manner (Ainsworth, 2006; Frederiksen & White, 2002; Van Merriënboer, Kester, & Paas, 2006).

Relational space

In the relational space, learners carry out *communicative activities* enabling them to have meaningful discussions in the content space (F.C. Kirschner, Paas, & Kirschner, 2009ab; Kreijns *et al.*, 2003). Such discussions are difficult, if not impossible, when learners are not aware of each others' knowledge, ideas, and activities and do not discuss them with their peers. Therefore, learner interaction in the relational space is aimed at establishing and maintaining a shared understanding of the content space; a common frame of reference where conflicting points of view can be detected and negotiated (Barron, 2003; Erkens *et al.*, 2005; P.A. Kirschner *et al.*, 2008). That is, learners have to carry out communicative activities such as making their own knowledge and ideas explicit to other team members, focusing, checking and argumentation. When made explicit, learners must try to maintain a shared topic of discourse and to repair a common focus if they notice a focus divergence. Simultaneously discussing different discourse topics makes it difficult to relate and understand the relevance of individual utterances, hindering establishing and maintaining a shared understanding of the content space. Learners coordinate their topic of discourse by *focusing* (Barron; Erkens *et al.*; Van Drie *et al.*, 2005). Also, not all concepts, principles, and procedures are relevant for carrying out a part-task, thus, learners have to guard the coherence and consistency of their shared understanding of the content space. By *checking*, learners ground their communication in a common understanding which was found to be one of the major communicative activities during collaborative problem-solving and related to the quality of the problem-solving process (Van der Linden, Erkens, Schmidt, & Renshaw, 2000). Furthermore, learners must come to agreement with respect to relevant concepts principles and procedures. By using *argumentation* they will try to change their partners viewpoint to arrive at the best way to carry out a part-task or at a definition of concepts acceptable for all. In this argumentation process they try to convince the other(s) by elaborating on their point of view, giving explanations, justifications and accounts (Andriessen, Baker, & Suthers, 2003; Erkens *et al.*; P.A. Kirschner *et al.*). Only when learners carry out such communicative activities their interaction can be sufficiently coordinated and multiple perspectives on the problem and the problem-solving strategy can arise.

2.2.2 Guiding learner interaction through representational scripting

Integrating scripting with the availability of representational tools (i.e., *passive representational scripting*) is intended to structure the problem-solving process making it more efficient and effective. *Scripting* shapes the use of the representational tools and, therefore, also the epistemic and social processes of collaboration (Slof *et al.*, 2010b; Weinberger *et al.*, 2005) by sequencing and making the different part-task demands explicit so that they can be provided with part-ask congruent support by the representational tools. Each representation tool provides a different domain-specific content scheme (i.e., problem representation) representing different perspectives on the problem. Visualizing the knowledge domain by providing external representations (ERs) influences learner interaction through their representational guidance (Suthers,

2006; Van Drie *et al.*, 2005; Zhang, 1997). Due to its ontology (i.e., objects, relations, and rules for combining them), every ER offers a restricted view of the knowledge domain, guiding learner interaction in a specific manner. Matching the representational guidance of the ERs (see Table 1) with the learner interaction required to carry out a part-task evokes proper part-task related and communicative activities, leading to more successful team learning-task performance. To effectively do this, one must avoid or neutralize the difficulties learners encounter when combining multiple ERs, namely problems translating from and coordinating between different kinds of ERs (Ainsworth, 2006), and incongruence between ER and part-task related activities (Vekiri, 2002). This means that the representational guidance of the ER provided in a specific representational tool must be congruent (i.e., ontologically matched) with the part-task demands and activities of a specific problem phase (Schnotz & Kürschner, 2008; Van Bruggen *et al.*, 2003).

Table 2.1
Congruence between Representational Tool and Phase-related Part-task Demands

Problem phase	Task demands	Representational tool	Representational guidance
Problem-orientation	Determining core concepts and relating them to the problem	Conceptual (static)	Visualizing concepts and their conceptual relationships
Problem-solution	Proposing multiple solutions to the problem	Causal (static)	Visualizing causal relationships between the concepts and the possible solutions
Solution-evaluation	Determining suitability of the solutions and coming to a definitive solution to the problem	Simulation (dynamic)	Visualizing mathematical relationships between the concepts and enabling manipulation of their values

2.3 Design and Research Questions

This study focuses on how the use of passive representational scripting affects both learner interaction and teams' complex learning-task performance in a CSCL-environment. To this end, four experimental conditions were defined. In triads, learners in all conditions had to collaboratively solve a case-based problem in business-economics which was divided into three problem phases, each coupled with different ERs. To study the effects of the passive representational scripting, the ERs were either matched or mismatched to the different problem phases (see Table 2.2).

Table 2.2
Overview of the Experimental Conditions

Problem phase	Condition and provided ER in the Representational Tool			
	Conceptual condition	Causal condition	Simulation condition	Matched condition
Problem-orientation	*Conceptual ER*	Causal ER	Simulation ER	*Conceptual ER*
Problem-solution	Conceptual ER	*Causal ER*	Simulation ER	*Causal ER*
Solution-evaluation	Conceptual ER	Causal ER	*Simulation ER*	*Simulation ER*

The scripting structured the problem-solving process in three phases, but only one of the three ERs was made available to the learners when carrying out a specific part-task. In three *non-matched* conditions, teams only received one of the ERs (i.e., conceptual ER, causal ER, or simulation ER) and had to use this ER for carrying out all three part-tasks. The provided ER ontologically matched only one of the three part-tasks and there was a mismatch for the other two. In the fourth, *matched* condition, teams received all three ERs in a phased order, receiving the ER most suited to each part-task. Here, thus, there was a match between all three ERs and all three part-tasks. Due to the presumed match between ERs and part-tasks, learners' understanding of the domain, part-task related activities and communicative activities were expected to increase, allowing the learners to reach better problem solutions. It was, therefore, hypothesized that learners in the matched condition:

(H1) experience a qualitatively better learning process, evidenced by:
  a) carrying out more part-task related cognitive and meta-cognitive activities,
  b) carrying out more communicative activities to coordinate their collaborative problem-solving process,

(H2) achieve a better team learning result, evidenced by arriving at better interventions and

(H3) achieve a better individual learning result, evidenced by higher post-test scores.

2.4 Method and Instrumentation

2.4.1 Participants

Participants were students from six business-economics classes in three secondary education schools in the Netherlands. The total sample consisted of 96 learners (59 male, 37 female; mean age = 16.67 years; *SD* = 0.77, *Min* = 15, *Max* = 18). Students were, within classes, randomly assigned to a total of 32 triads (i.e., teams of learners); eight per experimental condition.

2.4.2 Task and materials

Collaborative learning environment

Learners worked in a CSCL-environment called Virtual Collaborative Research Institute (VCRI, see Figure 2.1), a groupware application for supporting the collaborative performance of problem-solving tasks and research projects (Jaspers, Broeken, & Erkens, 2005). For this study, five tools that are

part of the VCRI were augmented with passive representational scripting. All tools, except the Notes tool, were shared among team members.

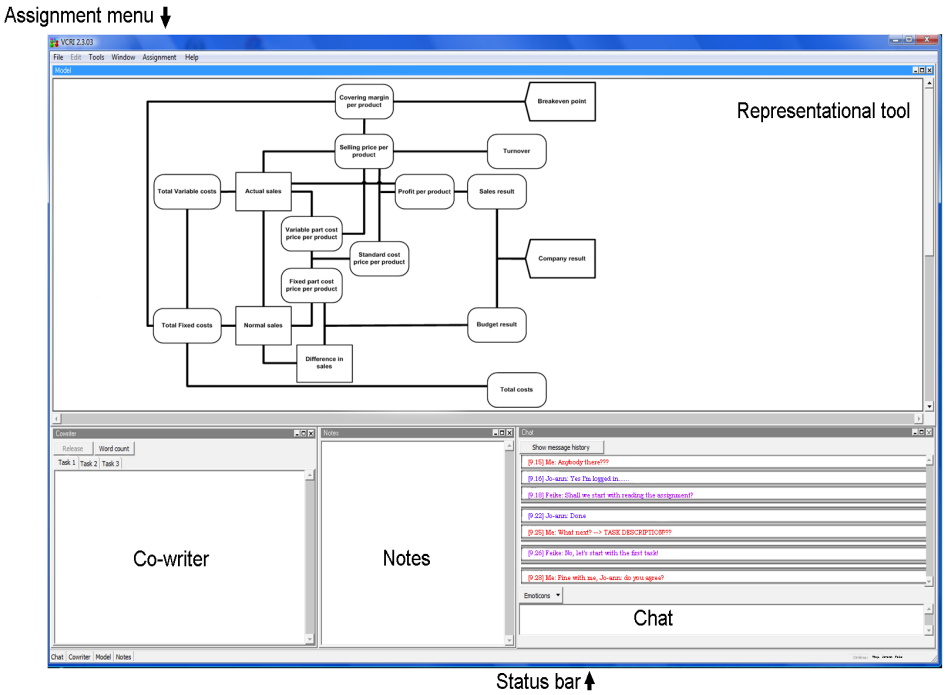

Figure 2.1 Screenshot of the VCRI-environment; conceptual representational tool (translated from Dutch).

The *Chat tool* enables synchronous communication and supports team members in externalizing and discussing their knowledge and ideas. The chat history is automatically stored and can be re-read by the team members. In the *Assignment menu*, team members can find the description of the problem-solving task/part-tasks. Besides this, additional information sources such as a definition list, formula list, and clues for solving the problem were also available here. The *Co-writer* is a shared text-processor where team members can collaboratively formulate and revise their decisions to the part-tasks. The *Notes tool* is an individual notepad that allows team members to store information and structure their own knowledge and ideas before making them explicit. The *Status bar* is an awareness tool that displays which team members are logged into the system and which tool a member is currently using. All teams in all conditions had access to these tools and information sources. In other words, the different conditions were information equivalent and only differed in the way that the ERs are intended to guide learner interaction and teams' complex learning-task performance.

Problem-solving task and tool use

All teams worked on a case-based problem in business-economics in which they had to advise an entrepreneur about changing the business strategy to increase profits (i.e., company result). Through the use of *scripting*, the problem-solving process was structured into a problem-orientation phase, a problem-solution phase, and a solution-evaluation phase each focusing on one of the part-tasks. To come up with a suitable advice, learners had to carry out three different part-tasks, namely (1) determine the main factors that determine the company's results and relate them to the problem, (2) determine how certain changes of the business strategy (i.e., interventions) might solve the problem by describing how they will affect the outcomes (i.e., company result), and (3) compare the effects of these interventions and formulate a definitive advice based on this comparison. All teams were coerced to carry out the part-tasks in a predefined order; they could only start with a new part-task after finishing an earlier part-task. When team members agreed that a part-task was completed, they had to 'close' that phase in the assignment menu. This 'opened' a new phase, which had two consequences for all teams, namely they (1) received a new part-task, and (2) had to enter their new decisions in a different window of the Co-writer and could not alter their prior decisions though these decisions remained visible. All conditions received the part-tasks in the same order (i.e., used the same script), but differed in the content-related guidance they received. Teams in the non-matched conditions received an ER that was only suited to one of the three phases/part-tasks and had to use this ER for carrying out all three part-tasks. In contrast, teams in de matched condition received a different ER for each phase/part-task which was ontologically matched to the specific demands of that phase.

The *problem-orientation phase* focused on creating a global qualitative problem-representation by asking learners to explain what they thought the problem was and to describe what the most important factors were that influenced the problem. During this phase, learners received the conceptual ER (see Figure 1.1, Section 1.2.3, p. 18) which made two aspects salient, namely the core concepts needed to carry out this part-task and which core concepts are qualitatively related to which other core concepts. Learners could, for example, see that 'company result' is determined by the 'total profit' and the 'efficiency result'. Such information should make it easier for them to create an overview of all relevant concepts (i.e., to broaden the problem space), supporting them in finding multiple solutions to the problem in the following phase. The conceptual ER available in this phase supports the creation of a global qualitative problem representation which can be elaborated on in the following problem phases.

The *problem-solution phase* focused on creating a causal problem representation (i.e., explicating the underlying business-economics principles) by asking learners to formulate several interventions and make clear how they might solve the problem. During this phase, learners received the causal ER (see Figure 1.2, Section 1.2.3, p. 19), 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 learners' qualitative understanding by providing the learners with possible interventions each of which had a different effect on the company result. This should make it easier to effectively explore the solution space and should, in turn, support learners in finding multiple solutions to the problem. Learners could, for example, see that an intervention as 'PR-campaign' affects 'actual sales, which in turn affects 'total profit'. The conceptual ER used in the first phase is not expressive enough for this part-task because the relations in that ER were not specified and learners did not receive information about possible interventions, forcing them to produce the advice themselves without sufficient understanding of the underlying qualitative principles of the knowledge domain.

Finally, the *solution-evaluation phase* focused on increasing learners' understanding of the knowledge domain with the aid of a quantitative problem representation. Learners were asked to determine the financial consequences of their proposed interventions and to formulate a definitive solution by negotiating the suitability of the different interventions with each other. During this phase, learners received a simulation ER (see Figure 1.3, Section 1.2.3, p. 20) which enabled them to simulate the financial consequences of their proposed solutions, by clicking on the arrows in the boxes. When adjusting (i.e., increasing or decreasing) the height or the quantity of a certain value, the simulation ER automatically computed the values of the other concepts. This is meant to facilitate the determination and negotiation of the suitability of the different proposed solutions and reaching a definitive advice. Learners could, for example, test how the 'PR-campaign' affects the 'actual sales' and whether this in turn affects the 'total profit'. Only the simulation ER is capable of providing this kind of support, because the relationships between the concepts in this ER were specified as algebraic equations.

2.4.3 Procedure

All teams spent three, 70-minute, lessons solving the problem during which each learner worked on a separate computer in a computer classroom. Before the first lesson, learners received an instruction about the CSCL-environment, team composition, and problem-solving task. The instruction made it clear that their team advice to the problem (i.e., teams' complex learning-task performance) would serve as a grade affecting their GPA. Learners worked on the problem in the computer classroom where all actions and decisions to the part-tasks were logged. During the lessons, the teacher was on stand-by for learning task related questions and a researcher was present for technical support.

2.4.4 Measurement of quality learner interaction

To examine the effect of condition data concerning the quality of the learner interaction were collected by logging the chat-utterances of the team members. The content of these chat-protocols is assumed to represent what learners know and consider important for carrying out their problem-solving task (Chi, 1997; Moos & Azevedo, 2008). To properly analyze these data, researchers should use a combination of qualitative and quantitative methods

(Chi; De Wever, Van Keer, Schellens, & Valcke, 2007; Mercer *et al.*, 2004). This allows the qualitative (i.e., contextual) nature of learner interaction to be quantified (i.e., systematically coded and compared) enabling researchers to account for differences in learning-task performance and generalize their results. Using so called 'concordancers' software (e.g., MEPA, Erkens, 2005; !Kwictex, Mercer *et al.*) minimizes the work associated with coding the chat-protocols and maximizes coding allowing the content of chat-protocols to be searched for the occurrence of important words or phrases within their linguistic context to show their specific function in the dialogue.

Level of analysis and segmentation

The chat-protocols were selected and transferred from the log-files using the Multiple Episode Protocol Analysis (MEPA) program (Erkens, 2005). MEPA uses a multidimensional data structure, allowing chat-protocols to be segmented into multiple levels for analysis, here the episodic level and the event level. Measurement at the *episodic level* provides insight into the number and nature of the discourse topics that learners discussed. An episode is regarded as a dialogue between minimally two learners in which a distinct discourse topic is discussed and which ends with a confirmation by at least two learners that they understood each other (Erkens *et al., 2005*). For example, discussing the suitability of a problem-solving strategy requires the involvement of multiple learners who each use more than one utterance to make their point. At the episodic level only the discourse topic itself is coded. Measurement at the *event level* provides insight in the discussion of the content of the knowledge domain and the communicative function of utterances. To this end, this analysis took place at a finer grain size, namely the utterance (Chi, 1997; Erkens *et al.*; Mercer *et al.*, 2004). For example, discussing a concept such as 'costs' is particularly important when solving the problem used in this study. A problem here is that even within in a single sentence, multiple concepts or statements may be expressed and thus require multiple codes (Erkens & Janssen, 2008; Strijbos, Martens, Prins, & Jochems, 2006). With a MEPA-filter which makes use of 300 'if-then' decision rules, the utterances were automatically segmented into smaller, still meaningful, subunits. Punctuation marks (e.g., full stop, exclamation mark, question mark, comma) and connecting phrases (e.g., 'and if', or 'but if') were used to segment the utterances. At the event level, all utterances relevant for the analysis are coded separately.

Content space: Coding schemes and reliability-measures

In the content space, learners carry out part-task related activities that enable them to properly discuss the content of the knowledge domain in question. Two coding schemes were applied to gain insight in the learner interaction. Measurement at the *episodic level* provided insight in the cognitive, meta-cognitive and off-task activities learners carried out during collaborative problem-solving. Learner interaction was segmented into different discourse topics which coding led to the measurement of the part-task related and off-task activities (see Table 2.3). The discourse topics were hand-coded and Cohen's kappa was computed for three chat-protocols which were coded

independently (total of 3,532 lines) by two coders. An overall Cohen's Kappa of .70 was found, an intermediate to good result (Cicchetti, Lee, Fontana, & Dowds, 1978).

Table 2.3
Coding and Category Kappa's (K_c) of the Meta-cognitive, Cognitive and Off-task Activities

Activities	Discourse topic	Discussion of	K_c
Meta-cognitive			.66
	Planning	the problem-solving strategy; how and when the team has to perform a specific activity	.50
	Monitoring	whether they have completed the part-tasks on time	.62
	Evaluating	the suitability of their problem-solving strategy	.66
Cognitive			.63
	Preparation	the goal of the problem-solving task and the different part-tasks	.64
	Executing	content-related topics and formulating / decisions to the part-tasks	.70
	Ending	how, where, and when the decisions to the part-tasks need to be registered	.53
Off-task			.73
	Social	non-task related topics	.74
	Technical	problems with the CSCL-environment	.70

Measurement at the *event level* provided insight into learner interaction with respect to discussion of the content of the knowledge domain. A learning-task analysis based on the work of Gagné, Wagner, and Briggs (1992) was conducted and resulted in 17 business-economics concepts and 9 possible interventions (see, for example, Figure 1.2, Section 1.2.3, p. 19). To make coding and analyses more manageable, concepts and solutions were categorized into five and three subcategories respectively. Furthermore, three possible ways of interrelating the concepts and solutions were included, resulting in the coding scheme in Table 2.4.

The chat-protocols were automatically searched for the occurrence of characteristic words which led to the identification and coding of the dependent variables (Erkens & Janssen, 2008; Mercer *et al.*, 2004). This was done automatically with a MEPA-filter which makes use of 900 'if-then' decision rules containing different explicit references to a concept, solution or relation (e.g., name, synonyms, etc.) which were coded as representing that concept, solution or relation. Through a process of testing and adapting the filter, overall Cohen's Kappa for concepts, solutions and relations ranging from .70. to .86, were reached compared to hand-coding four chat-protocols (total of 4,198 lines). These finding indicate that this automatic coding procedure is reliable.

Table 2.4
Coding and Category Kappa's (K_c) MEPA-filter of the Discussion of the Domain

Categories	Subcategories	Discussion of	K_c
Concepts			.86
	Sales	how many products are sold/have to produced	.87
	Selling price	what it costs to produce and sell a product and what the customer has to pay for the product	.50
	Costs	what the overall costs of the company are	.83
	Turnover	what the total income of the company is	.93
	Company result	whether it is profitable to run the company	.91
Solutions			.86
	Changing costs	how the overall costs can be decreased	.86
	Changing turnover	how the turnover can be increased	.90
	Changing both	the combining of the other two solutions	.80
Relations			.70
	Conceptual	the definition/meaning of a concept/solution	.73
	Causal	the causal relationship within/between concepts/solutions	.83
	Mathematical	the quantitative relationships within/between concepts	.73

Relational space: Coding scheme and reliability-measure

In the relational space, learners carry out communicative activities to properly manage their interaction in the content space. Each utterance was coded with respect to the type of dialogue act used (see Table 2.5). A dialogue act is regarded as a communicative action which is elicited for a specific purpose representing a specific function in the dialogue (Erkens *et al.*, 2005):

- argumentatives; indicating a line of reasoning,
- responsives; indicating responses to questions or proposals,
- informatives; indicating a transfer of information, often statements or evaluations,
- elicitatives; indicating questions or proposals requiring an answer,
- imperatives; indicating commands to take action or to draw attention.

The coding of the dialogue acts took place at the event level and was based on the occurrence of characteristic words or phrases (i.e., discourse markers, see Schiffrin, 1987) which indicates the communicative function of an utterance. The chat-protocols were searched for the occurrence of these discourse markers which led to the identification and coding of the dependent variables (Erkens & Janssen, 2008; Mercer *et al.*, 2004). This was automatically done with a MEPA-filter using 1,250 'if-then' decision rules that uses pattern matching to find typical words or phrases. When compared to hand-coding, an overall agreement of 79% was reached and a Cohen's Kappa of .75 was found (Erkens & Janssen). After coding, score-frequencies for each dialogue act were computed and combined resulting in the measurement of the variables focusing, checking and argumentation.

Table 2.5
Coding of the Communicative Activities

Activities	Dialogue Act	Description	Example discourse marker
Focusing	Elicitative proposal for action	Proposition for action	Let's start with the first part-task?
	Elicitative question open	Open question with a lot of alternatives	Shall we fist look at the description of the assignment or at the description of the part-tasks?
	Imperative action	Command to perform an action	Finish the decision to the second part-task
	Imperative focus	Command for attention	Look at the representational tool!
	Elicitative question verify	Question that can only be answered with yes or no	Do you refer to the company result??
Checking	Elicitative question set	Question where the alternatives are already given (set)	Are you for or against increasing sales?
	Responsive confirm	Confirming answer	Yes, we indeed should start a promotion campaign
	Responsive deny	Denying answer	No, that is not a good solution
	Responsive accept	Accepting answer	Oh, Yes that OK
Argumentation	Argumentative reason	Reason	Because this solution does not affect our costs
	Argumentative against	Objection	But this would cost more money
	Argumentative conditional	Condition	If we increase the selling price…
	Argumentative then	Consequence	Then the cost price decreases
	Argumentative disjunctive	Disjunctive	We can increase the actual sales through a promotion campaign or by decreasing the selling price or by ….
	Argumentative conclusion	Conclusion	Thus we can conclude that the third solution leads to the best company result.

2.4.5 Measurement of teams' complex learning-task performance

To examine the effect of condition on teams' complex learning-task performance, an assessment form was developed. Table 2.6 provides a description of the aspects on which the decisions were evaluated, the number of items, and their internal consistency scores (i.e., Cronbach's alpha). The problem-solving task consisted of three part-tasks in which the teams each had to take three decisions. All nine decisions were evaluated based on their *'suitability'*, *'elaboration'*, *'justification'*, and *'correctness'*, resulting in 36 items (9 decisions × 4 criteria). Also evaluated was whether teams used decisions from a subsequent phase and altered their way of reasoning (i.e., *'continuity'*). There were two phase transitions (i.e., transition from problem-orientation to problem-solution and transition from problem-solution to solution-evaluation) and, therefore, two items. Finally, the *'quality of the advice'* was evaluated by three items; number of concepts incorporated in the advice, financial consequence of the advice, and whether the definitive advice was in line with the guidelines provided in the original task description. This resulted in a total of 41 items which all could be coded as '0' (wrong), '1' (adequate) or '2' (good); the higher the code, the higher the quality of the decision. Teams could, thus, achieve a maximum score of 82 points for their learning-task performance (41 items × 2 points) and a minimum of 0 points. The internal consistency score for the whole complex learning-task performance was .89 and for the subscales, internal consistency scores of .53 or above were obtained.

Table 2.6
Items and Reliability of Teams' Complex Learning-task Performance

Criteria	Description	Items	α
Suitability	Whether the teams' decisions were suited to the different part-tasks	9	.61
Elaboration	Number of different business-economics concepts or financial consequences incorporated in the decisions to the different part-tasks	9	.53
Justification	Whether the teams justified their decisions to the different part-tasks	9	.73
Correctness	Whether the teams used the business-economics concepts and their interrelationships correctly in their decisions to the different part-tasks	9	.68
Continuity	Whether the teams made proper use of the decisions from a prior problem phase	2	.67
Quality advice	Whether the teams gave a proper definitive solution - Number of business-economics concepts incorporated in the advice - Number of financial consequences incorporated in the advice - Whether the advice conformed to the guidelines provided	3	.71
Total score	Overall score on the complex learning-task performance	41	.89

2.4.6 Measurement of individual learning results

Learners' recall and understanding of the knowledge domain was measured with a pre-test (20 items, α = .60) and a post-test (20 items, α = .79). Based on work of Gagné *et al.* (1992) a learning-task analysis was conducted which resulted in 17 business-economics concepts. According to Anderson and Krathwohl (2001), a knowledge domain consist of different knowledge dimensions which refer to the different ways (i.e., factual, conceptual, procedural) in which the concepts can be understood. *Factual knowledge* entails learners being familiar with the concepts of the knowledge domain. *Conceptual knowledge* entails learners understanding the interrelationships between the different concepts of the domain. *Procedural knowledge* entails learners knowing how to apply a certain technique or procedure and are capable of determining when applying that technique or procedure is appropriate. The multiple-choice items in both tests were drawn from the total pool of items and equally divided across the three knowledge dimensions and were, thus, unique. Because of the low reliability of the scores on the subscales of both tests (e.g., α ≤ .50) recall and understanding of the different dimensions was not tested. In the analyses, thus, only the overall scores on the pre-test and the post-test were used. Below an example for each type of question (translated from Dutch) is provided:

Factual knowledge
The cost price per product is the price that:

a) a customer has to pay for a product.
b) an entrepreneur has to pay to produce a product.
c) an entrepreneur has to pay to store a product.
d) an entrepreneur has to pay to produce and to sell a product.

Conceptual knowledge
Does an increase in selling price per product automatically lead to an increase in turnover?

a) No, when the selling price per product increases this may lead to a decrease in actual sales and, thus, not automatically to an increased turnover.
b) Yes, when the selling price per product increases this does not affect the actual sales and, thus, the turnover automatically increases.
c) No, the turnover is mainly affected by the number of customers willing to buy the product, an increase in selling price per product, therefore, does not automatically lead to an increase in turnover.
d) Yes, when the selling price per product increases the turnover automatically increases whether or not the actual increase or decrease.

Procedural knowledge

Entrepreneur Y has an electronics store and sells a wide variety of products such as TVs, stereos and computers. At the end of the week the entrepreneur has sold five computers with a selling price of €1,550.00 each and six TVs with a selling price per product of €1,350.00 per product. What was the turnover for the entrepreneur for the selling of the computers?

a) €6,750.00
b) €7,750.00
c) €8,100.00
d) €9,300.00

2.4.7 Data analysis

Individual learning results and quality learner interaction

When conducting studies on CSCL, team members mutually influence each other (i.e., behave more or less in the same way) leading to non-independence of measurement (De Wever *et al.*, 2007; Kenny, Kashy, & Cook, 2006). This is problematic because many statistical techniques (e.g., *t*-test, ANOVA) assume score-independence and such a violation compromises the interpretation of the output of their analyses (e.g., *t*-value, standard error, *p*-value, see Cress, 2008; Janssen, Erkens, Kirschner, & Kanselaar, 2010; Kenny *et al.*). This non-independence requires a statistical technique that addresses this. *Multilevel analysis* (MLA) is an approach suited to "appropriately grasp and disentangle the effects and dependencies on the individual level, the team level, and sometimes the classroom level" (Strijbos & Fischer, 2007, p. 391). The non-independence was determined here by computing the intraclass correlation coefficient and its significance (Kenny *et al.*) for all dependent variables concerning individual learning results and the quality of the interaction. This coefficient demonstrated non-independence ($\alpha < .05$) for all tests, justifying MLA for analyzing these data. MLA entails comparing the deviance of an empty model and a model with one or more predictor variable(s) to compute a possible decrease in deviance. The latter model is considered a better model when there is a significant decrease in deviance in comparison to the empty model (tested with a X^2-test). Almost all reported x^2-values were significant ($\alpha < .05$) and, therefore, the estimated parameters of these predictor variables (i.e., effects of condition) were tested for significance.

Teams' complex learning-task performance

A one-way MANOVA was used to examine the effect of condition on teams' complex learning-task performance. There was no need to use MLAs because the complex learning-task performance was measured at the team level instead of the learner level. Since there were specific directions of the results expected all analyses are one-tailed.

2.5 Results

Testing the assumptions of the statistical techniques led to the detection of several outliers. That is, the obtained scores differed three or more *SDs* from the grand mean concerning the analyses of the cognitive, meta-cognitive and off-task activities (three learners) and concepts, solutions and relations, and the communicative activities (four learners). The utterances of those learners were, therefore, deleted from the specific MLAs.

2.5.1 Cognitive, meta-cognitive and off-task activities

MLAs revealed that condition was not a predictor for the meta-cognitive activities ($\beta = 6.82$, $p = .09$), cognitive activities ($\beta = 1.04$, $p = .33$), and off-task activities ($\beta = 0.61$, $p = .30$) that were exhibited when comparing learners in the matched condition to those in the non-matched conditions. The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the different kinds of discourse topics are listed in Table 2.7.

When analyzing the different discourse topics for the conditions separately, several condition effects were found. First, a category effect for *cognitive activities* was found when comparing learners in the matched condition to learners in the simulation condition ($\beta = 5.39$, $p = .02$). As indicated by the $^{+}$ and $^{-}$ signs in Table 2.7, learners in the matched condition exhibited more cognitive activities in comparison to learners in the simulation condition. Learners in the simulation condition discussed fewer content-related discourse topics and formulated/revised their decisions to the part-task (i.e., executing) less often in comparison to learners in the matched condition ($\beta = 3.79$, $p = .03$). Furthermore, learners in the simulation condition discussed less whether they should end a part-task (i.e., ending) than learners in the matched condition ($\beta = 1.25$, $p = .02$). Finally, learners in the matched condition exhibited more technical-related activities than those in the non-matched conditions ($\beta = 0.50$, $p = .05$). When comparing the matched condition to the other conditions separately, the effects were significant for the causal ($\beta = 0.39$, $p = .02$) and the simulation condition ($\beta = 0.37$, $p = .02$).

As expected, learners in the matched condition carried out more cognitive activities than learners in the simulation condition. That is, they had more discussion about the content of the knowledge domain and formulated, revised, and registered more of their decisions. These differences were, however, not found for the comparison to learners in the conceptual and the causal condition. Although expected, learners in the matched condition did not discuss their problem-solving strategy, its suitability and whether their part-tasks were finished on time more often than learners in the non-matched conditions.

2.5.2 Concepts, solutions and relations

MLAs revealed that condition was a predictor for the number and kinds of concepts, solutions and relations that learners discussed. The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the discussion of the concepts, solutions and relations are listed in Table 2.8.

First, a marginally significant category effect for *concepts* was found; learners in the matched condition discussed more concepts in comparison to those in the non-matched conditions ($\beta = 5.27$, $p = .08$). When analyzing the different concepts separately, it appeared that learners in the matched condition discussed a concept as 'sales' more often than learners in both the conceptual ($\beta = 1.97$, $p = .04$) and the causal condition ($\beta = 2.79$, $p = .01$). Furthermore, learners in the matched condition discussed a concept as 'costs' more often than learners in both the conceptual ($\beta = 2.46$, $p = .08$) and the simulation condition ($\beta = 2.78$, $p = .05$). It should be noted that this difference was only marginally significant for learners in the conceptual condition. Second, a significant category effect for *solutions* was found; learners in the matched condition discussed more solutions in comparison to learners in the non-matched conditions ($\beta = 4.96$, $p = .05$). When analyzing the different kinds of solutions separately, it appeared that learners in the matched condition had a tendency of discussing solutions aimed at (1) decreasing the company's costs more often than learners in both the conceptual ($\beta = 1.97$, $p = .06$) and the causal condition ($\beta = 2.12$, $p = .06$), and (2) increasing the company's turnover more often than learners in the simulation condition ($\beta = 2.37$, $p = .02$). Finally, a marginally significant category effect for *relationships* was found; learners in the matched condition discussed more and different kinds of relationships than learners in the non-matched conditions ($\beta = 5.32$, $p = .08$). This was caused mainly by the fact that learners in the matched condition discussed mathematical relationships more often than learners in the non-matched conditions ($\beta = 0.72$, $p = .02$). When comparing the matched condition to the other conditions separately, it appeared that this was (1) the case for learners in the conceptual ($\beta = 0.71$, $p = .02$) and (2) marginally the case for learners in the simulation condition ($\beta = 0.73$, $p = .06$).

As expected, learners in the matched condition discussed more important concepts for solving the problem than learners in the non-matched conditions. Concepts as 'sales' and 'costs' are vital because they deal with how much income and expenses a company has (i.e., variables that determine the profitability of a company). Learners in the matched condition also discussed more solutions than learners in the non-matched conditions. This yielded - especially for solutions aimed at increasing the income or decreasing the costs of a company - a result in line with discussing concepts as 'sales' and 'costs' more often. Furthermore, learners in the matched condition also related the concepts to each other and to the solutions more often than learners in the non-matched conditions. When doing this, they made use of different kinds of relationships, namely conceptual, causal and mathematical ones.

Table 2.7
Multilevel Analyses for Effects of Matched condition versus Non-matched Conditions concerning the Meta-cognitive, Cognitive and Off-task activities

	Conceptual condition ($n_{learner}$ = 22)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 23)	Matched condition ($n_{learner}$ = 24)	Effects matched condition ($N_{learner}$ = 93)		
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	$x^2(3)$	β	*SE*
Meta-cognitive	18.96 (8.72)	20.33 (14.06)	21.95 (26.39)	32.61 (33.76)	17.08	6.82	4.84
Planning	2.59 (1.59)	1.62 (1.32)	1.45 (1.97)	2.82 (2.87)	4.32	0.11	0.32
Monitoring	12.75 (6.41)	15.23 (12.00)	16.23 (20.35)	24.75 (28.21)	16.00	6.01	3.85
Evaluating	3.62 (2.28)	3.48 (2.52)	4.27 (5.82)	5.04 (5.79)	5.22	0.71	0.89
Cognitive *	16.00 (17.44)	10.19 (7.03)	7.41 (6.93) -	18.32 (13.60) +	116.56	1.04	2.32
Preparation	2.92 (3.64)	1.29 (1.49)	1.50 (1.87)	2.25 (2.35)	4.10	0.35	0.41
Executing *	10.67 (16.23)	7.00 (6.30)	5.00 (4.77) -	12.64 (9.84) +	13.58	0.92	1.89
Ending *	2.41 (2.06)	1.90 (2.02)	0.91 (1.27) -	3.43 (4.17) +	7.46	0.49	0.47
Off-task	7.29 (5.41)	4.95 (4.33)	5.73 (5.51)	8.46 (6.24)	8.69	0.61	1.12
Social	5.62 (4.41)	4.05 (4.05)	4.77 (4.84)	5.79 (4.53)	5.54	0.10	0.90
Technical *	1.67 (1.61)	0.90 (0.94) -	0.95 (1.17) -	2.68 (2.16) +	8.00	0.50	0.31

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

Table 2.8
Multilevel Analyses for Effects of Matched condition versus Non-matched Conditions concerning the Discussion of the Domain

	Conceptual condition ($n_{learner}$ = 22)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 23)	Matched condition ($n_{learner}$ = 23)	Effects matched condition ($N_{learner}$ = 92)		
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	$x^2(3)$	β	*SE*
Concepts *	21.59 (22.30)	18.58 (18.73) -	19.86 (19.91) -	32.25 (20.81) +	16.81	5.27	3.82
Sales *	3.93 (6.64) -	2.29 (2.49) -	5.32 (5.62)	7.86 (7.00) +	12.49	1.97	1.00
Selling price	1.07 (1.66)	1.21 (1.89)	1.18 (2.47)	2.07 (2.54)	1.40	0.51	0.37
Costs *	5.70 (7.75) -	6.17 (7.40)	5.00 (6.03) -	10.57 (9.29) +	11.72	2.46	1.44
Turnover	3.78 (3.47)	3.17 (3.24)	2.54 (3.00)	4.39 (3.21)	4.36	0.29	0.56
Company result	7.11 (8.73)	5.75 (7.02)	5.82 (6.34)	7.36 (4.83)	6.55	0.05	1.20
Solutions *	14.19 (14.60)	15.12 (17.00)	14.00 (14.26)	24.11 (19.81)	15.46	4.96	2.95
Changing costs *	5.52 (8.56) -	5.13 (9.03) -	7.43 (9.85)	12.00 (12.01) +	12.59	3.18	1.92
Changing turnover *	6.11 (6.29)	6.71 (6.62)	4.86 (4.62) -	9.54 (9.11) +	10.40	1.74	1.13
Changing both	2.56 (3.23)	3.29 (6.52)	1.71 (1.98)	2.57 (2.99)	3.57	0.02	0.64
Relations	25.89 (20.65)	23.17 (19.23)	26.36 (21.63)	36.63 (22.35)	16.37	5.32	3.85
Conceptual	6.48 (4.76)	4.38 (4.17)	7.43 (5.77)	8.96 (6.08)	10.38	1.26	0.93
Causal	16.74 (14.97)	14.46 (13.94)	15.57 (13.53)	21.86 (14.18)	12.87	2.54	2.52
Mathematical *	2.67 (3.13) -	4.33 (4.82)	3.36 (3.76) -	5.82 (5.20) +	7.95	1.52	0.72

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

2.5.3 Communicative activities

MLAs revealed that condition was a predictor for the management of the interaction in the content space. The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the communicative activities are listed in Table 2.9.

A marginally significant effect for *coordination* was found, namely that learners in the matched condition had a tendency of exhibiting more communicative activities compared to learners in the non-matched conditions ($\beta = 17.96$, $p = .07$). For the specific communicative activities, the following results were obtained. First, a marginally significant category effect for *checking* was found; learners in the matched condition devoted more attention to guarding the coherence and consistency of their shared understanding of the content space than learners in the non-matched conditions ($\beta = 8.80$, $p = .07$). However, when comparing the matched condition to the other conditions separately, no significant results were obtained. Finally, a significant category effect was found for *argumentation*; learners in the matched condition exhibited more argumentative activities than learners in the non-matched conditions ($\beta = 6.20$, $p = .05$). When comparing the matched condition to the other conditions separately, this was only marginally the case for the conceptual condition ($\beta = 7.00$, $p = .08$).

As expected, learners in the matched condition were better able to establish and maintain shared understanding of the content space and to negotiate about it than learners in the non-matched conditions. This should have enabled learners in the matched condition to acquire multiple perspectives on the problem and the problem-solving strategy, which are both seen as beneficial to problem-solving. Although, in total, learners in the matched condition exhibited more communicative activities, more differences concerning specific communicative activities between conditions were expected.

2.5.4 Teams' complex learning-task performance

A one-way MANOVA on the total score on the teams' complex learning-task performance showed a significant difference for condition ($F(3, 28) = 1.72$, p = .03; Wilks' Lambda = 0.33; partial *eta* squared = .31). Bonferroni post hoc analyses showed that teams in the matched condition scored significantly higher than teams in both the conceptual ($p = .00$; $d = 2.19$) and the simulation condition ($p = .04$; $d = 1.26$). Table 2.10 shows the mean scores and standard deviations of the scores on the teams' learning-task performance.

When the results for the dependent variables were considered separately, using one-way ANOVAs with Bonferroni post hoc analyses, condition effects were found for suitability ($F(3, 28) = 2.99$, $p = .03$), justification ($F(3, 28) = 4.23$, $p = .01$) and correctness ($F(3, 28) = 2.99$, $p = .03$). The mean scores indicated that there were several significant differences between conditions. First, teams in the matched condition scored significantly higher on suitability than teams in the conceptual condition ($p = .01$; $d = 1.45$) and a trend was found in comparison to the teams in the simulation condition ($p = .07$; $d = 0.77$). Second, teams in the matched condition scored significantly higher on justification than teams in both the conceptual ($p = .01$; $d = 1.53$) and the simulation condition

(p = .02; d = 1.29). Finally, teams in the matched condition scored significantly higher on correctness than teams in the conceptual condition (p = .03; d = 1.83) and a trend was found in comparison to the teams in the simulation condition (p = .06; d = 1.04).

As expected, teams that received an ontologically congruent ER for each phase-related part-task scored higher on the team learning-task performance.

2.5.5 Individual learning results

Inspection of the means and standard deviations of learners' pre-test and post-test scores revealed differences between conditions (see Table 2.11). A one-way ANOVA showed a significant main effect between conditions on the pre-test score ($F(3, 86) = 3.34$, $p < .05$). This means that learners differed in the amount of prior knowledge and it was, therefore, necessary to correct for this when examining the effect of condition on learners' post-test scores. A t-test showed that the overall post-test score of 90 learners (not all 96 learners were present when the pre-test and/or post-test were administered) was not significantly higher than the overall pre-test score ($t(90) = -0.18$, $p > .05$). There were, thus, no individual learning gains. However, a MLA revealed that learners in the matched condition scored significantly higher than those in the other conditions ($\beta = 1.93$, $p = .04$). When comparing the conditions separately, a trend was found; learners in the matched condition scored higher than learners in the conceptual condition ($\beta = 1.89$, $p = .07$). Differences between the other conditions were not significant.

These results are not completely in line with our expectations. Learners in the matched condition only scored higher on the post-test in comparison to learners in the conceptual condition. Furthermore, there were no overall individual learning gains.

Table 2.9
Multilevel Analyses for Effects of Matched condition versus Non-matched Conditions concerning the Communicative Activities

	Conceptual condition ($n_{learner}$ = 22)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 23)	Matched condition ($n_{learner}$ = 23)	Effects matched condition ($N_{learner}$ = 92)		
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	$x^2(3)$	β	*SE*
Coordination	109.92 (56.60)	101.82 (54.65)	145.15 (88.45)	170.32 (137.58)	26.33	27.09	17.96
Focusing	21.75 (14.00)	20.06 (10.63)	28.55 (16.46)	32.73 (27.11)	15.93	4.63	3.49
Checking	55.04 (26.06)	51.41 (27.32)	69.60 (44.00)	83.00 (66.48)	21.71	12.83	8.80
Argumentation *	33.12 (24.06) -	30.35 (21.32)	47.00 (32.10)	54.59 (49.28) +	20.52	10.26	6.20

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

Table 2.10
One-way Multivariate Analysis of Variance for Effects of Matched condition versus Non-matched Conditions concerning Teams' Complex Learning-task Performance

Criteria	Conceptual condition (n_{team} = 8)	Causal condition (n_{team} = 8)	Simulation condition (n_{team} = 8)	Matched condition (n_{team} = 8)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Suitability *	12.25 (2.49) -	15.12 (1.64)	13.88 (3.36) -	15.75 (2.42) +
Elaboration	6.38 (3.74)	8.89 (2.70)	6.37 (2.83)	8.38 (2.33)
Justification *	3.50 (1.69) -	6.88 (3.56)	4.12 (2.70) -	7.50 (2.62) +
Correctness *	5.50 (2.45) -	8.25 (3.69)	7.12 (1.96) -	9.25 (2.05) +
Continuity	2.50 (1.41)	3.12 (1.13)	3.00 (1.31)	3.62 (0.52)
Quality advice	2.75 (1.04)	4.88 (1.64)	5.12 (2.48)	4.25 (1.28)
Total score *	32.88 (10.40) -	47.13 (12.30)	39.62 (0.39) -	48.75 (7.27) +

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

Table 2.11
Means and Standard Deviations for Differences between Conditions concerning the Pre-test and Post-test Scores

Test	Conceptual condition ($n_{learner}$ = 22)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 21)	Matched condition ($n_{learner}$ = 23)	Overall conditions ($N_{learner}$ = 90)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Pre-test	15.20 (1.85)	14.95 (2.76)	13.69 (2.20)	15.72 (2.05)	14.69 (2.37)
Post-test	13.70 (2.96)	15.00 (1.90)	14.47 (2.18)	15.50 (2.48)	14.87 (2.45)

2.6 Discussion

As is the case with many other researchers, the present study stresses the importance of using representational tools (Fischer *et al.*, 2002; Schnotz & Kürschner, 2008) and of employing scripting (P.A. Kirschner *et al.*, 2008; Weinberger *et al.*, 2005) to guide learner interaction and learning-task performance. However, instead of using them separately, this study combined the advantages of using multiple representational tools and scripting (i.e., representational scripting). The passive representational scripting structured the problem-solving process by sequencing and making the part-tasks explicit so that they could be provided with ontologically congruent representations. It was hypothesized that this would evoke more task-suited learner interaction and, as a consequence, better team learning-task performance than not receiving it. The results of our study confirmed that the problem-solving process for these teams of learners was more efficient and effective. The passive representational scripting shaped the use of the representational tools and guided learner interaction towards acquiring and applying suitable qualitative and quantitative problem representations. Those activities are often regarded as beneficial for collaborative problem-solving (Hmelo-Silver *et al.*, 2007; Jonassen, 2003; Ploetzner *et al.*, 1999). Specifically, teams in the matched condition (1) had more elaborated discussions of the content of the knowledge domain, and (2) were also better able to establish and maintain their shared understanding of the knowledge domain, a prerequisite for a proper discussion of it, than learners in the non-matched conditions. As a consequence, the teams receiving an ontologically congruent ER for each part-task (i.e., matched condition) gave better decisions to the part-tasks and came up with better definitive solutions to the problem than teams in the non-matched conditions.

Although the results seem very promising, there were some contrasting findings that require further discussion. First, learner interaction in the causal condition only slightly differed from that of the learners in the matched condition and their teams' complex learning-task performance was also very similar to what was found in the matched condition. Learners in both conditions received the causal ER, which showed all relevant concepts, solutions and their causal interrelationships, providing learners with multiple qualitative perspectives on the knowledge domain. It seems, therefore, important to recognize that causal reasoning is beneficial for collaborative problem-solving (Jonassen & Ionas, 2008). However, it does not completely explain the lack of differences. Perhaps combining the causal ER with both the conceptual and the simulation ER hinders problem-solving when learners experience difficulties integrating the different ERs. When learners do not know how to use an ER and/or combine multiple ERs, they might choose to stick with the familiar one and make no attempt to integrate the different ERs (Ainsworth, 2006; Bodemer & Faust, 2006). Second, learners in the matched condition did not discuss their problem-solving strategy, its suitability and whether their part-tasks were finished on time more often than learners in the non-matched conditions. Carrying out these meta-cognitive activities might not differ between because the scripting, which was the same for all conditions,

structured the problem-solving process into three phases, each focusing on one of the part-tasks and thereby affecting teams' problem-solving strategy (Dillenbourg, 2002; P.A. Kirschner *et al.*, 2008). Finally, learners' pre-test and post-test score did not differ significantly from each other resulting in no individual learning gains. This result might be explained by the (1) design of the passive representational scripting and/or (2) measurement of the learning gains. The design of the passive representational scripting was primarily aimed at supporting learners in applying domain knowledge in order to come to better and richer solutions and might, therefore, be less suited for knowledge acquisition. According to P.A. Kirschner, Sweller, and Clark (2006), carrying out complex learning task is an instructional method based on the epistemological content (i.e., methods and processes) instead of the domain content. Although both the epistemological and the domain content include factual, conceptual and procedural knowledge, learners do not necessarily use the same cognitive processes (Anderson & Krathwohl, 2001). That is, recalling and grasping the meaning of concepts, principles and procedures is often regarded as prerequisite for the higher-order cognitive processes required for carrying out complex learning tasks. Such learning tasks consist of part-tasks demanding learners to apply their understanding of the domain in order to analyze the problem, come up with proper solutions and evaluate their suitability and might be less supportive for acquiring more domain knowledge. Furthermore, the pre-test and the post-test measured recall and understanding of the knowledge domain. Both tests were, therefore, only useful for determining learning gains in terms of acquired domain knowledge. The tests did not enable learners to demonstrate whether they were better able to apply their understanding of the domain, an ability which also can be regarded as a form of learning gains. This also could be an explanation for the lack of differences in individual learning gains.

2.7 Implications and Future Research

This study has several implications for learning-environment design (e.g., CSCL-environment) for supporting learners in carrying out complex learning tasks. Collaborative problem-solving is facilitated and learning-task performance is better when the different part-tasks are made explicit, are properly sequenced, and each is provided with an ontologically congruent domain-specific content scheme. Using multiple ERs provides different perspectives of the knowledge domain and, when matched to the part-task demands and activities, the complementary function of those ERs can gradually increase learners understanding, and evoke proper part-task related and communicative activities (Ainsworth, 2006). However, when interpreting the results and the implications of this study, one has take into consideration that it was aimed at supporting learners collaboratively solving a problem in the field of business-economics. That is, a specific kind of complex learning task was used and situated in a specific knowledge domain. Although there are many other knowledge domains (e.g., physics, urban planning) and complex learning tasks (i.e., inquiry tasks, research projects) in which different part-tasks have to be carried out, the manner in which the use of representational tools is shaped

depends on the specifics of the complex learning task and the knowledge domain. The effect of the design of passive representational scripting and its use does, therefore, not automatically apply to all knowledge domains and all kinds of complex learning tasks.

Taking the contrasting findings and the limitations into mind, additional research into the effects of the passive representational scripting should be carried out to investigate whether these results can be generalized to other knowledge domains and other types of complex learning tasks. Future research should also focus on gaining more insight into the effects of different ontology's by studying how learners co-construct their own ERs. Such an approach entails that learners co-construct and adjust their own representations of the knowledge domain and are, therefore, more occupied with interrelating the different concepts and solutions than when the ERs are provided. Those studies probably provide more insight in the manner in which learners actually use the different concepts, solutions and ways of interrelating them. Furthermore, co-constructing and adjusting their own ERs might also provide more support for developing a better developed understanding of the knowledge domain leading to more individual learning gains. Finally, research on CSCL should measure both learner interaction and learning-task performance because this can provide a deeper understanding of the effects of the provided guidance (i.e., tools and/or strategies). This understanding should enable researchers to determine how (1) the design of the guidance affects learner interaction, and (2) this kind of guidance supports learners in carrying out complex learning tasks and learning from them (Dennen, 2008; Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010).

3. Fostering Complex Learning-task Performance through Scripting Teams' Use of Computer Supported Representational Tools[3]

Abstract
This study investigated whether scripting teams' use of computer supported representational tools fostered their collaborative performance of a complex business-economics problem. Scripting the problem-solving process sequenced and made its phase-related part-task demands explicit, namely (1) determining core concepts, (2) proposing multiple solutions, and (3) coming to a definitive solution. The representational tools facilitated learners in constructing specific representations of the domain (i.e., conceptual, causal, or mathematical) and were each suited for carrying out the part-task demands of a specific problem phase. Teams of learners in four experimental conditions had to carry out all part-tasks in a predefined order, but differed in the representational tool(s) they received during their collaborative problem-solving process. In three non-matched conditions, teams received either a conceptual, causal, or simulation representational tool which supported them in only carrying out one of the three part-tasks. In the matched condition, teams received the three representational tools in the specified order, each matching the part-task demands of a specific problem phase. The results revealed that teams in the matched condition constructed more task-appropriate representations and had more elaborated and meaningful discussions about the domain. As a consequence, those teams performed better on the complex learning task. However, similar results were obtained by teams who only received a representational tool for constructing causal representations for all part-tasks.

Keywords: Complex Learning Tasks, Computer Supported Collaborative Learning, External Representations, Pedagogical Issues, Representational Scripting

[3] Based on Slof, B., Erkens, G., Kirschner, P. A., Janssen, J., & Phielix, C. (2010). Fostering complex learning-task performance through scripting student use of computer supported representational tools. *Computers and Education, 55,* 1707–1720.

3.1 Introduction

There has been a recent surge in the interest of educational researchers for studying the effects of computer supported tools for fostering teams' complex learning-task performance (Demetriadis, Papadopoulos, Stamelos, & Fischer, 2008; Slof, Erkens, Kirschner, Jaspers, & Janssen, 2010; Zydney, 2010). Carrying out complex learning tasks requires learners to actively engage in a dynamic process of sense-making (P.A. Kirschner, Buckingham Shum, & Carr, 2003) by articulating and discussing multiple representations on the problem and their problem-solving strategy. Through externalizing one's knowledge, discussing this with peers, and establishing and refining the teams' shared understanding of the domain, learners often acquire new knowledge and skills and process them more deeply (Ding, 2009; Hmelo-Silver, Duncan, & Chinn, 2007; P.A. Kirschner, Beers, Boshuizen, & Gijselaers, 2008). Educators and instructional designers, however, should realize that learners (e.g., novices) need ample instructional support to make their problem-solving process more efficient and effective (P.A. Kirschner, Sweller, & Clark, 2006). Learners tend to focus on superficial details of problems instead of focusing on the underlying principles of the domain (Corbalan, Kester, & Van Merriënboer, 2009), and to employ weak problem-solving strategies such as working via a means-ends strategy towards a solution (Simon, Langley, & Bradshaw, 1981; Van Merriënboer & Kirschner, 2007). To this end, it would be beneficial to support learners in acquiring different problem representations of the domain in which they are working and in using those representations to solve the given problem (Frederiksen & White, 2002; Jonassen, 2003; Ploetzner, Fehse, Kneser, & Spada, 1999).

Research on Computer Supported Collaborative Learning (CSCL) has shown that collaboratively constructing and discussing domain-specific representations beneficially affects complex learning-task performance (Fischer, Bruhn, Gräsel, & Mandl, 2002; Lazakidou & Retalis, 2010; Wegerif, McClaren, Chamrada, Schreuer, Mansour *et al.*, 2010). Embedding representational tools in a CSCL-environment can facilitate learners' construction of different representations of the domain and, thereby, guide their interaction and, thus, their collaborative problem-solving process. A tools' ontology (i.e., objects, relations, rules for combining objects and relations) provides a specific kind of representational guidance which makes certain concepts and/or relationships (e.g., conceptual, causal, mathematical) salient in favor of others. In this way, a tools' representational guidance supports externalization of knowledge and ideas about specific aspects of a domain (Ertl, Kopp, & Mandl, 2008; Suthers, 2006; Van Bruggen, Boshuizen, & Kirschner, 2003). This may foster learners' understanding because it stimulates cognitive processes such as selecting relevant information, organizing information into coherent structures, and relating it to prior understanding (Liu, Chen, & Chang, 2010; Shaw, 2010; Stull & Mayer, 2007). Collaborative learning, due to its emphasis on dialogue and discussion, can stimulate the elaboration of these representations so that multiple perspectives on the domain and of the problem-solving strategy can arise (De Simone, Schmid, & McEwan, 2001; Hmelo-Silver *et al.*, 2007). When

learners are able to create a shared understanding of these different viewpoints and negotiate about them, this fosters their performance of complex learning tasks (Ding, 2009; Erkens, Jaspers, Prangsma, & Kanselaar, 2005; Mercer, Littleton, & Wegerif, 2004). Although the educational benefits of representational tools are widely recognized, some studies report mixed or even negative findings and, thus, question how learner interaction can best be guided (Bera & Liu, 2006; Elen, & Clarebout, 2007; Van Drie, Van Boxtel, Jaspers, & Kanselaar, 2005). This inconsistency in the literature hinders educators and instructional designers in designing representational tools that foster learners' performance of complex learning tasks.

3.2 Theoretical Background

3.2.1 Drawbacks in designing representational tools

Since representational tools guide learners in constructing and, thus, discussing specific representations of the domain, educators and instructional designers should realize that such tools are only appropriate for carrying out specific task demands (Ainsworth, 2006; Bodemer & Faust, 2006; Schnotz & Kürschner, 2008). The mere presence or availability of a representational tool does not, therefore, automatically support teams in solving complex problems. Important here is that those problems are usually composed of fundamentally different phase-related part-tasks demands (e.g., Van Bruggen *et al.*, 2003), namely:

- Problem-orientation; determining core concepts and relating them to the problem,
- Problem-solution; proposing solutions to the problem,
- Solution-evaluation; determining suitability of the solutions and coming to a definitive solution to the problem.

Each problem phase requires a different representation on the domain and, thus, requires a representational tool with a specific kind of representational guidance. When the design of the tool is incongruent with the demands of one or more phase-related part-tasks this should negatively affects teams' complex learning-task performance (Slof *et al.*, 2010c; Suthers, 2006; Van Bruggen *et al.*, 2003). Here, learners cannot properly make sense of the domain and are, thus, hindered in acquiring and applying their understanding of the domain. To evoke elaborate and meaningful discussions about the domain requires a representational tool that (1) is in line with its users' capabilities and intentions, and (2) makes clear what its users can and should do with it (P.A. Kirschner, Martens, & Strijbos, 2004; Veldhuis-Diermanse, 2002). If this is not the case, then learners might experience at least two difficulties when using them. First, *part-task related difficulties* may arise when learners do not have a realistic idea of the concepts and relationships they must use and how they should relate them to the problem. Due to this, learners experience difficulties in constructing and interpreting their representations and, thus, in acquiring a well-developed understanding of the domain (Bodemer & Faust, 2006; Brna, Cox, & Good, 2001; Liu *et al.*, 2010). Furthermore, learners might see constructing the

representation as an additional task demand instead of as support. When this is the case, after the concepts are interrelated in the representation, learners pay no further attention to the representation and, therefore, do not apply it to complete their learning task (De Simone *et al.*, 2001; Suthers, Hundhausen, & Girardeau, 2003; Van Amelsvoort, Andriessen, & Kanselaar, 2007). Second, learners in CSCL-environments often make use of multiple tools (e.g., chat tools, representational tools) in a non-sequential way which makes keeping track of each others' knowledge, ideas, and actions rather complicated. When learners are unable to properly interpret the conveyed messages and relate them to each other, they experience *communicative difficulties* (Andriessen, Baker, Suthers, 2003; Barron, 2003; Erkens *et al.*, 2005). Such difficulties often hinder learners in elaborating on and meaningfully discussing the content of the domain. Whether learners are able to have such discussions depends on how easily they can refer to and relate their contributions with those of others (i.e., deictic referencing, see Reinhard, Hesse, Hron, & Picard, 1997; Suthers *et al.*; Van Boxtel & Veerman, 2001). Important here is that the provided computer tools support learners in coordinating their collaboration process by carrying out communicative activities. That is, learners have to make their own knowledge and ideas explicit to other team members. When made explicit, learners must try to maintain a shared topic of discourse (i.e., achieve a common *focus*) and repair that focus if they notice focus divergence. Understanding and relating the relevance of individual messages may be hard when learners are simultaneously discussing different topics. Learners should, therefore, coordinate their topic of discourse by focusing (Erkens & Janssen, 2008; Van Drie *et al.*, 2005). Since not all concepts, principles, and procedures are relevant for carrying out a specific part-task learners also must maintain the coherence and consistency of their shared understanding by *checking* (Van der Linden, Erkens, Schmidt, & Renshaw, 2000). Furthermore, learners must come to an agreement about relevant concepts, principles and procedures. Through *argumentation* they can try to change their partners' viewpoint to arrive at the best way to carry out a part-task or at a definition of concepts acceptable for all. In this argumentation process they try to convince others by elaborating on their own point of view, and by explaining, justifying and accounting (Andriessen *et al.*; P.A. Kirschner *et al.*, 2008).

3.2.2 Scripting

Just providing a user/learner a tool does not guarantee use or proper use of that tool. To this end, learners must understand what they can and should do with the tool and how its use is integrated within learning task at hand (P.A. Kirschner *et al.*, 2004; Veldhuis-Diermanse, 2002). *Scripting* has been advanced as a technique to ensure proper alignment between the design of the representational tool, learners' tool use, and the required task demands (Dillenbourg, 2002; Weinberger, Ertl, Fischer, & Mandl, 2005). According to Dillenbourg a script is "a set of instructions regarding to how the team members should interact, how they should collaborate and how they should solve the problem" (p. 64). In this study learners worked collaboratively on a case-based business-economics problem in which they had to advise an entrepreneur about

changing the business strategy to increase profits (i.e., company result). Scripting was employed here to tailor the congruency of the tools' representational guidance to the phase-related part-task demands of this complex learning task. Integrating scripting with the availability of representational tools sequences and makes the different part-task demands explicit which should guide learners in carrying out appropriate part-task related activities. That is, learners may be evoked to carry out *cognitive activities* such as (1) discussing the goal of the problem-solving task/part-tasks, (2) discussing and selecting concepts, principles, and procedures in the domain, and (3) formulating and revising their decisions (Jonassen, 2003; Slof *et al.*, 2010c Vermunt, 1996). Learners may also be induced to employ a proper problem-solving strategy and reflect on its suitability through carrying out *meta-cognitive activities* (F. de Jong, Kollöffel, Van der Meijden, Kleine Staarman, & Janssen, 2005; Lazonder & Rouet, 2008; Narciss, Proske, & Koerndle, 2007; Vermunt). This requires that learners discuss (1) how they should approach the problem (i.e., plan), (2) whether they have finished the part-tasks on time (i.e., monitor), and (3) how suitable their approach was (i.e., evaluate/reflect). Carrying out such cognitive and meta-cognitive activities should enable teams to properly carry out their complex learning task.

3.2.3 Matching the tools' representational guidance to the part-tasks

To gain insight into the phase-related part-tasks and their required domain-specific representations, a learning-task analysis (Anderson & Krathwohl, 2001; Gagné, Briggs, & Wagner, 1992) was conducted. Based on these insights, the sequence and the demands of the part-tasks were specified and part-task congruent representational tools were developed (see Table 3.1).

Table 3.1
Congruence between Representational Tool and Phase-related Part-task Demands

Problem phase	Task demands	Representational tool	Representational guidance
Problem-orientation	Determining core concepts and relating them to the problem	Conceptual	Visualizing concepts and their conceptual relationships
Problem-solution	Proposing multiple solutions to the problem	Causal	Visualizing causal relationships between the concepts and the possible solutions
Solution-evaluation	Determining suitability of the solutions and coming to a definitive solution to the problem	Simulation	Visualizing mathematical relationships between the concepts and enabling manipulation of their values

In the *problem-orientation phase* learners have to explain what they think the problem is and describe what the most important factors are for solving it. The interaction should, therefore, be guided towards selecting the core concepts needed to carry out this part-task and discussing how those concepts are qualitatively related to each other. The design of the representational tool should facilitate learners in constructing and discussing a global qualitative problem representation by guiding and supporting them in conceptually relating the relevant concepts. Figure 1.1 (see Section, 1.2.3, p. 18) shows an experts' representation of the concepts and their conceptual interrelationships involved in this study. The conceptual representational tool facilitates representation of the concepts and their interrelationships shown in Figure 1.1. Selecting and relating concepts that the learners may regard as beneficial for solving the problem supports them in becoming more familiar with those concepts and in broadening their problem space. Learners receiving the conceptual tool could, for example, make explicit that the 'company result' is related to the 'total profit' and 'efficiency result'. This should guide those learners in elaborating (i.e., causal, mathematical) on the relationships in the two following problem phases, making it easier for them to find multiple solutions to the problem and to evaluate their effects.

In the *problem-solution phase* learners have to formulate several changes of the business strategy (i.e., interventions) and make clear how they might solve the problem (i.e., problem-solution) by describing how they will affect the outcomes (i.e., company result). The interaction should, thus, be guided towards formulating multiple interventions and discussing how each of these interventions affects the selected core concepts by further specifying the relationships between the concepts and the proposed interventions. The representational tool should facilitate construction and discussion of a causal problem representation by causally relating concepts to each other and to possible interventions. Figure 1.2 (see Section, 1.2.3, p. 19) shows an experts' representation of the concepts, the possible interventions and their causal interrelationships involved in this study. The causal representational tool facilitates representation of the concepts, interventions and their interrelationships shown in Figure 1.2. Selecting relevant concepts and interventions and causally relating them supports the effective exploration of the solution space and, thus, of finding multiple solutions to the problem. Learners receiving the causal representational tool could, for example, make explicit that an intervention such as a employing a 'promotion-campaign' (e.g., placing an advertisement in a paper) affects 'actual sales', which in turn affects 'total profit'. Only conceptually representing the interrelationships of the concepts, as in the first problem phase, is not expressive enough for this part-task since the relationships need to be further specified and learners need additional information about the possible solutions. If this is not the case, then learners are forced to come up with a solution (i.e., the advice) themselves without sufficient understanding of the underlying qualitative principles governing the domain.

Finally, in the *solution-evaluation phase* learners have to determine the financial consequences of their proposed interventions and formulate a suitable and definitive advice for the entrepreneur by discussing the suitability of the different interventions with each other. The interaction should, therefore, be guided towards determining and comparing the financial consequences by discussing the mathematical relationships between the selected concepts. The representational tool must, thus, facilitate constructing and discussing a quantitative representation by specifying the relationships as algebraic equations. Figure 1.3 (see Section, 1.2.3, p. 20) shows an experts' representation of the concepts and their mathematical interrelationships involved in this study. The simulation representational tool facilitates representation of the concepts and their interrelationships shown in Figure 1.3. Selecting relevant concepts and specifying the interrelationships as algebraic equations supports learners in evaluating the effects of their proposed interventions and, thus, in coming to a suitable advice. Learners receiving the simulation representational tool could, for example, simulate how an intervention such as employing a 'promotion-campaign' affects the 'actual sales' and whether this affects the 'total profit'. By entering values and adjusting them (i.e., increasing or decreasing), the values of the other related concepts are automatically computed. Since such quantitative representations can only be properly understood and applied when learners have well-developed qualitative understanding of the domain, this kind of support is only appropriate for carrying out this type of part-task.

3.3 Design and Research Questions

The research reported on here was aimed at determining how and why scripting the use of representational tools affects the performance of complex learning tasks in CSCL. To study the effects of the active representational scripting, four experimental conditions were defined by either matching or mismatching the tools' representational guidance to the part-task demands (see Table 3.2).

Table 3.2
Overview of the Experimental Conditions

Problem phase	Condition and provided representational tool			
	Conceptual condition	Causal condition	Simulation condition	Matched condition
Problem-orientation	*Conceptual tool*	Causal tool	Simulation tool	*Conceptual tool*
Problem-solution	Conceptual tool	*Causal tool*	Simulation tool	*Causal tool*
Solution-evaluation	Conceptual tool	Causal tool	*Simulation tool*	*Simulation tool*

Scripting the problem-solving process sequenced and made its phase-related part-task demands explicit, these part-task are (1) determining core concepts, (2) proposing multiple solutions, and (3) coming to a definitive solution. Teams of learners in four experimental conditions had to carry out all part-tasks in a predefined order, but differed in the representational tool(s) they received during their collaborative problem-solving process. In three non-matched conditions,

learners only received one of the representational tools (i.e., conceptual, causal, or simulation tool) for constructing the part-task related representations and carrying out all three part-tasks. The tools' representational guidance matched only one of the part-tasks and there was a mismatch for the other two. Those teams were, thus, only supported in carrying out one of the part-tasks. In the fourth, matched, condition, teams received all three representational tools in a phased order, receiving the tool considered to be most suited to the part-task demands of each problem phase. Due to this presumed match between tools' representational guidance and the part-tasks, it was hypothesized that teams in the matched condition would:

(H1) experience a qualitatively better learning process, evidenced by:
  a) constructing representations that are more suited for carrying out the part-tasks,
  b) carrying out more part-task related cognitive and meta-cognitive activities,
  c) carrying out more communicative activities to coordinate their collaborative problem-solving process,

(H2) achieve a better team learning result, evidenced by arriving at better interventions and

(H3) achieve a better individual learning result, evidenced by higher post-test scores.

3.4 Method and Instrumentation

3.4.1 Participants

Participants were students from six business-economics classes in three secondary education schools in the Netherlands. The total sample consisted of 93 learners (60 male, 33 female; mean age = 16.74 years; *SD* = .77, *Min* = 15, *Max* = 18). The students were, within classes, randomly assigned to a total of 31 teams of learners (i.e., triads); seven teams in the matched condition and eight teams in each of the three non-matched conditions.

3.4.2 Task and materials

Collaborative learning environment

All teams worked in a CSCL-environment called Virtual Collaborative Research Institute (VCRI, see Figure 3.1), a groupware application for supporting the collaborative performance of problem-solving tasks and research projects (Jaspers, Broeken, & Erkens, 2005). For this study, the tools that are part of the VCRI were augmented with active representational scripting. In the *Assignment menu*, team members can find the description of the problem-solving task/part-tasks. Besides this, additional information sources such as a definition list, formula list, and clues for solving the problem were also available here. The *Model menu* enabled team members in constructing and adjusting their representations by either adding or deleting relationships. At the start of the first lesson all diagram boxes - representing the different concepts - were placed on the left side of the *Representational tool* so team members could select them when they wanted to add a new relationship. The *Chat tool* enabled

synchronous communication and supported team members in externalizing and discussing their knowledge and ideas. The chat history is automatically stored and can be re-read by the team members. The *Notes tool* is an individual notepad that allowed team members to store information and structure their own knowledge and ideas before making them explicit. The *Co-writer* is a shared text-processor where team members could collaboratively formulate and revise their decisions. The *Status bar* is an awareness tool that displayed which team members were logged into the system and which tool a member used at a specific moment.

The different conditions were information equivalent and only differed in the way that the representational tools were intended to guide learner interaction and teams' complex learning-task performance.

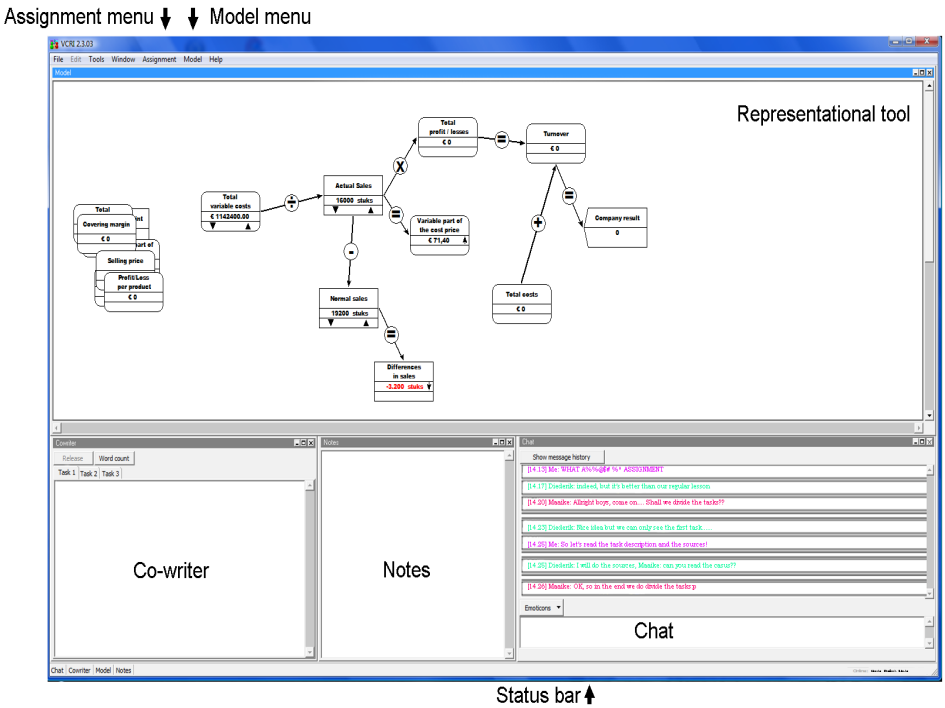

Figure 3.1 Screenshot of the VCRI-environment; simulation representational tool (translated from Dutch).

Problem-solving task and tool use

All teams were coerced to carry out the part-tasks in a predefined order (i.e., used the same script) and could, thus, only start with a new part-task after finishing an earlier part-task. When team members agreed that a part-task was completed, they had to 'close' that phase in the assignment menu. This 'opened' a new phase, which had two consequences for all learners, namely they were instructed to (1) carry out a new part-task and (2) revise their representation of the domain so it concurred with the decisions they gave to the new part-task.

Learners in the non-matched conditions were facilitated in elaborating on their previously constructed representation. Since those learners kept the same representational tool, all concepts and their relationships remained visible and could be revised as learners seemed appropriate for carrying out their new part-task. Learners in the matched condition were facilitated in acquiring and applying a different qualitative or quantitative perspective of the domain. That is, the previously selected concepts remained visible and learners were instructed to replace the relationships by specifying them in a causal manner or as algebraic equations with the aid of their new representational tool.

3.4.3 Procedure

All teams spent six, 45-minute, lessons solving the problem during which each team member worked on a separate computer. Before the first lesson, learners received an instruction about the CSCL-environment, the complex learning task, and the team composition. The instruction made it clear that their score on the complex learning task would serve as a grade affecting their GPA. Learners worked on the problem in the computer classroom where all actions and decisions were logged. During the lessons, the teacher was on stand-by for task related questions and a researcher was present for technical support.

3.4.4 Measurement of quality constructed representations

To examine the effect of condition on the quality of the constructed representations, a content analysis was conducted on all representations. The representations were selected at the end of each problem phase, just before learners 'closed' their part-task, and transferred from the log-files using the MEPA program (Erkens, 2005). Then they were coded with respect to how many concepts and relationships were represented and whether they were represented correctly. It should be noted that the (nine) possible interventions were also coded as concepts since learners receiving the causal tool were facilitated in representing them. When a concept was related to multiple other concepts, it received a code for each relationship and could, thus, be coded several times. The coding was done automatically with a MEPA-filter which makes use of 364 'if-then' decision rules containing explicit references to the concepts, the relationships and its correctness (based on the experts' representations).

3.4.5 Measurement of quality learner interaction

The chat-protocols were selected and transferred from the log-files using the MEPA program (Erkens, 2005). The content of these chat-protocols is assumed to represent what learners know and consider important for carrying out their problem-solving task (Chi, 1997; Moos & Azevedo, 2008). Using so called 'concordancers' software (e.g., MEPA, Erkens; !Kwictex, Mercer *et al.*, 2004) minimizes the work associated with coding the chat-protocols and maximizes coding allowing the content of chat-protocols to be searched for the occurrence of important words or phrases within their linguistic context to show their specific function in the dialogue.

To examine the effect of condition on the *part-task related activities*, two coding schemes were applied. Measurement of the discourse topics provided

insight into the *cognitive, meta-cognitive and off-task activities* carried out (see Table 3.3). The topics were hand-coded and Cohen's kappa was computed for three independently coded chat-protocols (3,532 lines) by two coders. An overall Cohen's Kappa of .70 was found, an intermediate to good result (Cicchetti, Lee, Fontana, & Dowds, 1978). Measurement of the interaction about the concepts, interventions and the ways of interrelating them provided insight into learners' discussion of the *content of the domain* (see Table 3.4). A problem here is that even within in a single sentence, multiple concepts or statements may be expressed and, thus, require multiple codes (Erkens & Janssen, 2008; Strijbos, Martens, Prins, & Jochems, 2006). With a MEPA-filter which makes use of 300 'if-then' decision rules, the utterances were automatically segmented into smaller, still meaningful, subunits. Punctuation marks (e.g., full stop, exclamation mark, question mark, comma) and connecting phrases (e.g., 'and if', or 'but if') were used to segment the utterances. After segmentation, the coding was done automatically with a MEPA-filter which makes use of 900 'if-then' decision rules containing explicit references to a concept, solution or relationship (e.g., name, synonyms, etc.) which were coded as representing that concept, solution or relationship. Overall Cohen's Kappa for concepts, solutions and relationships ranging from .68 to .83, were reached compared to hand-coding three chat-protocols (3,020 lines).

Table 3.3
Coding and Category Kappa's (K_c) of the Meta-cognitive, Cognitive and Off-task Activities

Activities	Discourse topic	Discussion of	K_c
Meta-cognitive			.69
	Planning	the problem-solving strategy; how and when the team has to carry out a specific activity	.58
	Monitoring	whether they have completed the part-tasks on time	.56
	Evaluating	the suitability of their problem-solving strategy	.64
Cognitive			.65
	Preparation	the goal of the problem-solving task and the different part-tasks	.45
	Executing	content-related topics and formulating / revising their decisions to the part-tasks	.70
	Ending	how, where, and when their decisions need to be registered	.51
Off-task			.76
	Social	non-task related topics	.80
	Technical	problems with the CSCL-environment	.60

Table 3.4
Coding and Category Kappa's (K_c) MEPA-filter of the Discussion of the Domain

Categories	Discussion of the	K_c
Concepts	business-economics concepts	.83
Solutions	possible interventions	.75
Relations	different kinds of interrelationships	.68
Conceptual	definition/meaning of a concept/solution	.69
Causal	causal relationship within/between concepts/solutions	.73
Mathematical	quantitative relationships within/between concepts	.62

To examine the effect of condition on the *communicative activities* learners exhibited, each utterance was coded with respect to the type of dialogue act used. A dialogue act is regarded as a communicative action which is elicited for a specific purpose representing a specific function in the dialogue (Erkens *et al.*, 2005; Mercer *et al.*, 2004). The coding was based on the occurrence of characteristic words or phrases (i.e., discourse markers; see Schiffrin, 1987) which indicate the communicative function of an utterance (see Table 2.5, Section, 2.4.4, p. 36). This was done automatically with a MEPA-filter using 1,250 'if-then' decision rules that uses pattern matching to find typical words or phrases. When compared to hand-coding, an overall agreement of 79% was reached and a Cohen's Kappa of .75 was found (Erkens & Janssen, 2008).

3.4.6 Measurement of teams' complex learning-task performance

To examine the effect of condition on complex learning-task performance, an assessment form for all three part-task and the quality of the definitive advice was developed. Table 3.5 provides a description of the aspects on which the decisions were evaluated, the number of items, and their internal consistency scores (i.e., Cronbach's alpha). The 41 items could all be coded as '0' (wrong), '1' (adequate) or '2' (good); the higher the code, the higher the quality of the decision. Teams could, thus, achieve a maximum score of 82 points for their learning-task performance (41 items × 2 points) and a minimum of 0 points. The internal consistency score for the whole complex learning-task performance was .92 and for the subscales, internal consistency scores of .56 or above were obtained.

3.4.7 Measurement of individual learning results

Recall and understanding of the knowledge domain was measured with a pre-test (20 items, $\alpha = .50$) and a post-test (20 items, $\alpha = .53$). The multiple-choice items in both tests were drawn from the total pool of items and equally divided across the three knowledge dimensions (i.e., factual, conceptual and procedural knowledge) and were, thus, unique (see Section 2.4.6, p. 38). Because of the low reliability of the scores on the subscales of both tests (e.g., $\alpha \leq .50$) learner recall and understanding of the different dimensions was not tested. In the analyses, thus, only the overall scores on the pre-test and the post-test were used.

Table 3.5
Items and Reliability of Teams' Complex Learning-task Performance

Criteria	Description	Items	α
Suitability	Whether the teams' decisions were suited to the different part-tasks	9	.81
Elaboration	Number of different business-economics concepts or financial consequences incorporated in the decisions to the different part-tasks	9	.56
Justification	Whether the teams justified their decisions to the different part-tasks	9	.71
Correctness	Whether the teams used the business-economics concepts and their interrelationships correctly in their decisions to the different part-tasks	9	.68
Continuity	Whether the teams made proper use of the decisions from a prior problem phase	2	.67
Quality advice	Whether the teams gave a proper definitive solution - Number of business-economics concepts incorporated in the advice - Number of financial consequences incorporated in the advice - Whether the advice conformed to the guidelines provided	3	.76
Total score	Overall score on the complex learning-task performance	41	.92

3.4.8 Data analysis

Quality constructed representations

Content analyses were conducted to examine the effect of condition on the quality of the constructed representations. To this end, learners' part-task related representations of the concepts, their relationships and the correctness of those relationships were analyzed.

Individual learning results and quality learner interaction

Multilevel analyses (MLAs) were used to examine the effects of condition on individual learning results and the quality of the interaction. This technique is suited to address the statistical problem of non-independence that is often associated with conducting studies on CSCL (e.g., Cress, 2008). Many statistical techniques (e.g., *t*-test, ANOVA) assume score-independence and a violation of this assumption compromises the interpretation of the output of their analyses (e.g., *t*-value, standard error, *p*-value, see Kenny, Kashy, & Cook, 2006). The non-independence was determined here by computing the intraclass correlation coefficient and its significance (Kenny *et al.*) for all dependent variables concerning individual learning results and the quality of the interaction. This coefficient demonstrated non-independence ($\alpha < .05$) for all tests, justifying MLA for analyzing these data. MLA entails comparing the deviance of an empty model and a model with one or more predictor variable(s) to compute a possible decrease in deviance. The latter model is considered a better model when there is a significant decrease in deviance in comparison to the empty model (tested with a x^2-test). Almost all reported x^2-values were significant ($\alpha < .05$) and, therefore, the estimated parameters of these predictor variables (i.e., effects of condition) were tested for significance.

Teams' complex learning-task performance

A one-way MANOVA was used to examine the effect of condition on teams' complex learning-task performance. There was no need to use MLAs because the complex learning-task performance was measured at the team level instead of the learner level. Since there were specific directions of the results expected all analyses are one-tailed.

3.5 Results

3.5.1 Quality constructed representations

The content analyses (see Figure 3.2) revealed several overall differences concerning the quality of the constructed representations between conditions. First, learners in the causal condition made (marginally) significant more errors in representing the relationships than learners in both the conceptual ($t(14) = -2.13$, $p = .05$) and the simulation ($t(14) = -2.07$, $p = .06$) conditions. Second, learners in the simulation condition represented fewer relations than learners in both the conceptual ($t(14) = -3.57$, $p = .00$) and the causal ($t(14) = -2.92$, $p = .01$) conditions. No other overall differences were obtained.

Furthermore, several conditions effects were obtained when analyzing the part-task related representations in relation to the phase-related part-tasks. First, compared to learners in the conceptual condition, learners in the matched condition significantly represented fewer *relationships* within their third representation than they did in their first ($t(13) = -2.69$, $p = .03$). Second, compared to learners in the causal condition, learners in the matched condition marginally significantly represented fewer concepts ($t(13) = -1.84$, $p = .08$) and relationships ($t(13) = -1.84$, $p = .08$) within their second representation than they did in their first. The same kind of result was obtained for relationships when comparing the first to the third representation ($t(13) = -2.91$, $p = .01$). Finally, compared to learners in the simulation condition, learners in the matched condition marginally significantly represented fewer concepts ($t(13) = -1.84$, $p = .08$) and relationships ($t(13) = -1.87$, $p = .08$) within their second representation than they did in their first. The same kind of result was obtained for relationships when comparing the first to the third representation ($t(13) = -2.37$, $p = .03$).

As expected, learners in the matched condition differed in representing the content of domain when carrying out the different part-tasks. After constructing a mostly correct global representation, learners became more selective in representing the concepts and specifying their relationships in a causal or mathematical manner.

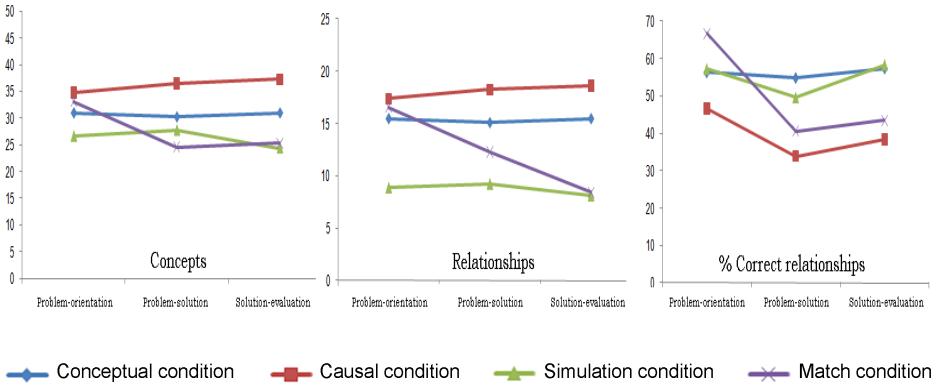

Figure 3.2 Content analyses for effects of condition concerning learners' tool use

3.5.2 Cognitive, meta-cognitive and off-task activities

MLAs revealed that condition was not a predictor for the meta-cognitive activities (β = 1.74, *p* = .26), cognitive activities (β = 2.64, *p* = .20), and off-task activities (β = -.30, *p* = .42) learners exhibited. The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the different kinds of discourse topics are listed in Table 3.7.

When analyzing the different discourse topics for the conditions separately, two condition effects were found. First, a significant category effect for *meta-cognitive activities* was found when comparing learners in the matched condition to learners in the simulation condition (β = 4.57, *p* = .04). As indicated by the $^{+}$ and $^{-}$ signs in Table 3.7, learners in the matched condition exhibited more meta-cognitive activities compared to learners in the simulation condition. Learners in the simulation condition discussed whether they had finished their part-tasks on time (i.e., monitoring) less compared to learners in the matched condition (β = 2.42, *p* = .03). Second, a significant category effect for *cognitive activities* was found when comparing learners in the matched condition with learners in the simulation condition (β = 5.23, *p* = .04). Learners in the simulation condition discussed fewer content-related discourse topics and formulated/revised their decisions (i.e., executing) less often compared to learners in the matched condition (β = 3.82, *p* = .05). Finally, learners in the simulation condition discussed what the goal of the problem-solving task and the different part-tasks was (i.e., preparation) less than learners in the matched condition (β = 0.72, *p* = .05).

Contrary to our expectations, learners in the matched condition only carried out more meta-cognitive and more cognitive activities than learners in the simulation condition. No significant differences were obtained for the comparison with learners in both the conceptual and the causal conditions.

Table 3.7
Multilevel Analyses for Effects of Matched condition versus Non-matched Conditions concerning the Meta-cognitive, Cognitive and Off-task Activities

	Conceptual condition ($n_{learner}$ = 24)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 24)	Matched condition ($n_{learner}$ = 21)	Effects matched condition ($N_{learner}$ = 93)		
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	$x^2(3)$	β	*SE*
Meta-cognitive *	23.54 (9.12)	30.32 (18.80)	17.65 (12.38) -	26.91 (13.20) +	17.15	1.74	2.66
Planning	4.54 (3.02)	6.59 (5.80)	2.96 (2.42)	5.32 (4.69)	9.03	0.73	0.77
Monitoring *	13.33 (5.79)	16.95 (11.17)	10.43 (6.81) -	15.27 (7.17) +	13.05	1.00	1.40
Evaluating	5.67 (2.35)	6.77 (4.41)	4.26 (4.45)	6.32 (4.29)	6.56	0.35	0.76
Cognitive *	20.71 (11.08)	23.68 (17.81)	15.57 (11.11) -	25.73 (11.94) +	15.27	2.64	3.03
Preparation *	2.83 (2.60)	4.23 (3.49)	1.83 (2.10) -	3.32 (1.94) +	7.39	0.25	0.46
Executing *	14.54 (8.56)	15.68 (11.79)	11.26 (8.56) -	18.59 (10.03) +	12.88	2.09	2.24
Ending	3.33 (2.78)	3.77 (4.06)	2.48 (2.02)	3.82 (2.84)	3.71	0.28	0.63
Off-task	9.96 (10.14)	9.82 (7.42)	5.78 (3.53)	9.41 (8.48)	10.19	-0.30	1.55
Social	8.50 (9.89)	7.86 (6.47)	4.22 (3.34)	6.64 (7.27)	9.09	-0.74	1.44
Technical	1.46 (1.38)	1.95 (1.79)	1.57 (1.59)	2.27 (2.29)	0.23	0.43	0.33

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

Table 3.8
Multilevel Analyses for Effects of Matched condition versus Non-matched Conditions concerning the Discussion of the Domain

	Conceptual condition ($n_{learner}$ = 24)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 24)	Matched condition ($n_{learner}$ = 21)	Effects matched condition ($N_{learner}$ = 93)		
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	$x^2(3)$	β	*SE*
Concepts	21.17 (15.28)	26.27 (20.66)	17.22 (13.92)	26.09 (14.76)	14.90	2.41	3.45
Solutions	20.62 (23.12)	29.86 (31.24)	21.27 (27.24)	16.36 (13.26)	14.70	1.27	3.59
Relations *	29.17 (16.21)	35.73 (29.01)	21.30 (17.00) -	32.82 (15.66) +	17.41	1.73	4.22
Conceptual	9.29 (4.97)	11.27 (9.88)	6.04 (4.94)	9.14 (5.41)	11.20	-0.04	1.33
Causal	15.38 (10.35)	19.59 (17.76)	10.96 (1.16)	18.91 (10.28)	14.43	0.59	2.62
Mathematical *	4.50 (5.06)	4.86 (3.69)	4.30 (5.04) -	4.77 (3.53) +	3.90	0.17	0.84

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

3.5.3 Concepts, solutions and relations

MLAs revealed that condition was not a significant predictor for the number and kinds of concepts ($\beta = 2.41$, $p = .25$), solutions ($\beta = 1.27$, $p = .36$) and relations ($\beta = 1.73$, $p = .34$) discussed. The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the discussion of concepts, solutions and relations are shown in Table 3.8.

When analyzing these variables for the conditions separately, two condition effects were found. First, a marginally significant category effect for *concepts* was found when comparing learners in the matched condition to learners in the simulation condition ($\beta = 4.49$, $p = .07$). Second, a significant category effect for *relationships* was found; learners in the matched condition discussed more and more different kinds of relationships than learners in the simulation condition ($\beta = 5.74$, $p = .05$). It appeared that this was (marginally) the case for the conceptual ($\beta = 1.54$, $p = .07$) and the causal relationships ($\beta = 3.85$, $p = .05$).

Contrary to our expectations, learners in the matched condition only had more elaborated discussions of the domain than learners in the simulation condition. No significant differences were obtained for the comparison with learners in both the conceptual and the causal conditions.

3.5.4 Communicative activities

MLAs revealed that condition was a (marginally) significant predictor for the communicative activities learners exhibited when comparing learners in the matched condition to those in both the conceptual ($\beta = 23.84$, $p = .06$) and the simulation conditions ($\beta = 42.00$, $p = .00$). The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the communicative activities are listed in Table 3.9.

When analyzing learners' communicative activities for the conditions separately, several category effects were found. First, a significant category effect for *focusing* was found; learners in the matched condition were better able to coordinate what their topic of discourse was than learners in both the conceptual ($\beta = 4.22$, $p = .05$) and the simulation conditions ($\beta = 6.68$, $p = .02$). Second, a significant category effect for *checking* was found; learners in the matched condition devoted more attention to guarding the coherence and consistency of their shared understanding of the domain than learners in both the conceptual ($\beta = 14.08$, $p = .04$) and the simulation conditions ($\beta = 23.03$, $p = .00$). Finally, a significant category effect was found for *argumentation*; learners in the matched condition exhibited more argumentative activities than learners in the simulation condition ($\beta = 12.17$, $p = .02$).

As expected, learners in the matched condition were better able to establish and maintain shared understanding of the domain than learners in both the conceptual and simulation conditions. These differences were, however, not found for the comparison with learners in the causal condition.

Table 3.9

Multilevel Analyses for Effects of Matched condition versus Non-matched Conditions concerning the Communicative Activities

	Conceptual condition ($n_{learner}$ = 24)	Causal condition ($n_{learner}$ = 24)	Simulation condition ($n_{learner}$ = 24)	Matched condition ($n_{learner}$ = 21)	Effects matched condition $N_{learner}$ = 93)		
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	$x^2(3)$	β	*SE*
Coordination *	124.33 (59.01)	173.82 (130.42)	87.65 (54.21) -	170.36 (79.22) +	30.06	24.02	19.40
Focusing *	22.87 (8.20) -	31.50 (23.37)	18.13 (12.28) -	31.09 (15.83) +	18.42	4.30	3.52
Checking *	57.33 (31.43) -	88.95 (69.43)	39.17 (26.471) -	84.14 (38.56) +	27.74	14.22	9.84
Argumentation *	44.12 (26.92)	53.36 (43.65)	30.35 (19.95) -	55.14 (32.18) +	20.90	5.41	6.61

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a + and the non-matched condition with a -.

3.5.5 Teams' complex learning-task performance

A one-way MANOVA on the total score for teams' complex learning-task performance showed a significant difference for condition ($F(3,27) = 4.38$, p = .01). Bonferroni post hoc analyses revealed that teams in the matched condition scored significantly higher than teams of learners in both the conceptual ($p = .01$; $d = 1.46$) and simulation conditions ($p = .01$; $d = 1.48$). When the results for the dependent variables were considered separately - using one-way ANOVAs with Bonferroni post hoc analyses - condition effects were found for 'justification' ($F(3,27) = 4.85$, $p = .01$) and 'correctness' ($F(3,27) = 3.97$, $p = .01$). The mean scores, standard deviations and condition effects (i.e., difference between matched condition and non-matched conditions) for the complex learning-task performance are listed in Table 3.10. The mean scores indicate that there were two significant differences between conditions. First, teams in the matched condition scored significantly higher on 'justification' than teams in both the conceptual ($p = .01$; $d = 1.56$) and simulation conditions ($p = .01$; $d = 1.56$). Second, teams in the matched condition scored significantly higher on 'correctness' than teams in both the conceptual ($p = .01$; $d = 3.97$) and simulation conditions ($p = .03$; $d = 2.52$).

As expected, teams of learner receiving part-task congruent representational tools scored higher on complex learning-task performance. Although expected, no significant differences were obtained between teams in the matched condition and the causal condition.

3.5.6 Individual learning results

Inspection of the means and standard deviations of learners' pre-test and post-test scores revealed some minor differences between conditions (see Table 3.11). A one-way ANOVA showed no significant differences between conditions on the pre-test score ($F(3, 84) = 1.59$, $p > .05$). This means that learners did not differ in the amount of prior knowledge and it was, therefore, not necessary to correct for this. A *t*-test showed that the overall post-test score of 88 learners (not all 93 learners were present when the pre-test and/or post-test were administered) was not significantly higher than the overall pre-test score ($t(88) = -0.38$, $p > .05$). There were, thus, no individual learning gains. MLAs revealed no significant differences between learners in the matched condition and learners in the conceptual ($\beta = -0.10$, $p > .05$), causal ($\beta = -0.44$, $p > .05$) and simulation ($\beta = 0.01$, $p > .05$) conditions on the post-test score. Nor were there significant differences between other conditions.

These results are contrary to our expectations; there were no individual learning gains and learners in the matched condition did not score higher on the post-test in comparison to learners in the other conditions.

Table 3.10
One-way Multivariate Analysis of Variance for Effects of Matched condition versus Non-matched Conditions concerning Teams' Complex Learning-task Performance

Criteria	Conceptual condition (n_{team} = 8)	Causal condition (n_{team} = 8)	Simulation condition (n_{team} = 8)	Matched condition (n_{team} = 7)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Suitability	14.38 (2.13)	15.38 (0.74)	13.75 (1.70)	15.57 (2.15)
Elaboration	11.62 (2.13)	13.50 (2.93)	11.75 (2.66)	13.71 (2.29)
Justification *	4.62 (2.20) -	7.50 (2.67)	4.62 (1.51) -	7.57 (1.90) +
Correctness *	7.12 (1.55) -	9.25 (2.49)	8.12 (1.36) -	9.86 (0.69) +
Continuity	3.50 (0.76)	3.75 (0.46)	3.00 (0.93)	3.29 (0.76)
Quality advice	4.00 (1.07)	5.00 (0.93)	3.88 (1.46)	4.43 (1.38)
Total score *	45.25 (7.23) -	54.38 (7.98)	45.12 (6.53) -	54.43 (6.29) +

Note. * $p < .05$, ** $p < .01$; if matched condition significantly > a non-matched condition than the matched condition is indicated with a **+** and the non-matched condition with a **-**.

Table 3.11
Means and Standard Deviations for Differences between Conditions concerning the Pre-test and Post-test Scores

Test	Conceptual condition ($n_{learner}$ = 23)	Causal condition ($n_{learner}$ = 22)	Simulation condition ($n_{learner}$ = 23)	Matched condition ($n_{learner}$ = 20)	Overall conditions ($N_{learner}$ = 88)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Pre-test	14.05 (2.12)	14.00 (2.07)	15.17 (1.38)	14.56 (1.76)	14.42 (1.89)
Post-test	14.13 (2.22)	13.55 (1.91)	14.39 (1.94)	14.09 (2.25)	14.04 (2.08)

3.5.7 Anomalies

Since the hypotheses were focused on comparing the performance of teams in the matched condition to teams in the non-matched conditions the analyses and results, thus far, have been reported accordingly. However, the means and standard deviations (see Tables 3.7-3.10) indicated that the quality of the interaction and complex learning-task performance of teams in the causal condition and the matched condition were quite similar. Teams in both the causal and matched conditions, in contrast to those in the other conditions, were facilitated to construct causal representations of the domain. This could have supported those teams in causal reasoning about the domain, an activity that is regarded as beneficial for learning (Jonassen & Ionas, 2008; McCrudden, Schraw, Lehman, & Poliquin, 2007). Guiding learners' causal reasoning about the content of the domain might, thus, account for the differences in learning process (i.e., learner interaction) and learning results (i.e., complex learning-task performance). Since these are noteworthy results, additional, two-tailed analyses were carried out to determine whether the results obtained for teams in the matched condition also applied for teams in the causal condition.

MLAs revealed that learners in the causal condition also exhibited more part-task related and communicative activities than learners in the simulation condition. Learners in the causal condition (marginally) significantly (1) exhibited more meta-cognitive activities ($\beta = 7.56$, $p = .04$) and off-task activities ($\beta = 2.09$, $p = .07$) and (2) discussed more and different kinds of relationships ($\beta = 7.78$, $p = .07$). Also, learners in the causal condition were significantly better able to coordinate their part-task related activities ($\beta = 46.56$, $p = .05$). These results were obtained for all categories. A one-way MANOVA with Bonferroni post hoc analyses revealed that teams in the causal condition marginally significantly outperformed teams in both the conceptual ($p = .08$; $d = 1.14$) and the simulation conditions ($p = .08$; $d = 1.16$) on the complex learning-task performance.

These results indicate that the problem-solving process of teams of learners in the causal condition were also efficient and effective.

3.6 Discussion

Embedding representational tools in CSCL-environments is often regarded as beneficial for learning. Such tools can facilitate teams' construction and discussion of different representations of the domain and, thereby, guiding their learning process and, thus, foster their learning-task performance (Fischer *et al.*, 2002; Wegerif *et al.*, 2010). Although its importance is widely recognized, there are, however, also studies that report mixed or negative effects on learning (Elen & Clarebout, 2007; Van Drie *et al.*, 2005). An important reason for these contrasting findings seems that the complexity of the learning task is not properly taken into account when designing representational tools. Since a representational tool is often suited for coping with the demands of a specific task, it hinders learners in carrying out learning tasks which consist of multiple part-tasks (Ainsworth, 2006; Van Bruggen *et al.*, 2003).

The present study, therefore, examined how and why embedding part-task congruent representational tools in a CSCL-environment fostered learners' collaborative problem-solving performance. Scripting the problem-solving process sequenced and made its phase-related part-task demands explicit, namely (1) determining core concepts, (2) proposing multiple solutions, and (3) coming to a definitive solution. By doing so, each problem phase could be foreseen with a part-task congruent representational tool. Scripting learners' use of representational tools was aimed at guiding their learning process (i.e., quality of the constructed representation and learner interaction) and their learning results (i.e., complex learning-task performance). The results indicate that teams of learners that received the complete array of tools (i.e., matched condition) were indeed fostered in their complex learning-task performance. That is, those teams formulated better decisions with respect to the part-tasks and came up with better definitive solutions to the problem than learners in both the conceptual and the simulation conditions. This difference in learning results might be explained by the differences concerning learners' learning process. Learners in the matched condition started by constructing a broad representation and gradually became more selective in representing the concepts and specifying their relationships in a causal or mathematical manner. This is the way that solving such a problem should theoretically be carried out (e.g., Van Merriënboer & Kirschner, 2007). In contrast, learners who only had access to one of the representational tools (i.e., conceptual, causal, or simulation) represented more or less the same concepts and relationships and were, thus, less occupied with fine-tuning their representations to the different part-task demands. Although the quality of the constructed representation differed for each part-task, almost no differences between the conditions concerning learners' part-task related activities were obtained. Since teams in all conditions had to construct a representation of the domain for each part-task, the learning activity in itself did not differ per condition. So perhaps learners in all conditions were stimulated to discuss the content of the domain and their problem-solving strategy. This explanation seems consistent with the literature on CSCL which shows that the collaborative construction of external representations stimulates learners' cognitive and meta-cognitive activities (e.g., De Simone *et al.*, 2001). On the other hand, the lack of differences might also be due to the role of scripting. Structuring the problem-solving process into three phases, each focusing on one of the part-tasks, could have affected learners' part-task related activities in the same manner (Dillenbourg, 2002; P.A. Kirschner *et al.*, 2008). Whereas the discussion about the domain and the problem-solving strategy were quite the same, learners in the matched condition exhibited more communicative activities than learners in both the conceptual and simulation conditions. That is, they were better able to establish and maintain a shared understanding of the domain, which is regarded as a prerequisite for having a meaningful discussion of the domain (e.g., Van der Linden *et al.*, 2000). It seems that the deictic power of the representational tool hindered learners in establishing and maintaining shared understanding of the domain (Suthers *et al.*, 2003; Van Boxtel & Veerman, 2001). In other words,

when learners are unable to specify (i.e., conceptual tool) or being forced to explicitly specify (i.e., simulation tool) the relationship between concepts this hinders learners in properly referring to and relating their contributions in CSCL-environments.

Although the results indicate that scripting learners' tool use seems beneficial for problem-solving, there were some contrasting findings that require further discussion. First, this study did not reveal no significant differences between learners' pre-test and post-test score, resulting in no learning gains and no differences on learners' post-test score between conditions. This lack of differences might be explained by the measurement of the learning gains since both tests measured recall and understanding of the knowledge domain. The tests did, therefore, not enable learners to demonstrate whether they were better able to apply their understanding of the domain, an ability which also can be regarded as a form of learning gains. Furthermore, it might also be explained by the design of the active representational scripting. The guidance was primarily aimed at supporting teams of learners in carrying out a complex learning task. Such learning tasks often consist of part-tasks demanding learners to apply their understanding of the domain in order to analyze the problem, come up with proper solutions and evaluate their suitability and might, thus, be less supportive for acquiring more domain knowledge (P.A. Kirschner *et al.*, 2006). That is, recalling and grasping the meaning of concepts, principles and procedures is often regarded as prerequisite for the higher-order cognitive processes required for carrying out complex learning tasks. Since the design was aimed at applying domain knowledge in order to come to better and richer solutions it might, therefore, be less suited for knowledge acquisition. Second, learner interaction and teams' complex learning-task performance in the matched condition was very similar to that in the causal condition. Since learners in both conditions received the causal representational tool they were both facilitated in constructing and discussing a causal domain representation. Supporting learners' causal reasoning seems, thus, important for problem-solving (Jonassen & Ionas, 2008; McCrudden *et al.*, 2007). This result raises questions about whether constructing and applying multiple representations of a domain is beneficial for complex learning-task performance. When learners regard a specific representation as beneficial for learning and/or encounter difficulties in combining multiple representations, they might choose to stick with a more familiar one and make no attempt to combine them (Ainsworth, 2006; Bodemer & Faust, 2006). Finally, learners in the causal condition represented more concepts and relationships in comparison to learners in the other conditions. This evoked more elaborate discussions of the domain which could have supported them in carrying out their complex learning task. It is, however, noteworthy that the relationships that they represented were more often incorrect in comparison to the conceptual and the simulation conditions. The construction and discussion of representations might, thus, be more important for complex learning-task performance than the correctness of the representations (Brna *et al.*, 2001; Cox, 1999). It might also be that permitting learners to make errors during their complex learning-task

performance may provide opportunities for learning. In this way, construction of incorrect representations can be regarded as a productive exercise in failure (Kapur, 2008).

3.7 Implications and Future Research

The obtained results mainly confirmed the expectations and are in line with those of others who stress the importance of sequencing and interrelating multiple (i.e., qualitative and quantitative) representations of the knowledge domain during the collaborative performance of a complex learning task (Ertl *et al.*, 2008; Frederiksen & White, 2002; Jonassen, 2003; Ploetzner *et al.*, 1999). These results also have several implications for designing learning environments (e.g., CSCL-environments) aimed at fostering teams' complex learning-task performance. Combining the advantages of scripting and using multiple representational tools facilitates learners in constructing and discussing different representations of the domain. When properly matched to the part-task demands, the complementary function of those representations can evoke elaborated and meaningful discussion of the domain and foster teams' complex learning-task performance (e.g., Ainsworth, 2006). To our knowledge, such an approach has not been used in other studies. Ertl *et al.*, for example, used a condition in which scripting was employed to structure the problem-solving process and a specific representation was applied. Their design, however, did not allow them to compare the effects found with those of conditions in which scripting and learners' use of multiple representational tools were combined. However, when interpreting the results and the implications of this study one has to take into consideration that there were contrasting findings that require additional research to investigate:

- whether learners indeed require qualitative as well as quantitative representations during their collaborative performance of complex learning tasks,
- whether learners combine qualitative and quantitative representations during their collaborative performance of complex learning tasks, and
- how constructing different representations of the domain content affects the quality (i.e., correctness) of learners' discussions of the domain.

4. Representational Scripting: Fostering Complex Learning-task Performance through Guiding Teams' Qualitative and Quantitative Reasoning[4]

Abstract
This study investigated how and why scripting the construction of qualitative and quantitative representations of the domain fostered learners collaborative performance of a complex business-economics problem. Scripting the problem-solving process sequenced and made its phase-related part-task demands explicit, namely defining the problem and proposing multiple solutions, followed by determining suitability of the solutions and coming to a definitive problem solution. Two representational tools facilitated learner construction of causal or mathematical domain representations. Each was suited for carrying out the part-task demands of one specific problem-solving phase; the causal was matched to problem-solution phase and the mathematical to the solution-evaluation phase. Teams of learners in four experimental conditions had to carry out all part-tasks in a predefined order, but differed in the representational tool(s) they received during their collaborative problem-solving process. The provided tools were matched, partly matched or mismatched to the part-task demands. Teams in the causal-only and simulation-only conditions received either a causal or a simulation tool respectively and were, thus, only supported in carrying out one of the two part-tasks. Teams in the simulation-causal condition received both tools, but in an order that was mismatched to the part-task demands. Teams in the causal-simulation condition received both tools in an order that matched the part-task demands of the problem phases. Results revealed that teams receiving part-task congruent tools constructed more task-appropriate representations and had more elaborated and meaningful discussions about the domain. As a consequence, those teams performed better on the complex learning task.

Keywords: Complex Learning Tasks; Computer Supported Collaborative Learning; Learner Interaction; Qualitative and Quantitative Representations; Representational Scripting

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[4] Based on Slof, B., Erkens, G., Kirschner, P. A., Janssen, J., & Jaspers, J. G. M. Representational scripting: Fostering complex learning-task performance through guiding teams' qualitative and quantitative reasoning. *Manuscript submitted for publication.*

4.1 Introduction

The current interest in complex learning is often regarded as education's response to the rapidly changing demands of society and work (Kopers, Giebers, Van Rosmalen, Sloep, Van Bruggen *et al.*, 2005; Sharples, 2010; Van Merriënboer & Kirschner, 2007). Complex learning is necessary to carry out the activities endemic to modern real-life tasks which are complex because they (1) cannot be described in full detail, (2) give no certainty about what the best solution is, and (3) require different perspectives on the problem and the problem-solving strategy for their solution (Jonassen, 2003; Kester, Kirschner, & Corbalan, 2007; Spector, 2008; Van Merriënboer & Kirschner). Learning to flexibly solve complex problems is, thus, an educational priority.

To this end, corporations and schools are increasingly implementing educational approaches such as collaborative problem-solving into their training programs and curricula. The premise underlying this approach is that through *externalizing* one's knowledge, *discussing* this with peers, and *establishing* and *refining* a teams' *shared understanding* of the problem and problem-domain, teams and individuals acquire knowledge and skills which can better be transferred to and applied in different situations (Hmelo-Silver, Duncan, & Chinn, 2007; Kim & Hannafin, in press; Van Blankenstein, Dolmans, Van der Vleuten, & Schmidt, in press; Van den Bossche, Gijselaers, Segers, Woltjer, & Kirschner, in press). Educators and instructional designers, however, must realize that these elements of problem-solving are those which are carried out by experts and that learners (e.g., novices) need ample instructional support and guidance to make approximate such a problem-solving approach (P.A. Kirschner, Sweller, & Clark, 2006; Mayer, 2004; Reiser, 2004; Van Merriënboer & Kirschner, 2007). Without guidance, learners focus on superficial details of problems instead of on the underlying domain principles (Corbalan, Kester, & Van Merriënboer, 2009; T. de Jong & Ferguson-Hessler, 1996), and employ weak problem-solving strategies such as working via a means-ends strategy towards a solution (Simon, Langley, & Bradshaw, 1981; Jonassen, 2003). The support provided should be aimed at gradually increasing their level of expertise, for example by mimicking the processes of experts in a way that learners are supported in acquiring and applying a well-developed understanding of the domain in question (Dufresne, Gerace, Thibodeau-Hardiman, & Mestre, 1992; Frederiksen & White, 2002; Quintana, Reiser, Davis, Krajcik, Fretz *et al.*, 2004). In most domains, this understanding consists of the availability of both qualitative and quantitative representations of the domain which enable constructing meaningful problem representations and flexibly coordinating between them (T. de Jong, Ainsworth, Dobson, Van der Hulst, Levonen *et al.*, 1998; Kozma, 2003; Löhner, Van Joolingen, & Savelsbergh, 2003; Slof, Erkens, Kirschner, Janssen, & Phielix, 2010). This combination of representations is beneficial because different representations initiate different kinds of operators which act to produce new information supporting problem solvers in coming to suitable solutions to problems (Chi, 2000; Scaife & Rogers, 1996).

Qualitative representations represent the concepts underlying a particular domain and the inference rules which interrelate them and, thus, give them meaning. These representations stimulate reasoning about the concepts, their underlying causal principles, and the circumstance under which those principles can legitimately be applied, enabling problem solvers to effectively define the problem and propose multiple solutions for solving it. *Quantitative representations* represent the formalism(s) underlying a particular domain to describe the definitions of and functional relationships between concepts, for example via algebraic equations in the domain of business-economics. Such representations stimulate reasoning about the concepts and their mathematical relationships (e.g., algorithms), enabling problem solvers to evaluate the effects of proposed solutions and, thus, in coming to a definitive solution (Bredeweg & Forbus, 2003; Frederiksen & White, 2002; Jonassen, 2003; McCrudden, Schraw, Lehman, & Poliquin, 2007; Ploetzner, Fehse, Kneser, & Spada, 1999).

This implies that working with multiple representations might be a good way to guide and support the learning process with respect to complex learning. Although it is acknowledged that this can foster understanding and problem-solving, not all studies confirm this. Common here is that learners experience considerable difficulties translating information from different kinds of representations and coordinating between them (Bodemer & Faust, 2006; T. de Jong *et al.*, 1998; Kozma, 2003; Vekiri, 2002). Learners, for example, might not understand/know:

- which parts of the domain are/can be represented,
- the relationship between the representations and the task/problem,
- how to select, use or construct appropriate representations,
- how and why different kinds of representations should be interrelated.

When learners cannot properly make use of multiple representations they are forced to stay with a familiar or a simple representation of the domain, hindering them in acquiring and applying a well-developed understanding of the domain. Unfortunately, current educational approaches in most domains, are often aimed at teaching the functional - quantitative - relationships between concepts (e.g., Law of Ohm), which neglects teaching the underlying qualitative principles. When learners do not properly understand the underlying principles of the domain they are often unable to give meaning to the functional relationships (Frederiksen & White, 2002; Ploetzner *et al.*, 1999). This raises the question how and why educators and instructional designer can guide learners' problem-solving process and, thus, their complex learning-task performance. The research reported on in this chapter introduces an instructional approach - active representational scripting - as a possible solution and examines how and why this affects complex learning-task performance.

4.2 Theoretical Background

4.2.1 Design principles behind the active representational scripting

Integrating scripting with representational tools (i.e., *active representational scripting*) is intended to gradually guide learners in acquiring a well developed understanding of a domain and applying this understanding during their problem-solving process. Using such tools can facilitate constructing domain-specific representations and, thereby, guide reasoning about the domain. A tools' ontology (i.e., its objects, relations, and rules for combining objects and relations) provides a specific kind of representational guidance which makes certain concepts and/or interrelationships (e.g., causal, mathematical) salient in favor of others. In this way, a tools' representational guidance supports externalization of knowledge and ideas about specific aspects of the domain (Ertl, Kopp, & Mandl, 2008; Fischer, Bruhn, Gräsel, & Mandl, 2002; Slof *et al.*, 2010a; Suthers, 2006). This fosters understanding since it stimulates cognitive and meta-cognitive activities such as (1) selecting relevant information, (2) organizing information into coherent structures, (3) relating information to prior understanding, (4) determining knowledge and comprehension gaps, and (5) generating new ideas, questions and plans (Edelson, 1996; Hilbert & Renkl, 2008; Nesbit & Adesope, 2006; Shaw, 2010; Stull & Mayer, 2007). Embedding representational tools in collaborative settings, such as computer supported collaborative learning (CSCL)-environments, may even further stimulate the elaboration of these representations, due to the environment's emphasis on dialogue and discussion, so that multiple perspectives on the domain arise (De Simone, Schmid, & McEwan, 2001; Hmelo-Silver *et al.*, 2007; Janssen, Erkens, Kirschner, & Kanselaar, 2010; Wegerif, McClaren, Chamrada, Schreuer, Mansour *et al.*, 2010). Creating a shared understanding of these different viewpoints and discussing them may foster understanding and, thus, facilitate the problem-solving process even more (Ding, 2009; Erkens, Prangsma, & Jaspers, 2006; Mercer, Littleton, & Wegerif, 2004; Van den Bossche *et al.*, in press).

The mere presence or availability of a single representational tool, however, will not automatically support the solving of complex problems since such problems are composed of different *part-tasks,* namely (1) determining what the problem to be solved is, (2) proposing possible multiple solutions to the defined problem, (3) determining the suitability of the different solutions and (4) coming to a definitive solution. To do all of this, multiple perspectives of the problem domain (i.e., problem representations) are required (Duffy, Dueber, & Hawley, 1998; Van Bruggen, Boshuizen, & Kirschner, 2003). A difficulty here is that a representational tool guides learners in constructing and discussing specific representations of the domain and is, thus, not appropriate for carrying all aspects of the task (Ainsworth, 2006; Brna, Cox, & Good, 2001; Mayer, 1990; Schnotz & Kürschner, 2008; Van Drie, Van Boxtel, Jaspers, & Kanselaar, 2005). In other words, a tools' ontology provides a specific kind of guidance, which is specified through its expressiveness and processability (see Table 4.1).

Expressiveness refers to which concepts and interrelationships can be represented (i.e., a tools' specificity) and how accurately this is done (i.e., a tools' precision). *Processability* refers to the differences in processing the information from the representation caused by the difference in expressiveness, and which determines the number and quality of inferences that can be made. Less expressive (i.e., less specific and less precise) ontologies have the advantage of being highly processable (Larkin & Simon, 1987) making it easy to make many inferences from them (i.e., elaboration). Such ontologies guide learners in elaborating on the concepts of the domain and in relating them to the problem (e.g., Jonassen, 2003). These ontologies, however, do not have much expressive power (Cox, 1999); the inferences made from them are neither specific nor precise. The *order* of an ontology (Frederiksen & White, 2002) determines the quality of the inferences that can be made (i.e., kind of reasoning used). A *first order* representational tool supports reasoning about causal relationships and guides discussion and/or thought about the problem and possible solutions. A *second order* ER is more expressive - and thus more specific and precise - which supports quantitative inference-making enabling negotiation and/or determination of suitability of the proposed solutions.

Table 4.1
Ontology and Guidance Specifications for a Representational Tool

Ontology				Representational guidance
Expressiveness		Processability		
Specificity	Precision	Elaboration	Order	
Low-medium	Causal Relations	Quasi-structured	First	Qualitative inference-making
High	Mathematical relations	Fully Structured	Second	Quantitative inference-making

However, when the design of the tool is incongruent with the demands of a specific part-task this will lead to communication problems and decreased learning-task performance (Slof, Erkens, Kirschner, Jaspers, & Janssen, 2010; Suthers, 2006; Van Bruggen *et al.*, 2003). This could be because the tool is not expressive enough. To this end, it might prove beneficial if learners were facilitated in their construction and discussion of different perspectives in a task-appropriate manner (Frederiksen & White, 2002; Ploetzner *et al.*, 1999; Vekiri, 2002). In other words, learners should receive different representational tools for which the representational guidance of each tool is congruent (i.e., ontologically matched) with the demands of each part-task. To ensure alignment of the tool, its use, and the part-task demands scripting can be employed (Dillenbourg, 2002; Weinberger, Ertl, Fischer, & Mandl, 2005). According to Dillenbourg, a script is "a set of instructions regarding to how the team members should interact, how they should collaborate and how they should solve the problem" (p. 64). Integrating scripting with the availability of representational tools sequences and makes the different part-task demands explicit and tailors the congruency of the representational guidance to the

part-task demands of the complex problem. This should actively engage learners in a process of making sense of the domain in question by articulating and discussing multiple perspectives on the problem and of the problem-solving strategy (Hmelo-Silver *et al.*, 2007; Jonassen, 2003; Ploetzner *et al.*, 1999). Active representational scripting, thus, is intended to evoke learner interaction in both the content and the relational space (Barron, 2003, Slof *et al.*, 2010ac).

In the *content space* learners carry out part-task related activities that enable them to acquire a well-developed understanding of the domain and to apply this during their problem-solving process. To this end, the active representational scripting stimulates learners to carry out *cognitive activities* such as (1) discussing the goal of the problem-solving task/part-tasks, (2) discussing and selecting concepts, principles, and procedures in the domain, and (3) formulating and revising their decisions (Jonassen, 2003; Slof *et al.*, 2010ac; Vermunt, 1996). Learners may also be induced to employ a proper problem-solving strategy and reflect on its suitability through carrying out *meta-cognitive activities* (F. de Jong, Kollöffel, Van der Meijden, Kleine Staarman, & Janssen, 2005; Molenaar, Van Boxtel, & Sleegers, in press; Moos & Azevedo, 2008; Vermunt). This requires that learners discuss (1) how they should approach the problem (i.e., plan), (2) whether they have finished the part-tasks on time (i.e., monitor), and (3) how suitable their approach was (i.e., evaluate).

In the *relational space* learners carry out communicative activities enabling them to have meaningful discussions in the content space (Barron, 2003; Kreijns, Kirschner, & Jochems, 2003). To this end, the representational tool supports learners in coordinating their collaboration process by carrying out communicative activities (Clark & Brennan, 1991; Hmelo-Silver, Chernobilsky, & Jordan, 2008; Reiser, 2004). Three important communicative activities are; (1) focusing, (2) checking, and (3) argumentation (see Erkens, Jaspers, Prangsma, & Kanselaar, 2005). That is, in collaborative settings learners have to make their own knowledge and ideas explicit to other team members. When made explicit, learners must maintain a shared topic of discourse (i.e., achieve a common *focus*) and repair that focus if they notice that there is or has been a focus divergence. Also, understanding and relating the relevance of individual messages may be difficult when learners are discussing different topics simultaneously. Learners should, therefore, coordinate their topic of discourse by focusing (Dillenbourg & Traum, 2006; Erkens *et al.*). Since not all concepts, principles, and procedures are relevant for carrying out a specific part-task, learners also must maintain the coherence and consistency of their shared understanding by *checking* (Van der Linden, Erkens, Schmidt, & Renshaw, 2000). Furthermore, learners must come to an agreement about relevant concepts, principles and procedures. Through *argumentation* they can try to change their partners' viewpoints to arrive at the best way to carry out a part-task or at a definition of concepts acceptable for all. In this argumentation process, they try to convince others by elaborating on their own point of view and by explaining, justifying and accounting for their viewpoints (Andriessen, Baker, & Suthers, 2003; P.A. Kirschner, Beers, Boshuizen, & Gijselaers, 2008).

4.2.2 Complex learning-task performance in business-economics

Learners collaborated on solving a case-based business-economics problem in which they had to advise an entrepreneur about changing the business strategy to increase profits (i.e., company result). To gain insight into the part-tasks and their required domain-specific representations, a learning-task analysis (Anderson & Krathwohl, 2001; Gagné, Briggs, & Wagner, 1992) was conducted. Based on these insights, the sequence and the demands of the part-tasks were specified and part-task congruent representational tools were developed (see Table 4.2).

Table 4. 2
Congruence between Representational Tool and Phase-related Part-task Demands

Problem phase	Task demands	Representational tool	Representational guidance
Problem-solution	Defining the problem and proposing multiple solutions to the problem	Causal	Visualizing causal relationships between the concepts and the possible solutions
Solution-evaluation	Determining suitability of the solutions and coming to a definitive solution to the problem	Simulation	Visualizing mathematical relationships between the concepts and enabling manipulation of their values

In the *problem-solution phase* learners, first, have to explain what the problem is and what the most important factors are for its solution. Then, they have to formulate several changes of the business strategy (i.e., interventions) and make clear how they might solve the problem (i.e., problem-solution) by describing how they will affect the outcomes (i.e., company result). Learner interaction should, thus, be guided towards selecting the core concepts and discussing how these concepts are qualitatively related to each other and to the possible interventions so that multiple solutions can be formulated. The representational tool should facilitate construction and discussion of a causal problem representation by causally relating the concepts to each other and to possible interventions. Figure 1.2 (see Section, 1.2.3, p. 19) shows an experts' qualitative representation of the domain. The causal representational tool facilitates representing the concepts, the interventions and their causal interrelationships. Selecting relevant concepts and interventions and causally relating them supports the effective exploration of the solution space and, thus, of finding multiple solutions to the problem. Learners receiving such a tool could, for example, make explicit that an intervention such as 'receiving a rebate from a supplier' affects the 'total variable costs' which in turn affects the 'total costs'. Through gradually increasing learners' understanding of the underlying qualitative principles governing the domain, it should be easier for them to come up with an intervention that will solve the problem.

In the *solution-evaluation phase* learners have to determine the financial consequences of their proposed interventions and formulate a definitive advice

by discussing the suitability of the different interventions with each other. Learner interaction should, therefore, be guided towards determining and comparing the financial consequences by discussing the functional relationships between the selected core concepts by means of algebraic equations. The representational tool must, thus, facilitate construction and discussion of a quantitative representation by specifying the relationships as algebraic equations. Figure 1.3 (see Section, 1.2.3, p. 20) shows a quantitative presentation of the domain as seen by an expert. The simulation representational tool facilitates representing the concepts and their mathematical interrelationships. Selecting relevant concepts and specifying the interrelationships as algebraic equations supports evaluating the effects of the proposed interventions and, thus, in coming to a suitable advice. Learners receiving such a tool could, for example, simulate how an intervention such as 'receiving a rebate from a supplier' affects the 'total variable costs' and whether this affects the 'total costs'. By manipulating the input values, the values of the other related concepts are automatically computed. Since such quantitative representations can only be properly understood and applied when learners have a well-developed qualitative understanding of the domain, this kind of support is only appropriate for carrying out this type of part-task.

4.3 Design and Research Questions

To study the effects of scripting the use of representational tools, four experimental conditions were defined. This was done by mismatching, partly matching or matching the tools' representational guidance to the demands of each problem phase (see Table 4.3).

Table 4.3
Overview of the Experimental Conditions

Problem phase	Condition and provided representational tool			
	Causal-only condition	Simulation-only condition	Simulation-causal condition	Causal-simulation condition
Problem-Solution	Causal tool	Simulation tool	Simulation tool	Causal tool
Solution-Evaluation	Causal tool	Simulation tool	Causal tool	Simulation tool

Scripting the problem-solving process sequenced and made the phase-related, part-task demands explicit. These demands are (1) defining the problem and proposing multiple solutions, and (2) determining the suitability of the solutions and coming to a definitive solution. Teams in all experimental conditions had to carry the part-tasks in a predefined order, but differed in the representational tool they received. In the *partly matched* conditions (i.e., causal-only, simulation-only), teams received either a causal or a simulation tool for carrying out both part-tasks and for constructing the part-task related representations. The tools' representational guidance matched only one of the part-task demands. Teams in the *matched* (i.e., causal-simulation) and the *non-matched*

(i.e., simulation-causal) conditions received both representational tools in a phased order. The difference between these conditions was that the tools were part-task congruent or not. In the simulation-causal condition the teams received both tools, but in an order that was mismatched to the part-task demands (i.e., a simulation tool for the solution phase and a causal tool for the evaluation phase). In contrast, teams in the causal-simulation condition received representational tools considered to be well-suited to the part-task demands of each problem phase.

Due to this presumed match between the tools' representational guidance and all part-tasks demands, it was hypothesized that teams of learners in the matched condition would:

(H1) experience a qualitatively better learning process, evidenced by:
  a) constructing representations that are more suited for carrying out the part-tasks,
  b) carrying out more part-task related cognitive and meta-cognitive activities,
  c) carrying out more communicative activities to coordinate their collaborative problem-solving process,

(H2) achieve a better team learning result, evidenced by arriving at better interventions and

(H3) achieve a better individual learning result, evidenced by higher post-test scores.

4.4 Method and Instrumentation

4.4.1 Participants

Participants were students from six business-economics classes in three secondary schools in the Netherlands. The total sample consisted of 102 students (61 male, 41 female; mean age = 15.7 years; *SD* = .56, *Min* = 15, *Max* = 17). The students were, within classes, randomly assigned to 34 teams of learners; nine teams in the causal-only, simulation-only and simulation-causal conditions and seven teams in the causal-simulation condition.

4.4.2 Task and materials

Collaborative learning environment

The teams worked in a CSCL-environment called Virtual Collaborative Research Institute (VCRI; Jaspers, Broeken, & Erkens, 2005; see Figure 4.1), a groupware application for supporting the collaborative performance of problem-solving tasks and research projects. For this study, the tools in VCRI were augmented with active representational scripting. In the *Assignment menu*, team members can find the description of the problem-solving task/part-tasks. Furthermore, additional information sources such as a definition list, formula list, and clues for solving the problem were also available here. The *Model menu* enabled team members to construct and adjust their representations by either adding or deleting relationships. At the start of the first lesson all diagram boxes - representing the different concepts/solutions - were placed on the left side of the *Representational tool* so team members could select them when they wanted

to add a new causal or mathematical relationship. The *Chat tool* enabled synchronous communication and supported team members in externalizing and discussing their knowledge and ideas about the content of the domain and their problem-solving strategy. The chat history is automatically stored and can be re-read by the team members. The *Co-writer* is a shared text-processor where team members could collaboratively formulate and revise their decisions concerning the part-tasks. The *Notes tool* is an individual notepad that allowed team members to store information and structure their own knowledge and ideas before making them explicit to the other members. The *Status bar* is an awareness tool that displayed which team members were logged into the system and which tool a member used at a specific moment. The different conditions were information equivalent and, thus, only differed in the way the representational tools were intended to guide performance.

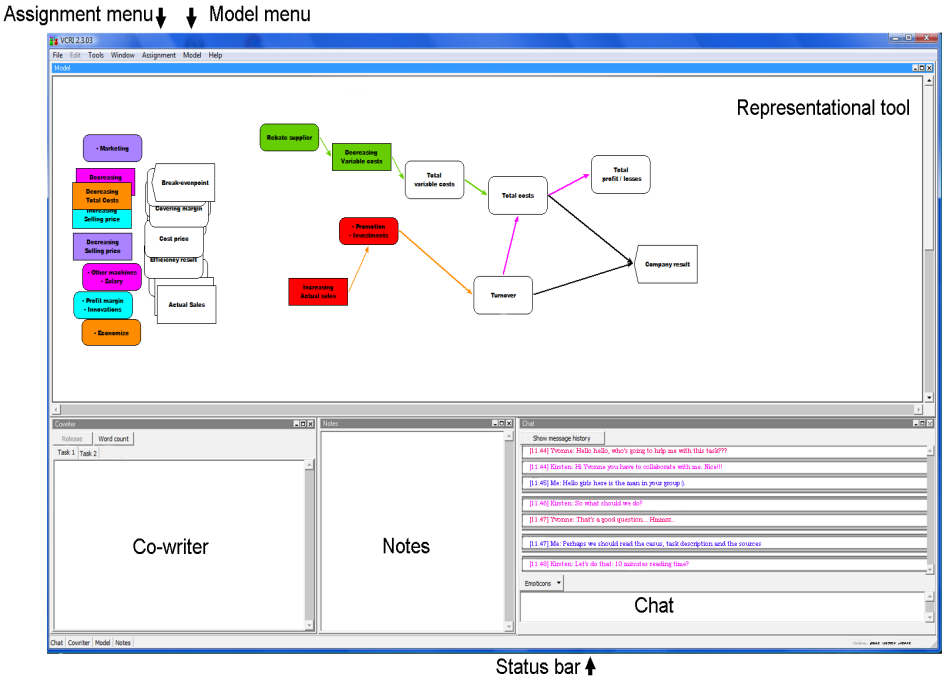

Figure 4.1 Screenshot of the VCRI-environment; causal representational tool (translated from Dutch).

Problem-solving task and tool use

All teams were identically 'coerced' (i.e., scripted) to carry out the phase-related part-tasks in a predefined order namely starting with the problem-solution phase and ending with the solution-evaluation phase. When the team members agreed that the part-task demands of the first phase were completed, they had to 'close' that phase in the assignment menu. This 'opened' the second phase, which had two consequences for all team members, namely they were instructed to carry out the part-task demands of this phase and then

revise their representation of the domain so it concurred with the decisions they made when carrying out this part-task. Teams in the causal-only and simulation-only conditions were facilitated in elaborating on their previously constructed representation. Since those teams kept the same representational tool, all concepts and their relationships remained visible and could be revised as the team members deemed appropriate for carrying out the task demands of the following phase. Teams in the simulation-causal and causal-simulation conditions were facilitated in acquiring and applying a different qualitative or quantitative perspective of the domain. Their previously selected concepts remained visible and they were instructed to replace the relationships by specifying them in either a causal manner (i.e., simulation-causal) or as algebraic equations (i.e., causal-simulation) with the aid of their new tool.

4.4.3 Procedure

All 34 teams of learners spent four, 45-minute, lessons solving the problem during which learners worked on separate computers. Before the first lesson, learners received an instruction about the team composition, the complex learning task and the CSCL-environment. The instruction made clear that their score on the complex learning task would serve as a grade affecting their GPA. Learners worked on the problem in the computer classroom and all actions and decisions were logged. During the lessons, the teacher was on stand-by for task-related questions and a researcher was present for technical support.

4.4.4 Measurement of quality constructed representations

A content analysis was conducted on the phase-related representations to examine the quality of the constructed representations. To this end the representations were selected at the end of each problem phase, just before a problem phase was 'closed', and transferred from the log-files using the Multiple Episode Protocol Analysis program (MEPA; Erkens, 2005). The representations were coded automatically by comparing them with the experts' representations.

4.4.5 Measurement of quality learner interaction

MEPA was also used to examine the quality of the learner interaction. The content of these chat-protocols was assumed to represent what learners know and consider important for carrying out the problem-solving task (Chi, 1997; Moos & Azevedo, 2008). Quality was measured by coding the protocols on how learners interacted in the content and the relational space.

In the *content space*, two coding schemes were used to measure the discourse topics and the content of the domain that was discussed. Measurement of discourse topics was aimed at gaining insight into the *meta-cognitive, cognitive and off-task activities* learners carried out (see Table 4.5). The topics were hand-coded and Cohen's kappa was computed for three independently coded chat-protocols (2,457 lines) by two coders. An overall Cohen's Kappa of .74 was found, an intermediate to good result (Cicchetti, Lee, Fontana, & Dowds, 1978). Measurement of the content of the domain was aimed at gaining insight into the discussion of *concepts, interventions and the ways of interrelating them* (see Table 4.6). A problem here is that even within in a single sentence, multiple concepts or statements may be expressed and, thus,

require multiple codes (Erkens & Janssen, 2008; Strijbos, Martens, Prins, & Jochems, 2006). With a MEPA-filter which makes use of 300 'if-then' decision rules, the utterances were automatically segmented into smaller, still meaningful, subunits. Punctuation marks (e.g., period, exclamation point, question mark) and connecting phrases (e.g., 'and if', or 'but if') were used to segment utterances. After segmentation, coding was done automatically with a MEPA-filter which makes use of 814 'if-then' decision rules containing explicit references to a concept, solution or relationship (e.g., name, synonyms, etc.) which were coded as representing that concept, solution or relationship. When three chat-protocols (2,457 lines) were compared to automatically coded protocols overall Cohen's Kappa's ranging from .65 to .73 were found.

Table 4.5
Coding and Category Kappa's (K_c) of the Meta-cognitive, Cognitive and Off-task Activities

Activities	Discourse topic	Discussion of	K_c
Meta-cognitive			.75
	Planning	the problem-solving strategy; how and when the team has to carry out a specific activity	.65
	Monitoring	whether they have completed the part-tasks on time	.71
	Evaluating	the suitability of their problem-solving strategy	.78
Cognitive			.72
	Preparation	the goal of the problem-solving task and the different part-tasks	.55
	Executing	content-related topics and formulating / revising their decisions to the part-tasks	.85
	Ending	how, where, and when their decisions need to be registered	.75
Off-task			.79
	Social	non-task related topics	.83
	Technical	problems with the CSCL-environment	.76

In the *relational space*, measurement of the communicative activities was aimed at examining how learners coordinated their problem-solving process. As can be seen in Table 2.5 (see Section, 2.4.4, p. 36) each utterance was coded with respect to the type of dialogue act used. A dialogue act was regarded as a communicative action which is elicited for a specific purpose representing a specific function in the dialogue (Erkens *et al.*, 2005; Mercer *et al.*, 2004). Coding was based on the occurrence of characteristic words or phrases (i.e., discourse markers; see Schiffrin, 1987) indicating the communicative function of an utterance. This was done automatically with a MEPA-filter using 1,250 'if-then' decision rules that uses pattern matching to find typical words or phrases. When compared to hand-coding, an overall agreement of 79% was reached and a Cohen's Kappa of .75 was found (Erkens & Janssen, 2008).

Table 4.6
Coding and Category Kappa's (K_c) MEPA-filter of the Discussion of the Domain

Categories	Discussion of the	K_c
Concepts	business-economics concepts	.70
Solutions	possible interventions	.73
Relations	different kinds of interrelationships	.65
Causal	causal relationship within/between concepts/solutions	.73
Mathematical	quantitative relationships within/between concepts	.57

4.4.6 Measurement of teams' complex learning-task performance

To examine performance quality, an assessment form for both phase-related part-tasks and for the quality of the definitive advice was developed. Table 4.7 provides a description of the aspects on which the decisions were evaluated, the number of items, and their internal consistency scores (i.e., Cronbach's alpha). All 28 items could be coded as '0' (wrong), '1' (adequate) or '2' (good); the higher the code, the higher the quality of the decision. Teams could, thus, achieve a maximum score of 56 points for their complex learning-task performance (28 items × 2 points) and a minimum of 0 points. The internal consistency score for the whole complex learning-task performance was .84.

Table 4.7
Items and Reliability of Teams' Complex Learning-task Performance

Criteria	Description	Items	α
Suitability	Whether the teams' decisions were suited to the different part-tasks	6	.65
Elaboration	Number of different business-economics concepts or financial consequences incorporated in the decisions to the different part-tasks	6	.47
Justification	Whether the teams justified their decisions to the different part-tasks	6	.51
Correctness	Whether the teams used the business-economics concepts and their interrelationships correctly in their decisions to the different part-tasks	6	.55
Continuity	Whether the teams made proper use of the decisions from the problem-solution phase	1	-
Quality advice	Whether the teams gave a proper definitive advice - Number of business-economics concepts incorporated in the advice - Number of financial consequences incorporated in the advice - Whether the advice conformed to the guidelines provided	3	.71
Total score	Overall score on the complex learning-task performance	28	.84

4.4.7 Measurement of individual learning results

Recall and understanding of the knowledge domain was measured with a pre-test (20 items, $\alpha = .46$) and a post-test (20 items, $\alpha = .48$). The multiple-choice items in both tests were drawn from the total pool of items and equally divided across the three knowledge dimensions (i.e., factual, conceptual and procedural knowledge) and were, thus, unique (see Section 2.4.6, p. 38). Because of the low reliability of the scores on the subscales of both tests (e.g., $\alpha \leq .50$) learner recall and understanding of the different knowledge dimensions was not tested. In the analyses, thus, only the overall scores on the pre-test and the post-test were used.

4.4.8 Data analysis

Quality constructed representations

The effect of condition on quality of the constructed representations was examined by analyzing the part-task related representations of the concepts, their relationships and the correctness of those relationships.

Individual learning results and quality learner interaction

The effect of condition on quality of the learner interaction was determined via Multilevel analyses (MLAs) which addresses the statistical problem of non-independence often associated with CSCL research (Cress, 2008; Strijbos & Fischer, 2007). Many statistical techniques (e.g., *t*-test, ANOVA) assume score-independence and violating this assumption compromises the interpretation of the output of their analyses (e.g., *t*-value, standard error, *p*-value, see Kenny, Kashy, & Cook, 2006). Non-independence was determined by computing the intraclass correlation coefficient and its significance (Kenny *et al.*) for all dependent variables relating to learner interaction. This coefficient demonstrated non-independence ($\alpha < .05$) for all tests, justifying using MLA for analyzing these data. MLA entails comparing the deviance of an empty model and a model with one or more predictor variable(s) to compute a possible decrease in deviance. The latter model is considered a better model when there is a significant decrease in deviance in comparison to the empty model (tested with a x^2-test). Almost all reported x^2-values were significant ($\alpha < .05$) and, therefore, the estimated parameters of these predictor variables (i.e., effects of condition) were tested for significance.

Teams' complex learning-task performance

The effect of condition on teams' complex learning-task performance was examined through conducting a one-way ANOVA on the total score teams received. Planned orthogonal contrasts were constructed to examine whether there a significant difference could be found between the (1) the partly matched conditions and the matched/non-matched conditions), (2) matched condition (i.e., causal-simulation) and the non-matched condition (i.e., simulation-causal), and (3) two partly matched conditions (i.e., causal-only versus simulation-only). Since there were specific directions of the results expected all analyses are one-tailed.

4.5 Results

4.5.1 Quality constructed representations

When analyzing the quality of the constructed representations in relation to the task demands of the problem phases, the content analyses revealed several differences between conditions (see Figure 4.2). First, teams in the partly matched conditions (i.e., causal-only and simulation-only) showed a stable pattern in representing domain content. Those teams either represented many concepts and relationships in their constructed representations or did not. Compared to teams in the simulation-only condition, teams in the causal-only condition overall represented significantly more concepts ($t(16) = 2.56$, $p = .02$) and relationships ($t(16) = 4.24$, $p = .00$). Second, teams in the matched (i.e., causal-simulation) and non-matched (i.e., simulation-causal) conditions had a more diverse pattern in representing the domain content. Those teams adjusted their representations more often when carrying out the part-tasks. Compared to teams in the simulation-causal condition, teams in the causal-simulation condition significantly represented (1) more relationships during the problem-solution phase ($t(14) = 2.77$, $p = .03$) but made more errors in representing those relationships ($t(14) = 4.18$, $p = .00$), (2) fewer relationships during the solution-evaluation phase ($t(14) = -2.29$, $p = .05$) but made less errors in representing the relationships ($t(14) = -3.59$, $p = .00$).

Overall, these analyses show that teams using multiple representational tools, in contrast to teams using a single tool, varied more in representing the content of the domain. This was, however, only beneficial for teams in the causal-simulation condition since they became more selective in representing the concepts and specifying their relationships as algebraic equations.

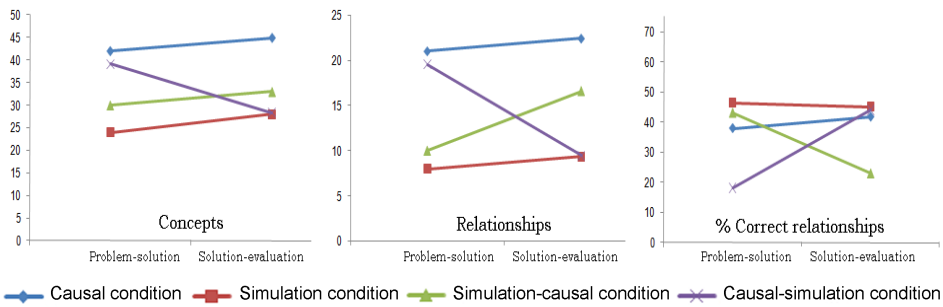

Figure 4.2 Content analyses for effects of condition concerning learners' tool use

4.5.2 Cognitive, meta-cognitive and off-task activities

Inspection of the means and standard deviations (see Table 4.8) revealed differences between conditions concerning the meta-cognitive and cognitive activities learners exhibited. Multilevel analyses (MLAs) revealed that condition was a significant predictor for these differences (see Tables 4.9-4.11). First, a category effect for *meta-cognitive activities* was found when comparing learners in the causal-simulation condition to learners in both the simulation-only

(β = 5.37, p = .07) and simulation-causal conditions (β = 6.17, p < .05). Learners in the causal-simulation condition exhibited more meta-cognitive activities than learners in both other conditions. This was mainly due to the fact that learners in the causal-simulation condition discussed whether they had finished their part-tasks on time (i.e., monitoring) more often than learners in both the simulation-only (β = 3.96, p < .05) and simulation-causal conditions (β = 4.17, p < .05). Second, learners in the causal-simulation condition discussed what the goal of the problem-solving task and the different part-tasks was (i.e., *preparation*) more often than learners in both the causal-only (β = 1.04, p < .05) and simulation-only conditions (β = 1.16, p < .05). Finally, learners in the causal-simulation condition discussed whether they should end a part-task (i.e., *ending*) more often than learners in the causal-only (β = 1.33, p < .01), simulation-only (β = 0.81, p = .05) and simulation-causal (β = 1.14, p < .05) conditions.

Overall, these analyses show that learners in the causal-simulation condition exhibited more meta-cognitive and cognitive activities than learners in the other conditions.

4.5.3 Concepts, solutions and relations

Differences were found for learners' discussion of the domain between conditions (see Table 4.12). MLAs revealed two category effects when comparing learners in the causal-simulation condition to learners in the simulation-causal condition (see Table 4.13). First, a marginally significant category effect for *concepts* (β = 11.91, p = .07) was found; learners in the causal-simulation discussed more concepts than learners in the simulation-causal condition. Second, a significant category effect for *relations* (β = 16.47, p < .05) was found; learners in the causal-simulation condition discussed more and different kinds of relationships than learners in the simulation-causal condition. The MLAs also revealed that learners in the causal-simulation condition discussed more mathematical relationships than learners in both the causal-only (β = 4.96, p < .05) and simulation-causal (β = 6.36, p < .05) conditions.

Overall, these analyses show that teams in the causal-simulation condition had more elaborate discussions about the domain than teams in the simulation-causal condition.

Table 4.8

Means and Standard Deviations for Differences between Conditions concerning the Meta-cognitive, Cognitive and Off-task Activities

	Causal-only condition ($n_{learner}$ = 27)	Simulation-only condition ($n_{learner}$ = 27)	Simulation-causal condition ($n_{learner}$ = 27)	Causal-simulation condition ($n_{learner}$ = 21)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Meta-cognitive	17.55 (9.11)	14.78 (9.94)	13.85 (8.06)	20.14 (10.71)
Planning	5.14 (3.41)	3.81 (3.31)	3.46 (3.15)	4.62 (3.61)
Monitoring	10.50 (6.08)	9.19(6.01)	8.92 (5.62)	13.14 (7.78)
Evaluating	1.91 (2.11)	1.78 (2.28)	1.46 (1.30)	2.38 (2.36)
Cognitive	15.36 (11.37)	17.63 (11.38)	14.23 (9.71)	20.52 (8.04)
Preparation	1.86 (1.94)	1.74 (1.70)	2.54 (2.23)	2.90 (1.70)
Executing	12.50 (9.62)	14.37 (9.93)	10.50 (7.69)	15.29 (7.96)
Ending	1.00 (1.16)	1.52 (1.55)	1.19 (1.47)	2.33 (2.20)
Off-task	11.00 (7.78)	11.89 (11.32)	7.77 (5.52)	9.62 (5.91)
Social	9.41 (7.16)	10.30 (10.16)	7.04 (5.75)	8.57 (5.96)
Technical	1.59 (1.84)	1.59 (2.37)	0.73 (1.49)	1.05 (1.50)

Table 4.9

Estimates for Random Intercept Model for Differences between Conditions concerning the Meta-cognitive Activities

	Meta-cognitive		Planning		Monitoring		Evaluating	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*
γ_{00} = Intercept	19.63	2.29	4.59	0.75	12.30	1.40	2.74	0.60
β_1 = causal-simulation vs. causal-only	2.39	3.59	-0.53	1.19	2.57	2.18	0.37	0.94
β_2 = causal-simulation vs. simulation-only	5.37	3.45	0.80	1.14	3.96*	2.09	0.60	0.91
β_3 = causal-simulation vs. simulation-causal	6.17*	3.47	1.15	1.15	4.17*	2.10	0.86	0.91
Variance								
Team level	67.09		9.45		35.51		1.85	
Individual level	24.51		2.00		5.31		2.63	
Deviance	681.67		494.19		612.64		377.51	
Decrease in deviance	16.17**		8.32*		14.02**		5.05	

Note. * $p < .05$, ** $p < .01$.

Table 4.10
Estimates for Random Intercept Model for Differences between Conditions concerning the Cognitive Activities

	Cognitive		Preparation		Executing		Ending	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*
γ_{00} = Intercept	21.11	2.50	2.90	0.43	15.29	2.59	2.33	0.36
β_1 = causal-simulation vs. causal-only	4.70	4.00	1.04*	0.61	2.34	3.57	1.33**	0.51
β_2 = causal-simulation vs. simulation-only	2.89	3.85	1.16*	0.57	0.92	3.45	0.81	0.48
β_3 = causal-simulation vs. simulation-causal	6.29	3.87	0.37	0.58	4.78	3.46	1.14*	0.49
Variance								
Team level	76.53		3.55		52.92		2.56	
Individual level	32.95		0.11		29.14		0.07	
Deviance	696.33		392.88		666.55		362.49	
Decrease in deviance	15.72**		6.82*		14.45**		8.17*	

Note. * $p < .05$, ** $p < .01$.

Table 4.11
Estimates for Random Intercept Model for Differences between Conditions concerning the Off-task Activities

	Off-task		Social		Technical	
	β	*SE*	β	*SE*	β	*SE*
γ_{00} = Intercept	9.62	2.18	8.57	2.16	1.05	0.45
β_1 = causal-simulation vs. causal-only	-1.47	3.03	-0.85	2.99	-0.58	0.63
β_2 = causal-simulation vs. simulation-only	-2.27	2.91	-1.72	2.88	-0.54	0.60
β_3 = causal-simulation vs. simulation-causal	1.88	2.92	1.58	2.89	0.31	0.61
Variance						
Team level	50.65		39.42		3.10	
Individual level	16.46		19.56		0.39	
Deviance	654.12		637.65		386.91	
Decrease in deviance	17.76**		12.67**		5.04	

Note. * $p < .05$, ** $p < .01$.

Table 4.12
Means and Standard Deviations for Differences between Conditions concerning the Discussion of the Domain

	Causal-only condition ($n_{learner}$ = 27)	Simulation-only condition ($n_{learner}$ = 27)	Simulation-causal condition ($n_{learner}$ = 27)	Causal-simulation condition ($n_{learner}$ = 21)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Concepts	17.05 (18.66)	24.48 (20.29)	15.92 (11.76)	27.95 (20.69)
Solutions	14.55 (15.53)	16.41(17.58)	12.27 (10.33)	20.43 (15.65)
Relations	22.18 (19.81)	26.00 (18.28)	17.58 (13.25)	34.14 (20.61)
Causal	14.05 (13.20)	15.15 (12.44)	10.58 (9.73)	20.71 (13.35)
Mathematical	8.14 (7.37)	10.85 (7.78)	7.00 (4.75)	13.43 (9.03)

Table 4.13
Estimates for Random Intercept Model for Differences between Conditions concerning the Discussion of the Domain

	Concepts		*Solutions*		*Relations*		Causal		Mathematical	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*
γ_{00} = Intercept	27.95	5.91	20.43	4.96	34.14	5.62	20.71	3.88	13.43	2.02
β_1 = causal-simulation vs. causal-only	9.60	8.14	4.97	6.82	10.66	7.75	5.80	5.35	4.96*	2.80
β_2 = causal-simulation vs. simulation-only	3.47	7.88	4.02	6.61	8.14	7.49	5.57	5.17	2.58	2.69
β_3 = causal-simulation vs. simulation-causal	11.91	7.90	8.22	6.62	16.47*	7.51	10.14*	5.19	6.36*	2.71
Variance										
Team level	158.72		104.22		184.54		78.18		39.75	
Individual level	191.87		137.25		159.45		79.35		15.30	
Deviance	783.55		746.81		790.15		714.55		634.31	
Decrease in deviance	20.33**		17.59**		21.68**		18.41**		16.85**	

Note. * $p < .05$, ** $p < .01$.

4.5.4 Communicative activities

Differences were also found between conditions on the communicative activities learners exhibited (see Table 4.14). MLAs revealed that condition was a significant predictor for how learners coordinated their collaborative problem-solving process when comparing learners in the causal-simulation condition to learners in the causal-only ($\beta = 79.35$, $p < .05$), simulation-only ($\beta = 71.96$, $p < .05$) and simulation-causal ($\beta = 100.59$, $p < .05$) conditions (see Table 4.15). When analyzing the communicative activities separately, several category effects were obtained. First, a significant category effect was found for *checking*; learners in the causal-simulation condition attended more to guarding the coherence and consistency of their shared understanding of the domain than learners in the causal-only ($\beta = 43.69$, $p < .05$), simulation-only ($\beta = 38.24$, $p < .05$) and simulation-causal ($\beta = 49.11$, $p < .01$) conditions. Second, a significant category effect was found for *argumentation*; learners in the causal-simulation condition exhibited more argumentative activities than learners in the causal-only ($\beta = 24.92$, $p < .05$), simulation-only ($\beta = 24.28$, $p < .05$) and simulation-causal ($\beta = 32.97$, $p < .05$) conditions. Finally, a significant category effect was found for *focusing*; learners in the causal-simulation condition devoted more attention to coordinate what their topic of discourse was than learners in the simulation-causal condition ($\beta = 18.60$, $p < .05$).

Overall, these analyses show that learners in the causal-simulation condition were better able to establish and maintain shared understanding of the domain and also to argue about it than learners in the other conditions.

Table 4.14
Means and Standard Deviations for Differences between Conditions concerning Communicative Activities

	Causal-only condition ($n_{learner}$ = 27)	Simulation-only condition ($n_{learner}$ = 27)	Simulation-causal condition ($n_{learner}$ = 27)	Causal-simulation condition ($n_{learner}$ = 21)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Coordination	108.86 (70.44)	122.52 (78.84)	92.62 (56.44)	194.48 (120.67)
Focusing	25.14 (17.73)	27.70 (19.23)	18.23 (13.19)	37.14 (22.86)
Checking	49.45 (30.99)	57.67 (38.60)	46.04 (28.18)	95.90 (62.88)
Argumentation	34.27 (27.92)	37.15 (26.48)	28.35 (20.52)	61.43 (40.60)

Table 4.15
Estimates for Random Intercept Model for Differences between Conditions concerning Communicative Activities

	Coordination		Focusing		Checking		Argumentation	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*
γ_{00} = Intercept	194.48	27.54	37.14	6.03	95.90	13.15	61.43	9.18
β_1 = causal-only vs. causal-simulation	79.35*	37.90	11.27	8.30	43.69*	18.12	24.92*	12.66
β_2 = simulation-only vs. causal-simulation	71.96*	36.72	9.44	8.04	38.24*	17.53	24.28*	12.24
β_3 = simulation-causal vs. causal-simulation	100.59*	36.80	18.60*	8.05	49.11**	17.58	32.97*	12.27
Variance								
Team level	3,052.03		149.33		887.11		463.24	
Individual level	4,290.99		204.58		914.14		435.48	
Deviance	1,059.00		780.80		938.34		876.60	
Decrease in deviance	34.04**		22.53**		30.46**		27.15**	

Note. * $p < .05$, ** $p < .01$.

4.5.5 Teams' complex learning-task performance

First, inspection of the means and standard deviations of the total score for teams' complex learning-task performance revealed differences between conditions (see Table 4.16). A one-way ANOVA revealed there was a significant effect of condition on learning-task performance, $F(3, 21.50) = 7.00$, $p < .01$, $\omega^2 = .33$ (Brown-Forsythe because homogeneity of variance assumption was violated). Next, the constructed planned orthogonal contrasts were carried out to compare (1) the single tool partly matched conditions to the multiple tool matched and non-matched conditions), (2) the matched condition (i.e., causal-simulation) to the non-matched condition (i.e., simulation-causal), and (3) the two partly-matched conditions (i.e., causal-only versus simulation-only). This analysis revealed that teams in the multiple tool conditions significantly outperformed the teams in the single tool conditions, $t(21.61) = 3.97$, $p < .01$ (equal variances not assumed), $r = .65$ and that teams in the matched causal-simulation condition significantly outperformed teams in non-matched simulation-causal condition, $t(15.40) = 7.24$, $p < .01$ (equal variances not assumed), $r = .88$. No significant difference was found between teams in the causal-only and simulation-only conditions, $t(30) = 1.50$, $p > .05$, $r = .26$. To examine the differences between the non-matched condition and the partly matched conditions, post-hoc tests (Games-Howell) were carried out, revealing no significant differences, $t(16) = 1.01$, $p > .05$, $r = .24$, and $t(16) = 1.36$, $p > .05$, $r = .32$ respectively. This indicates that team complex learning-task performance in the non-matched simulation-causal condition did not differ from performance in the partly matched causal-only or simulation-only conditions.

Overall, the results show that constructing different kinds of representations is beneficial to constructing only one kind of representation, but that this advantage is only significant when a tools' representational guidance is matched to the task demands of each problem phase.

4.5.6 Individual learning results

Inspection of the means and standard deviations of learners' pre-test and post-test scores revealed differences between conditions (see Table 4.17). A one-way ANOVA showed no significant differences between conditions on the pre-test score ($F(3, 92) = 0.56$, $p > .05$). This means that learners did not differ in the amount of prior knowledge and it was, therefore, not necessary to correct for this. A *t*-test showed that the overall post-test score of 96 learners (not all 102 learners were present when the pre-test and/or post-test were administered) was significantly higher than the overall pre-test score ($t(96) = 1.89$, $p = .00$). There were, thus, individual learning gains. MLAs, however, revealed no significant differences between learners in the causal-simulation condition and learners in the causal-only ($\beta = 0.11$, $p > .05$), simulation-only ($\beta = 0.22$, $p > .05$) and simulation-causal ($\beta = 0.20$, $p > .05$) conditions. Nor were there differences between other conditions.

Overall, these results are not completely in line with the expectations; there were individual learning gains, however, no significant differences between conditions were obtained.

Table 4.16
Means and Standard Deviations for Differences between Conditions concerning Teams' Complex Learning-task Performance

Criteria	Causal-only condition (n_{team} = 9)	Simulation-only condition (n_{team} = 9)	Simulation-causal condition (n_{team} = 9)	Causal-simulation condition (n_{team} = 7)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Suitability	9.89 (2.62)	9.89 (1.83)	10.00 (2.24)	12.00 (0.00)
Elaboration	6.22 (2.33)	6.33 (1.87)	7.22 (2.59)	9.00 (0.58)
Justification	3.00 (1.50)	3.11 (1.36)	4.00(1.73)	5.14 (1.46)
Correctness	4.44 (1.67)	4.22 (1.20)	5.11 (1.54)	6.14 (0.38)
Continuity	1.44 (0.73)	1.56 (0.53)	1.56 (0.73)	2.00 (0.00)
Quality advice	3.22 (1.39)	2.89 (1.27)	3.67 (1.12)	4.86 (0.90)
Total score	28.22 (7.50)	28.00 (4.44)	31.56 (6.46)	39.14 (1.22)

Table 4.17
Means and Standard deviations for Differences between Conditions concerning the Pre-test and Post-test Scores

Test	Causal-only condition ($n_{learner}$ = 25)	Simulation-only condition ($n_{learner}$ = 25)	Simulation-causal condition ($n_{learner}$ = 26)	Causal-simulation condition ($n_{learner}$ = 20)	Overall conditions ($N_{learner}$ = 96)
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Pre-test	10.63 (2.95)	11.20 (2.04)	11.44 (2.58)	10.72 (2.27)	11.02 (2.48)
Post-test	13.22 (2.56)	12.92 (2.65)	13.00 (2.64)	13.25 (2.38)	13.11 (2.54)

4.6 Discussion

This study examined how and why scripting learners' use of representational tools (i.e., active representational scripting) in a CSCL-environment affects collaborative performance of a complex business-economics problem. To examine the effects of such an instructional approach, a combined effect oriented and process oriented research approach on collaborative learning was used (Dennen, 2008; Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010).

The effect oriented view revealed that teams of learners receiving representational tools that were completely matched to the part-task demands of the problem phases, (i.e., a causal representation followed by a simulation representation) performed better on the complex learning task. That is, those teams formulated better decisions with respect to the part-tasks and came up with better definitive solutions to the problem than teams in the partly matched (i.e., causal-only, simulation-only) and non-matched (i.e., a simulation representation followed by a causal one) conditions. No significant difference between the partly matched and non-matched conditions was found. Furthermore, learners form all conditions acquired a better understanding of the domain.

To try to explain how and why the active representational scripting affected the learning process, a process oriented approach was used. Four differences concerning the quality of the learning process were found. First, teams in the both the matched and non-matched conditions adjusted their representations of the domain to the part-task demands of the problem phases. However, this was only beneficial for teams in the matched condition since they started with the construction of a broad representation and gradually became more selective in representing the concepts and specifying their relationships as algebraic equations. This is the way that solving such a problem should theoretically be carried out (e.g., Van Merriënboer & Kirschner, 2007). In contrast, teams who had access to only one of the representational tools (i.e., the partly matched conditions) showed a stable pattern in representing the content of the domain. Those teams either represented many concepts and relationships (i.e., causal-only) or they did not (i.e., simulation-only) and were, thus, less occupied with fine-tuning their representations to the different part-task demands.

Second, teams in the matched condition carried out more cognitive and meta-cognitive activities than teams in the other conditions. They more often discussed (1) whether they had finished their part-tasks on time (i.e., monitoring), (2) what the goal of the problem-solving task and the different part-tasks were (i.e., preparation), and (3) whether they should end a part-task (i.e., ending). Carrying out those meta-cognitive and cognitive activities is often regarded as beneficial to collaborative problem-solving (Hmelo-Silver *et al.*, 2007; Jonassen, 2003; Ploetzner *et al.*, 1999).

Third, in the teams in the matched condition more elaborate discussions were carried out on the content of the domain than in teams in the non-matched condition. The active representational scripting shaped the use of the representational tools and guided learners' content-related interaction

towards acquiring and applying suitable qualitative and quantitative problem representations.

Finally, teams in the matched condition were better able to establish and maintain a shared understanding of the domain, which is regarded as a prerequisite for having a meaningful discussion of the domain (e.g., Clark & Brennan, 1991). Matching a representational tools' guidance to the part-task demands of the problem phases, thus, supports learners communication. This result is consistent with other studies on CSCL which show that the computer tools provided by the environment must enable learners to easily refer to and relate their contributions to those of others (i.e., deictic referencing, see Suthers, Hundhausen, & Girardeau, 2003).

Although the results indicate that scripting learners' tool use seems beneficial for solving complex problems and learning, some of the findings require further discussion. Unexpectedly, almost no differences for learners' discussion of the content of the domain were found in comparisons of teams in the matched condition to those in the partly matched conditions. The role of scripting might account for the lack of significant differences. Structuring the problem-solving process into phases, each focusing on one of the part-tasks, could have affected the content related interaction in a phase-equivalent manner (Dillenbourg, 2002; P.A. Kirschner *et al.*, 2008). That is, all teams were instructed to construct a domain representation for each part-task and were, thereby, stimulated to discuss the content of the domain. This explanation is consistent with literature on CSCL which shows that the collaborative construction of representations stimulates learners' cognitive activities (De Simone *et al.*, 2001; Janssen *et al.*, 2010a). This line of reasoning might seem to contradict the result that teams of learners in the non-matched condition had fewer discussions about the content of the domain than teams of learners in the matched condition. However, when the instructions for problem-solving are not congruent with the representational tools used, the scripting might negatively affect learners' discussion about the content of the domain.

Another limitation may lie in the measurement of the quality of the learning process. Solely coding and counting the number of concepts and relationships discussed and represented, though useful, might not lead to full understanding of the dynamics of collaborative learning (see Hmelo-Silver *et al.*, 2008). It does, for example, not provide insight into (1) the evolution of understanding and the correctness of the content-related interaction and (2) how learners translate information from and coordinate information between their constructed representations.

Also, no differences between conditions concerning individual learning were obtained. Since the pre-test and the post-test measured recall and understanding of the knowledge domain and were, thus, only useful for determining learning gains in terms of acquired domain knowledge. The tests did not enable students to demonstrate whether they were better able to apply their understanding of the domain, an ability which also can be regarded as a form of learning gains. This might be an explanation for the lack of differences in learning gains between the causal-simulation and the other conditions.

4.7 Implications and Future Research

The results show that combining scripting with the availability of multiple representational tools (i.e., active representational scripting) aids learner construction and discussion of the domain. When properly matched to part-task demands, the specific ontology of the representations can evoke elaborated and meaningful discussion of the domain and foster complex learning-task performance (Ainsworth, 2006; Slof *et al.*, 2010ac). These results are in line with those of others who stress the importance of creating and interrelating qualitative and quantitative representations of the domain for learning (T. de Jong *et al.*, 1998; Frederiksen & White, 2002; Jonassen, 2003; Ploetzner *et al.*, 1999). Those studies, however, do not provide guidelines for designing learning environments (e.g., CSCL-environments) aimed at fostering complex learning-task performance. The present study supports two principles for designing instruction to foster complex learning-task performance. First, to support the acquisition of a well-developed understanding of a domain, instruction should gradually increase the complexity of the domain; introducing qualitative representations before quantitative (see also Bredeweg & Forbus, 2003; T. de Jong *et al.*; Löhner *et al.*, 2003; Ploetzner *et al.*). Second, to support applying one's understanding in a domain, instruction should allow for constructing representations that are congruent with the tasks that need to be carried out (see also, Schnotz & Kürschner, 2008; Van Bruggen *et al.*, 2003).

To refine these general principles, additional research is needed to investigate how and why:

- constructing different representations affects the evolution of understanding of the domain and the quality (i.e., correctness) of content-related discussions of the domain, and
- learners translate and coordinate between the constructed representations.

5. General Discussion and Conclusions

Learning to solve complex problems is regarded as an important educational goal due to the rapidly changing demands posed by society and work environments (Hmelo-Silver, Duncan, & Chinn, 2007; Van Merriënboer & Kirschner, 2007). To this end, businesses and schools are increasingly implementing instructional approaches such as collaborative problem-solving in their training programs and curricula. Although educators and instructional designers acknowledge the educational benefits, they also realize that learners (e.g., novices) need ample instructional support to make their problem-solving process more efficient and effective (P.A. Kirschner, Sweller, & Clark, 2006; Mayer, 2004; Reiser, 2004). Since learners often lack a well-developed understanding of the domain, they should be supported in acquiring different perspectives (i.e., qualitative and quantitative) on the domain and applying these perspective to solve the problem (Dufresne, Gerace, Thibodeau-Hardiman, & Mestre, 1992; Frederiksen & White, 2002; Kozma, 2003). Embedding representational tools in collaborative settings, such as CSCL-environments, may provide this guidance. Such tools can facilitate learners in visualizing and discussing the content of the domain and thereby guide their problem-solving process (Fischer, Bruhn, Gräsel, & Mandl, 2002; Suthers, 2006; Zhang, 1997). However, the mere presence or availability of a representational tool does not automatically support learners in carrying out complex learning tasks. Since representational tools are only suited to coping with the demands of a specific task they may hinder learners in carrying out learning tasks, such as solving complex problems, that consist of different kinds of part-tasks (Ainsworth, 2006; Van Bruggen, Boshuizen, & Kirschner, 2003). This raises the question of how and why educators and instructional designers can employ representational tools to foster complex learning-task performance.

The studies described in this thesis introduced an instructional approach - *representational scripting* - as a possible solution and examined the effects of its two types, namely (1) passive representational scripting (i.e., providing part-task congruent expert representations) and (2) active representational scripting (i.e., constructing part-task congruent representations). To examine how and why representational scripting affects the complex learning-task performance of a team, an *effect oriented* and a *process oriented* research approach were combined (Dennen, 2008; Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010). Data on *learning results* (i.e., complex team learning-task performance and individual learning results) and *learning process* (i.e., constructed representations and learner interaction) were collected, coded and analyzed. The next section provides a summary of each study and the results are used to answer the general research question. This is followed by a discussion of the limitations of the studies and suggestions for future research.

5.1 Summary of the Studies and Synthesis

5.1.1 Study 1: Passive representational scripting

As set out in Chapter 2, this study investigated the effects of passive representational scripting. Scripting the problem-solving process sequenced and made its part-task demands explicit, namely (1) problem-orientation, (2) problem-solution, and (3) solution-evaluation. Each representational tool provided teams with a specific representation of the domain (i.e., conceptual, causal, or mathematical) and was each suited to carrying out specific part-task demands (i.e., *passive representational scripting*). It was hypothesized that scripting the interpretation of part-task congruent representations would guide the learning process, resulting in better team and individual learning. To examine this, 96 secondary education students from six business-economics classes were randomly assigned per class to a total of 32 teams which were equally divided over four experimental conditions. All teams were scripted to carry out the part-tasks in the predefined order, but differed in the representation(s) they received. In the three *non-matched* conditions, teams only received one of the representational tools - one representation - and were thus supported in carrying out only one of the part-tasks. In the *matched* condition, teams received all three representations in a part-task congruent manner. That is, the provided representations were matched to the phase-related task demands, namely the conceptual representation to the problem-orientation task, the causal representation to the problem-solution task and the mathematical representation to the solution-evaluation task.

The results show that teams in the matched condition (1) had indeed more elaborate discussions of the domain content (i.e., more concepts, relationships, and solutions), and (2) were also better able to establish and maintain their shared understanding of the knowledge domain (i.e., coordinate their problem-solving process) than teams in the non-matched conditions. These differences in learning process might explain why teams in the matched condition made better decisions on the part-tasks and came up with better definitive solutions to the problem than teams in the non-matched conditions. However, contrary to expectation, teams in the matched condition did not carry out more meta-cognitive activities (e.g., discuss problem-solving strategy and its suitability) than teams in the non-matched conditions. Furthermore, learner interaction and the complex learning-task performance of teams in the causal condition were also very similar to what was found in the matched condition. Finally, the learners' pre-test and post-test scores did not differ significantly, showing no individual learning gains.

The results of the first study indicate that *scripting the interpretation and discussion of part-task congruent representations fosters complex learning-task performance in teams*. However, they also might question whether:

- an educational approach such as complex learning can foster individual learning in terms of acquired declarative domain knowledge and
- (over-)scripting a learning process hinders learners in developing meta-cognitive strategies that can be applied to different situations.

5.1.2 Study 2: Active representational scripting

As described in Chapter 3, this study investigated the effects of the active representational scripting. Scripting the problem-solving process sequenced and made its part-task demands explicit, namely (1) problem-orientation, (2) problem-solution, and (3) solution-evaluation. The representational tools facilitated teams in constructing specific representations of the domain (i.e., conceptual, causal, or mathematical) and were each suited for carrying out specific part-task demands (i.e., *active representational scripting*). It was hypothesized that scripting the construction of part-task congruent representations would guide the learning process, resulting in better team and individual learning. To examine this, 93 secondary education students from six business-economics classes were randomly assigned per class to a total of 31 teams. The teams were more or less equally divided over the four experimental conditions; eight teams in the three *non-matched* conditions and seven teams in the *matched* condition. All teams were required to carry out the part-tasks in a predefined order, but differed in the representational tool(s) they received. In three non-matched conditions, teams received one of the representational tools facilitating the construction of a specific representation and, thus, supported them in carrying out only one of the part-tasks. In the matched condition, teams received all three representational tools in a part-task congruent manner, namely the conceptual tool for problem-orientation, the causal tool for problem-solution and the simulation tool for solution-evaluation. The results show that teams in the matched condition, as expected, formulated better decisions with respect to the part-tasks and came up with better definitive solutions to the problem than teams who received only a conceptual or a simulation tool for all part-tasks. This might be explained by the differences in the learning process. That is, teams in the matched condition were more occupied with fine-tuning their representations to the different part-task demands than teams in the non-matched conditions. Furthermore teams in the matched condition devoted more attention to coordinating their problem-solving process. However, unexpectedly, the same kinds of results were found for teams receiving a representational tool for constructing causal representations for all part-tasks. Also, no differences concerning cognitive (e.g., discussing the goal of the problem-solving task) and meta-cognitive activities (e.g., monitoring whether the part-tasks were completed on time) were obtained. Finally, no individual learning gains were obtained.

The results of the second study indicate that *scripting construction and discussion of part-task congruent representations fosters complex learning-task performance in teams*. These results, however, also raise several questions:

- Does complex learning-task performance require combinations of qualitative and quantitative representations of the domain?
- Why does learner interaction about the domain content between conditions not differ when the quality of the constructed representations does?
- Is an educational approach such as complex learning suited to fostering individual learning in terms of acquired declarative domain knowledge?

5.1.3 Study 3: Qualitative and quantitative representations

This study, as described in Chapter 4, investigated the effects of constructing qualitative and quantitative representations of the domain. To this end active representational scripting was employed to guide and support teams in combining and interrelating qualitative and quantitative representations with respect to complex learning. Scripting the problem-solving process sequenced and made its part-task demands explicit, namely (1) problem-solution, and (2) solution-evaluation. The representational tools facilitated the construction of domain-specific representations (i.e., causal, or mathematical) and were each suited to carrying out specific part-task demands. It was hypothesized that scripting the construction and discussion of qualitative and quantitative representations would guide the learning process, resulting in better team and individual learning. To examine this, 102 secondary education students from six business-economics classes were randomly assigned per class to a total of 34 teams. All teams were scripted to carry the part-tasks in the predefined order, but differed in the representational tools they received. Teams in the *partly matched* conditions (i.e., causal only, n = 9; simulation only, n = 9), received either a causal or a simulation tool for carrying out both part-tasks. Teams in the *matched* (i.e., causal simulation, n = 7) and the *non-matched* (i.e., simulation causal, n = 9) conditions received both representational tools in a phased order. In contrast to teams in the simulation-causal condition, teams in the causal-simulation condition received representational tools considered to be well-suited to the task demands of each part-task (i.e., causal tool for the problem-solution and a simulation tool for solution-evaluation). The results show that teams receiving part-task congruent tools did indeed construct more task-appropriate representations and had qualitatively better discussions about the domain. That is, those teams exhibited more cognitive behavior (i.e., discussed whether a part-task should be ended) and meta-cognitive activities (i.e., monitored whether part-tasks were completed on time) than teams in the partly and non-matched conditions. Furthermore, they also devoted more attention to coordinating their problem-solving process. These differences might explain why teams in the matched condition formulated better decisions with respect to the part-tasks and came up with better definitive solutions to the problem than teams in the other conditions. No significant difference between teams in the partly matched and non-matched conditions was found. Although individual learning gains (i.e., differences between learners' pre-test and post-test score) were found, unexpectedly, no significant differences between conditions were found.

The results of the third study indicate that *constructing and discussing qualitative and quantitative representations fosters complex learning-task performance in teams*. Although promising, it does not provide insight into:

- how constructing qualitative and quantitative representations affects the evolution of understanding and quality (i.e., correctness) of content-related discussions of the domain and
- how (teams of) learners translate information from different kinds of representations and coordinate between them.

5.1.4 Synthesis

The three studies discussed each provide insight into how and why representational scripting can foster complex learning-task performance. This section continues by focusing on integrating the obtained results. The overall picture of the thesis gradually emerges in the answers to the general research question, specified as follows:

> *How and why does visualizing domain content in a part-task congruent manner affect the collaboration process and complex learning-task performance in teams and individual learning?*

The first part of the general research question addresses *how* visualizing the domain content in a part-task congruent manner affects complex learning. Representational scripting was found to indeed foster *complex learning-task performance in teams*. That is, the teams formulated better decisions with respect to the part-tasks and came up with better definitive solutions to the problem. This was the case for both passive representational scripting (Study 1) and active representational scripting (Study 2), indicating that providing as well as constructing part-task congruent representations are effective for complex learning. Although both types were not directly compared (e.g., not the same classes, differences in time) and, thus, no hypotheses were formulated, it is noteworthy that more or less the same kinds of team learning results were obtained. It could be that being given the best representation for each part-task leads to the same results as constructing one yourself (Scheiter, Gerjets, & Catrambone, 2006). Another explanation might be that the representational scripting was employed in a CSCL-environment. Due to the environmental emphasis on dialogue and discussion, providing and constructing part-task congruent representations may have affected discussions and, thus, the team's learning-task performance in the same way (De Simone, Schmid, McEwen, 2001).

Unexpectedly, very similar results were obtained for teams either receiving or constructing causal representations of the domain for all part-tasks. This finding emphasizes the importance of causal reasoning about the domain for complex learning (Jonassen & Ionas, 2008; McCrudden, Schraw, Lehman, & Poliquin, 2007). It also raises questions as to whether working with multiple representations of a domain is indeed beneficial for complex learning-task performance (Ainsworth, 2006; Bodemer & Faust, 2006). Study 3, therefore, examined whether combining and interrelating qualitative and quantitative representations is more effective for complex learning. The results support the assumption that constructing multiple representations does indeed foster complex learning. As stated by many others, working with qualitative as well as quantitative representations might, thus, be a good way to guide and support the learning process with respect to complex learning (Bredeweg & Forbus, 2003; T. de Jong, Ainsworth, Dobson, Van der Hulst, Levonen *et al.,* 1998; Frederiksen & White, 2002; Jonassen, 2003; Ploetzner, Fehse, Kneser, & Spada, 1999).

No differences concerning *individual learning*, evidenced by comparing learners' pre-test and post-test scores, were obtained for both passive and active representational scripting. These findings are in line with those of others examining the effects of problem-based learning (Dochy, Segers, Van den Bosche, & Gijbels, 2003; Mergendoller, Maxwell, & Bellisimo, 2006) and might be accounted for by the nature of complex learning tasks. An educational approach such as problem-solving often consists of part-tasks that demand learners to apply their understanding of the domain in order to analyze the problem, come up with proper solutions and evaluate their suitability and might, thus, be less supportive to acquiring more domain knowledge. That is, recalling and grasping the meaning of concepts, principles and procedures is often regarded as prerequisite for the higher-order cognitive processes required to carry out complex learning tasks (P.A. Kirschner *et al.*, 2006). In contrast, the results of Study 3 indicate that collaboratively carrying out a complex learning-task can foster individual learning. Since no differences between conditions were obtained, this probably cannot be explained by the design of the representational scripting. Perhaps, the design of Study 3 could explain the difference in results. The teams participating in Study 3 carried out two part-tasks instead of three (Study 1 and Study 2), which had at least one important consequence, namely teams worked with a causal qualitative and/or a quantitative representation. Thus teams no longer worked with a conceptual - more abstract - representation of the domain which might have improved individual learning. Such representations are often more difficult to grasp and apply than causal qualitative and quantitative representations (Frederiksen, White, & Gutwill, 1999; Markovits, Doyon, & Simoneau, 2002). This seems consistent with the findings in Study 1 and Study 2 that teams working only with conceptual representational tools received the lowest scores for complex learning-task performance.

The second part of the general research question addresses *why* visualizing the domain content in a part-task congruent manner affects complex learning. Since the studies took place in a collaborative setting, the nature and quality of the team collaboration process were examined. The studies show that representational scripting affects the learning process in several ways.

First, the results of Study 2 and Study 3, as expected, show that using part-task congruent representational tools supports teams in *constructing representations beneficial to complex learning-task performance*. That is, those teams started by constructing a broad representation and gradually became more selective in representing the concepts and specifying their relationships (i.e., causally or mathematically). This is the way that solving such a problem should theoretically be carried out (e.g., Van Merriënboer & Kirschner, 2007). In contrast, teams who only had access to one of the representational tools represented more or less the same concepts and relationships and were, thus, less occupied with fine-tuning their representations to the part-task demands endemic to the different problem phases. This is, for example, in line with a

study by Greene (1989) which shows a strong relationship between the quality of constructed representation and task performance.

Second, as expected, all three studies show that either providing or constructing part-task congruent representations stimulates learners to carry out more *communicative activities* such as (1) externalizing one's knowledge and ideas, (2) creating and maintaining a shared understanding of these and (3) negotiating on their suitability. Carrying out those activities during collaborative problem-solving is positively related to the quality of the collaboration process and, thus, regarded as beneficial for teams' task performance (Barron, 2003; Erkens, Jaspers, Prangsma, & Kanselaar, 2006).

Finally, several unexpected results were obtained concerning *part-task related activities*. That is, the results of Study 1 and Study 2 show that either providing or constructing part-task congruent representations does not evoke more *cognitive* (e.g., discussing the goal of the problem-solving task) and *meta-cognitive activities* (e.g., monitoring whether the part-tasks are completed on time). In general, this lack of difference might be due to the role of scripting. Structuring the problem-solving process into three phases, each focusing on one of the part-tasks, could have affected the part-task related activities of teams in the same manner (Beers, Boshuizen, Kirschner, & Gijselaers, 2005; Dillenbourg, 2002). In line with the expectations, but contrary to the former two studies, the results of Study 3 show that constructing part-task congruent qualitative and quantitative representations does stimulate learners to carry out more cognitive and meta-cognitive activities. This might be accounted for by the design of the representational scripting that was employed in Study 3. The main reason underlying this change in design was that the conceptual tool hindered complex learning-task performance and did not seem appropriate for the problem-orientation task. Therefore, the task demands of this part-task (e.g., determine core concepts and relating them to the problem) were integrated with those of the problem-solution task (e.g., proposing multiple solutions to the problem) in one part-task which was called problem-solution. Integrating the part-tasks altered the design of the representational scripting, namely (1) part-task demands were formulated more openly, and (2) the 'new' problem phases were provided with a causal representational tool. So, decreasing the scripting of the problem-solving process and increasing the construction of causal qualitative representations in favor of conceptual representations of the domain perhaps evoked more cognitive and meta-cognitive activities.

As expected, providing part-task congruent representations did lead to more *discussions about the domain content* (e.g., concepts, principles and solutions). However, this result was not obtained when teams constructed part-task congruent representations (Study 2 and Study 3). A possible explanation for this finding might be that providing and constructing domain-specific representations have their own specific communicative benefits and pitfalls. Whereas provided representations need to be inspected and discussed, the content of constructed representations (1) is sometimes considered to be common knowledge that requires no explicit discussion or

(2) does not serve as a tool for generating new ideas (Munneke, Andriessen, Kanselaar, & Kirschner, 2007).

In conclusion, the three studies reported on in this thesis introduced an instructional approach - representational scripting - as a possible means of fostering complex learning. The obtained results strongly indicate that providing (i.e., passive representational scripting) and constructing (i.e., active representational scripting) part-task congruent representations guides a team's collaboration process and, thus, performance on a complex business-economics problem. To avoid turning complex learning into *another brick in the wall* (Pink Floyd, 1979), this thesis advocates proper guidance for learners (i.e., novices). To this end educators and instructional designers should develop instructional support that is aimed at:

- *acquiring a well-developed understanding of a domain*, instruction should gradually increase the complexity of the domain by introducing qualitative representations before quantitative ones and
- *applying one's understanding in a domain*, instruction should allow for working with domain-specific representations that are congruent with the tasks that need to be carried out.

5.2 General Discussion

Although this thesis provides ample empirical support for the design principles behind the representational scripting and its beneficial effects on complex learning, there still remain some unaddressed issues. This section, therefore, continues by addressing at least some of these issues.

5.2.1 Domain-specific and decision-making tools

This thesis focused on guiding complex learning by providing (Study 1) and constructing (Study 2 and Study 3) part-task congruent representations of the domain content. In this respect, different perspectives of the domain were visualized according to their specific concepts and specific ways of interrelating them (i.e., conceptual, causal or mathematical). Whereas the obtained results, and those of others, advocate the use of domain-specific guidance (Fischer *et al.*, 2002; Van Boxtel, Van der Linden, & Kanselaar, 2000) and representational tools to guide complex learning, this may not support all aspects of complex learning. As described in Chapter 1, the associated learning tasks are complex because they (1) cannot be described in full detail, (2) give no certainty about the best solution, and (3) require different perspectives on the problem and the problem-solving strategy for their solution (Jonassen, 2003; Spector, 2008; Van Merriënboer & Kirschner, 2007).

Since domain-specific support mainly addresses the third aspect, it might also prove beneficial to guide reasoning about the suitability of the solutions (i.e., second aspect). Supporting the decision-making process by visualizing the advantages, disadvantages and constraints of solutions might also foster complex problem-solving (Andriessen, Baker, & Suthers, 2003; Jeong & Joung, 2007; P.A. Kirschner, Buckingham Shum, & Carr, 2003). However, as is the case with other kinds of representational tools, mixed and even negative effects of using decision-making tools have also been reported (Buckingham Shum &

Hammond, 1994; Van Drie, Van Boxtel, & Kanselaar, 2005; Veerman, 2000). This might be accounted for by a lack of prior domain knowledge and/or argumentation skills (Munneke *et al.*, 2007). On the other hand, it might be due to a mismatch between the tools' ontology and the demands of the task (Buckingham Shum, 1996; Suthers, 2001). This is often accounted for by the differences in ontology between Issue Based Information Systems (IBIS, see Conklin & Begeman, 1988) and Decision Representation Language (DRL, see Lee & Lai, 1991) notations. *IBIS notations* facilitate learners to visualize issues (i.e., questions), positions (i.e., alternative answers), to which arguments (pro and con) may be attached. Such notations are not very specific or structured and thereby support easy exploring and listing of the different positions one might take. *DRL notations* are developed to facilitate qualitative decision making by visualizing the claims, rebuttals, counter claims, and constraints for the different positions. Such notations support relating the positions to each other, determining their suitability and coming to a definitive position.

Since the same kind of problem addressed in this thesis (i.e., matching tools' ontology to the task demands) is apparent here, it would be interesting to study whether IBIS-based tools support learners in carrying out the task demands of the problem-solution phase and if DRL-based tools are more suited to the task demands of the solution-evaluation phase. Another line of research might focus on how and why combining the use of domain-specific and decision-making tools in a part-task congruent manner fosters complex learning.

5.2.2 Methodology

The studies reported on in this thesis made use of the same complex learning task and examined the effects of the representational scripting with the same process- and product-oriented methodology. Although such an approach is advocated for studying collaborative learning (Dennen, 2008; De Wever, Van Keer, Schellens, & Valcke, 2007; Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010; Sweller, Kirschner, & Clark, 2007), the classroom experiences and the obtained results raise several methodological issues.

First, the issue of *ecological validity*. Conducting lengthy in-school studies takes advantage of a more ecologically valid research setting than the laboratory. The studies reported on in this thesis were integrated into the curriculum of participating schools and both post-test scores as well as the complex learning-task performance affected the GPA. Unfortunately this resulted in at least acceptable but still low reliability scores for both the pre-test and post-test. When tailoring the measurement of the learning gains to the specifics of the curriculum there were no suitable standardized measurement instruments available. These instruments, therefore, had to be developed in cooperation with the teachers which made them more ecologically valid for measuring the individual and team learning gains. Although this is how teachers usually work with and assess their learners, this approach could compromise both the reliability of the instruments and the generalization of the results. Since the studies were, in total, conducted in 18 different classes divided over four different schools this concern does not appear to be

substantial but it cannot be ruled out completely. Furthermore, teams did not find communicating through a chat tool supportive for their collaboration process; most learners tended to communicate verbally with their team members. Although the teachers explained that this was part of the task and was required to ensure a sound study, it was not always possible to prevent verbal communication between team members. Consequently not every action could be logged which, again, might compromise the generalization of the results. Since all learners appeared to share this tendency, it is assumed that there were no differences between the conditions in this respect. However, it might raise the question whether it is ecologically valid to embed CSCL-environments in classrooms (Elen & Clarebout, 2007). Future research might, for example, address this by permitting learners from different schools to collaborate with each other.

Second, *examining the effects of complex learning* in terms of acquired declarative knowledge of the domain could be questioned. As is the case with others (Dochy *et al.*, 2003; Mergendoller *et al.*, 2006), such learning gains were not obtained, except in Study 3. In favor of representational scripting it can be argued that the design employed in Study 3 is the most supportive type and may, thus, also foster individual learning. A more plausible explanation, however, might be that other forms of assessment are required to gain more insight into the possible learning gains of complex learning (Bigelow, 2004; Loyens & Gijbels, 2008; Rikers, Van Gog, & Paas, 2008). Future research might, therefore, take an interest in measuring deep understanding of the domain content, collaboration skills, problem-solving skills and the ability to apply the acquired knowledge and skills in other situations (i.e., transfer). More concretely, instead of administering a post-test aimed at measuring learners' recall (i.e., reproduction) of concepts, principles and procedures, new assessment forms measuring learners application (i.e., production) of the content of the domain should be developed. For example, another but related problem might be used to measure whether individual learners or teams of learners gained more domain knowledge or problem-solving skills. Again, the quality of the decisions and solutions could be evaluated and insight into the learning process could be measured by either observing or using stimulated recall interviews afterwards.

Finally, *measuring the quality of the learning process* by solely coding and counting the number of concepts and relationships discussed might not lead to a full understanding of the dynamics of collaborative learning (Bromme, Hesse, & Spada, 2005; Hmelo-Silver, Chernobilsky, & Jordan, 2008; Suthers, 2006). For example, it does not provide insight into (1) the evolution of understanding and the correctness of the content-related interaction and (2) how learners translate information from and coordinate information between their constructed representations. One approach to address this in problem-based learning is to determine how many errors learners make when interrelating the concepts to each other per problem phase. Insight into the quality can be gained by comparing the number and kinds of errors learners make in each phase.

Another approach may be to focus more on the quality of the knowledge-construction process by determining and comparing the exhibited learning activities at the individual and group level (Gunawardena, Lowe, & Anderson, 1997; Schellens & Valcke, 2005). Examples of these often cyclic and phase-related activities are:

Phase 1: sharing and comparing
- Cognitive activities: observing, defining, clarifying,

Phase 2: determining inconsistencies
- Cognitive activities: identifying, stating, asking, restating,

Phase 3: negotiating what is to be agreed
- Cognitive activities: proposing new co-constructions that encompass the negotiated resolution of the differences,

Phase 4: testing tentative constructions
- Cognitive activities: testing and matching constructions to personal understanding and external resources,

Phase 5: statement/application of newly constructed knowledge
- Cognitive activities: revising and sharing of the new ideas that have been constructed.

5.2.3 Generalization of the representational scripting

Since beneficial effects of the representational scripting were obtained in all three studies, educators and instructional designers might want to employ this instructional approach in their educational practices. This section, therefore, addresses several issues concerning the generalization of the representational scripting.

Domain and task specificity

The conducted studies all took place in the field of business-economics. Although many domains (e.g., meteorology, physics, urban planning, science) require multiple problem representations, the effects of a particular design depend on the characteristics of the learning task and the involved knowledge domains (De Vries, 2003; Elen & Clarebout, 2007; Veerman, 2000). When designing tools and/or learning environments, one should take this carefully into account. The effect of the design of the representational scripting does not automatically apply to all complex learning tasks and knowledge domains. To address this, educators and instructional designers should gain insight into the specifics of the learning tasks by conducting a learning-task analysis (Anderson & Krathwohl, 2001; Gagné, Briggs, & Wagner, 1992). If analysis reveals that the entire task needs to be sequenced in part-tasks, their required domain-specific perspectives need to be determined. Based on these insights, the sequence and the demands of the part-tasks can specified and part-task congruent (representational) tools can be developed.

Visualizing and discussing

Though the design of representational scripting is intended to foster learners' cognitive behavior, the effects on individual and team learning were studied in a collaborative setting. This might not seem problematic since both

providing (i.e., passive representational scripting) and constructing (i.e., active representational scripting) part-task congruent representations guided complex learning-task performance. However, this strategy makes it hard to determine which aspect actually caused the beneficial effect: providing or constructing part-task congruent representations and/or discussing them? Thus, from this thesis it may be concluded only that *visualizing the domain in a part-task congruent manner and discussing those representations* can foster complex learning. Since other studies have shown that individual learner-task performance can also be guided by providing representations or letting them construct their own (Larkin & Simon, 1987; Vekiri, 2002; Zhang, 1997), it might be that representational scripting can also be beneficially applied in this setting. Future research might address this by examining if representational scripting also guides individual learners when carrying out complex learning tasks. In addition, the effect of first inspecting or constructing a part-task congruent representation on their own and thereafter discussing their findings with their team members might stimulate individual and team cognitive processes even more.

In the same line of reasoning, it could also be argued that inspecting or constructing a part-task congruent representation might be more beneficial for carrying out the task demands of a specific problem phase. Based on the comparison of the results of Study 1 and Study 2, it could be argued that inspecting a representation is more suited to the problem-orientation task since it evoked more content-related discussions. This might support learners in orienting themselves to the problem by determining the core concepts and relating them to the problem. Constructing, in contrast, forces learners to be more specific (i.e., use certain concepts, relationships and interventions) which could support them in formulating multiple solutions to the problem. Carrying out such a task-demand may be hindered by inspecting a representation since all concepts are already related to each other and to possible interventions.

Development of expertise

The premise behind representational scripting is that learners' understanding is gradually refined which enables them to grasp the complex learning task and carry it out efficiently and effectively. To this end, the support is aimed at gradually increasing learners' level of expertise so that they are supported in acquiring and applying a well-developed understanding of the domain in question (see also Frederiksen & White, 2002; Quintana, Reiser, Davis, Krajcik, Fretz *et al.*, 2004; Van Merriënboer & Kirschner, 2007). Representational scripting tries to achieve this by providing or constructing different perspectives of the domain in a part-task congruent manner. In doing so, the development of expertise is seen as gradually increasing the complexity of the interrelationships between the concepts of the domain. This view on expertise is often referred to as model order progression (Frederiksen & White, 2002). This, however, is not the only view on the development of expertise. Frederiksen & White also mention model elaboration progression which emphasizes the gradual introduction of more concepts and their (different kinds) interrelationships. In contrast to order progression, all concepts are not

introduced at the same time and there is a less strict distinction between qualitative and quantitative since these are often combined in the same perspective of the domain. The effects on learning are, however, often disappointing (Swaak, Van Joolingen, & De Jong, 1998). Since model order progression and model elaboration progression have not often been compared to each other, it is unclear which approach is more beneficial for learning. Mulder, Lazonder, & De Jong (submitted) have made this comparison in the domain of science. Their results show that model order progression is more in line with the supportive needs of learners than model elaboration progression. However, since this study was conducted in the domain of science, it does not automatically apply to all other domains. A future line of research could be to study whether the obtained difference can also be found in other domains. A related point is the question of when learners are ready to progress to another model, whether this be one with a different perspective (i.e. qualitative or quantitative) or one with new concepts and their interrelationships. In representational scripting this is based on the task demands of a following problem phase but this does not necessarily mean that learners fully understand the model from the prior phase and are capable of grasping the new model. Future research on model progression might examine under which conditions learners should or should not gain access to a different model of the domain (Mulder *et al.*).

Course and curricular level

Guiding complex learning through representational scripting in a business-economics course may be beneficial, but is this also the case when representational scripting is employed in the whole curriculum? In other words, how much should learners' cognitive behavior be structured and when should this be more problematized (see Reiser, 2004)? There seems to be a delicate balance between the two since learners (i.e., novices) encounter difficulties when carrying out complex tasks without guidance when on a curricular level they should be able to perform such tasks on their own. Perhaps educators and instructional designers can address this by gradually diminishing the amount of instructional support (*fading*; Kollar, Fischer, & Slotta, 2007). With regard to representational scripting, this might be achieved by letting learners carry out multiple but comparable tasks and decreasing the amount of guidance step-by-step. It would be interesting to study which aspect of representational scripting should be decreased first, sequencing the part-task and their task demands or part-task congruent support?

In sum, employing representational scripting in a collaborative setting in the domain of business-economics seems to foster complex learning. There are, however, multiple reasons to assume that this does not automatically apply to other domains, learning tasks and settings. Future research aimed at examining the generalization of the representational scripting should, therefore, address the issues raised in this chapter.

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Nederlandse Samenvatting (Dutch Summary)

Introductie

Het kunnen oplossen van complexe problemen wordt vanwege snel veranderende werk- en maatschappelijke omstandigheden gezien als een belangrijke vaardigheid (Hmelo-Silver, Duncan & Chinn, 2007; Van Merriënboer & Kirschner, 2007). Scholen en bedrijven implementeren daarom steeds vaker onderwijsvormen zoals gezamenlijk probleemoplossen in hun curricula en trainingsprogramma's. Alhoewel de educatieve voordelen door vele onderwijzers en educatieve ontwerpers erkend worden, zien zij ook in dat leerlingen ondersteuning nodig hebben bij het uitvoeren van dit soort complexe leertaken (P.A. Kirschner, Sweller, & Clark, 2006; Mayer, 2004; Reiser, 2004). Een veel genoemde reden hiervoor is dat leerlingen vaak niet over voldoende domeinkennis beschikken om deze problemen op een effectieve en efficiënte wijze op te lossen. Mogelijkerwijs kunnen leerlingen hierin ondersteund worden door op gefaseerde wijze verschillende perspectieven op het domein (kwalitatieve en kwantitatieve) te verwerven en toe te passen bij het probleemoplossen (Dufresne, Gerace, Thibodeau-Hardiman, & Mestre, 1992; Frederiksen & White, 2002; Kozma, 2003). Om dit te realiseren wordt vaak gepleit voor het gebruik van visualisatie tools binnen samenwerkingssituaties, zoals bijvoorbeeld computer ondersteund samenwerkend leren. Dit soort tools maakt het mogelijk om de inhoud van het domein te visualiseren - aanbieden of construeren van representaties - en hierover te discussiëren met anderen. Het uitvoeren van deze activiteiten wordt verondersteld het probleemoplossingproces van leerlingen te ondersteunen (Fischer, Bruhn, Gräsel, & Mandl, 2002; Suthers, 2006). Het *aanbieden van representaties* kan het cognitieve gedrag, en dus leertaak prestatie, van leerlingen beïnvloeden omdat relevante informatie en handelingsregels direct afgelezen en toegepast kunnen worden bij het uitvoeren van een leertaak (Larkin & Simon, 1987; Stull & Mayer, 2007; Zhang, 1997). Wanneer leerlingen, echter, de aangeboden informatie en regels oppervlakkig verwerken - niet integreren met hun huidige begrip van het domein - dan kan dit het uitvoeren van de leertaak juist belemmeren (Hilbert & Renkl, 2008; Lee & Nelson, 2005). Door leerlingen zelf *representaties te laten construeren* wordt verwacht dat zij de informatie en regels actiever verwerken en hierdoor beter relateren aan en integreren met hun huidige begrip van het domein (Stern, Aprea, & Ebner, 2003; Van Meter & Garner, 2005). Toch blijkt ook dat leerlingen vaak moeite hebben met het construeren van representaties en dat dit dus niet altijd tot positieve leereffecten leidt (Reader & Hammond, 1994; Scheiter, Gerjets, & Catrambone, 2006). Zo weten leerlingen vaak niet hoe ze een representatie moeten maken en/of hoe deze samenhangt met de leertaak. Een andere reden hiervoor kan zijn dat het in gedachten houden van de (1) leertaak, (2) benodigde domeinkennis en (3) wijze waarop een representatie gemaakt dient te worden, cognitief erg belastend kan zijn. Wanneer deze belasting te groot wordt, dan is het waarschijnlijk dat leerlingen geen baat hebben bij het construeren van representaties (Leutner, Leopold, & Sumfleth, 2009; Zhang, 1997).

Een ander belangrijk aspect waar rekening mee dient te worden gehouden bij het ontwerpen en gebruiken van visualisatie tools is dat deze het domein op een specifieke wijze representeren en daarom niet geschikt zijn voor het uitvoeren van alle (leer-)taken (Ainsworth, 2006; Cox, 1999; Schnotz & Kürschner, 2008). Dit is vooral problematisch voor het oplossen van complexe problemen omdat deze vaak uit meerdere deeltaken - probleemoriëntatie, probleemoplossing en oplossingevaluatie - bestaan en deze ieder hun eigen taakvereisten hebben (Duffy, Dueber, & Hawley, 1998; Van Bruggen, Boshuizen, & Kirschner, 2003). Het oplossen van complexe problemen vereist hierdoor meerdere perspectieven op het domein en daarom het gebruik van verschillende visualisatie tools (Ainsworth, 2006; Van Bruggen *et al.*, 2003).

Centrale Vraagstelling

Het centrale thema van dit proefschrift is of het visualiseren van het domein op een deeltaakspecifieke wijze leerlingen kan ondersteunen bij het oplossen van een complex probleem. Daarom zijn twee verschillende typen van een educatief ontwerp - scripting middels representaties - ontwikkeld, namelijk het (1) aanbieden en (2) construeren van deeltaakspecifieke representaties en hun effecten onderzocht. De centrale vraagstelling luidt daarom als volgt:

Hoe en waarom beïnvloedt het visualiseren van de inhoud van het domein op deeltaakspecifieke wijze het samenwerkingsproces en de complexe leertaak prestatie van teams en het individuele leerresultaat?

De volgende onderzoeksvragen zijn afgeleid uit de centrale vraagstelling:

1. Wat zijn de effecten van het *aanbieden* van deeltaakspecifieke representaties op het samenwerkingsproces, de complexe leertaak prestatie en het individuele leerresultaat?
2. Wat zijn de effecten van het *construeren* van deeltaakspecifieke representaties op het samenwerkingsproces, de complexe leertaak prestatie en het individuele leerresultaat?
3. Wat zijn de effecten van het construeren van kwalitatieve en kwantitatieve domeinspecifieke representaties op het samenwerkingsproces, de complexe leertaak prestatie en het individuele leerresultaat?

De uitgevoerde studies waren ieder gericht op het beantwoorden van één van de bovenstaande onderzoeksvragen. Studie 1 (Hoofdstuk 2) richtte zich op het onderzoeken van de effecten van het aanbieden van deeltaakspecifieke ondersteuning. Studie 2 (Hoofdstuk 3) betrof het onderzoeken van de effecten van het construeren van deeltaakspecifieke ondersteuning. Studie 3 (Hoofdstuk 4) verlegde de focus naar het onderzoeken van de effecten op het construeren van kwalitatieve en kwantitatieve domeinspecifieke representaties.

In alle studies werd gewerkt met 15 tot 18-jarige participanten van verschillende Management en Organisatie klassen uit het voortgezet onderwijs. In elke studie werden de participanten, binnen klassen, at random, toegewezen aan teams (triades, zie Laughlin, Carey, & Kerr, 2008; Schellens & Valcke, 2005). De teams kregen de opdracht om een complex bedrijfseconomisch

probleem op te lossen en werkten hierbij in een digitale leeromgeving genaamd Virtual Collaborative Research Institute (VCRI zie Hoofdstukken 2-4). Data betreffende *leerresultaten* (i.e., leertaak prestatie en individuele leerresultaten) en het *leerproces* (i.e., geconstrueerde representaties - Studie 2 en Studie 3 - en de kwaliteit van de leerling-interactie) werden verzameld, gecodeerd en geanalyseerd.

Hieronder volgt een samenvatting van de verschillende studies, waarna een algemene discussie van de resultaten, de beperkingen en mogelijkheden voor toekomstig onderzoek beschreven worden.

Studie 1: Aanbieden van deeltaakspecifieke representaties

Studie 1 (Hoofdstuk 2) richtte zich op het onderzoeken van de effecten van het aanbieden van deeltaakspecifieke representaties. De ondersteuning structureerde de probleemoplossingtaak in drie deeltaken, namelijk (1) probleemoriëntatie, (2) probleemoplossing en (3) oplossingevaluatie. Daarnaast werd iedere deeltaak voorzien van een domeinspecifieke representatie (i.e., conceptueel, causaal of mathematisch) welke ieder geschikt was voor het uitvoeren van een specifieke deeltaak. De verwachting was dat de deeltaakspecifieke ondersteuning de leerling-interactie en zodoende het probleemoplossingproces op een gunstige wijze zou gaan beïnvloeden. Om dit te onderzoeken werden 96 leerlingen van 6 Management en Organisatie klassen, binnen klassen, at random, toegewezen aan in totaal 32 teams. Alle teams werden gelijkmatig over vier experimentele condities verdeeld en voerden de opeenvolgende deeltaken uit, maar verschilden in de representatie(s) die zij ontvingen. In de drie *mismatched* condities ontvingen de teams slechts één van de representaties voor alle deeltaken en werden dus alleen ondersteund in het uitvoeren van één van de deeltaken. In de *matched* conditie ontvingen de teams alle representaties op een gefaseerde wijze; voor iedere deeltaak een deeltaakcongruente representatie. De resultaten tonen aan dat teams in de matched conditie meer deeltaakspecifieke interactie (i.e., concepten, oplossingen en relaties) hadden en beter in staat waren om hun probleemoplossingproces te coördineren. Deze verschillen in het leerproces kunnen wellicht verklaren dat teams in de matched conditie meer succesvol waren in het oplossen van het gestelde probleem. In tegenstelling tot de verwachtingen, voerden de teams in de matched conditie niet meer meta-cognitieve activiteiten uit (b.v., discussiëren over de oplossingstrategie) dan teams in de mismatched condities. Ook waren er nagenoeg geen verschillen wat betreft leerling-interactie en de kwaliteit van de probleemoplossing tussen teams in de matched conditie en teams die enkel een causale representatie ontvingen. Ten slotte, verschilden de voor- en natoets scores van de leerlingen niet significant van elkaar en zijn er dus geen individuele leerresultaten gevonden.

De resultaten van de eerste studie geven aan dat *het aanbieden van deeltaakspecifieke representaties leerlingen kan ondersteunen bij het gezamenlijk oplossen van een complex bedrijfseconomisch probleem*. Toch roepen de resultaten ook vragen op als:

- Is probleemoplossend leren wel een geschikte onderwijsvorm voor het verwerven van declaratieve kennis?
- Kan het (over-)scripten van het leerproces leerlingen beperken in het ontwikkelen van meta-cognitieve vaardigheden welke in verschillende situaties toegepast kunnen worden?

Studie 2: Constructie van deeltaakspecifieke representaties

Studie 2 (Hoofdstuk 3) richtte zich op het onderzoeken van de effecten van het construeren van deeltaakspecifieke representaties. De ondersteuning structureerde de probleemoplossingtaak in drie deeltaken, namelijk (1) probleemoriëntatie, (2) probleemoplossing en (3) oplossingevaluatie. Daarnaast stelden de aangeboden visualisatie tools de leerlingen in staat om domeinspecifieke representaties (i.e., conceptueel, causaal of mathematisch) te construeren welke ieder geschikt waren voor het uitvoeren van een specifieke deeltaak. De verwachting was dat de deeltaakspecifieke ondersteuning de leerling-interactie en zodoende het probleemoplossingproces op een gunstige wijze zou gaan beïnvloeden. Om dit te onderzoeken werden 93 leerlingen van 6 Management en Organisatie klassen, binnen klassen, at random, toegewezen aan in totaal 31 teams. Alle teams voerden de opeenvolgende deeltaken uit, maar verschilden in de visualisatie tool(s) die zij dienden te gebruiken. In de drie *mismatched* condities (n = 8 per conditie) ontvingen de teams één van de visualisatie tools voor alle deeltaken en werden dus alleen ondersteund in het uitvoeren van een specifieke deeltaak. In de *matched* conditie (n = 7) ontvingen de leerlingen alle visualisatie tools op een gefaseerde wijze; voor iedere deeltaak konden zij een domeinspecifieke representatie construeren. De resultaten tonen aan dat teams in de matched conditie tot een kwalitatief betere probleemoplossing kwamen dan teams die enkel een conceptuele of een simulatie visualisatie tool kregen voor alle deeltaken. Wellicht kan dit verklaard worden door de verschillen in het leerproces. Ten eerste, construeerden teams in de matched conditie meer deeltaakspecifieke representaties. Ten tweede, waren zij beter in staat om hun probleemoplossingproces te coördineren. In tegenstelling tot de verwachtingen, bleek dat teams die enkel causale representaties construeerden ongeveer gelijke resultaten behaalden als teams in de matched conditie. Verder waren er ook geen significante verschillen tussen de condities wat betreft de uitgevoerde cognitieve (b.v., discussiëren over het doel van de leertaak) en meta-cognitieve activiteiten (b.v., monitoren of de taken op tijd zijn afgerond). Ten slotte, zijn er geen individuele leerresultaten gevonden.

De resultaten van de tweede studie geven aan dat *het construeren van deeltaakspecifieke representaties leerlingen kan ondersteunen bij het gezamenlijk oplossen van een complex bedrijfseconomisch probleem.* Alhoewel dit veel belovend lijkt, roept het toch ook enkele vragen op:

- Is het voor het oplossen van complexe problemen nodig om kwalitatieve en kwantitatieve representaties van het domein te combineren?
- Is probleemoplossend leren wel een geschikte onderwijsvorm voor het verwerven van declaratieve kennis?

Studie 3: Kwalitatieve en kwantitatieve representaties

Studie 3 (Hoofdstuk 4) richtte zich op het onderzoeken van de effecten van het construeren van kwalitatieve en kwantitatieve domeinspecifieke representaties. Om teams te ondersteunen in het combineren en het aan elkaar relateren van beide soorten representaties werd het construeren van deeltaakspecifieke representaties toepast. De ondersteuning structureerde de probleemoplossingtaak in twee deeltaken, namelijk (1) probleemoplossing en (2) oplossingevaluatie. Daarnaast stelden de aangeboden visualisatie tools de leerlingen in staat om domeinspecifieke representaties (i.e., causaal of mathematisch) te construeren welke ieder geschikt waren voor het uitvoeren van een specifieke deeltaak. De verwachting was dat de constructie van kwalitatieve en kwantitatieve representaties de leerling-interactie en zodoende het probleemoplossingproces op een gunstige wijze zou gaan beïnvloeden. Om dit te onderzoeken werden 102 leerlingen van 6 Management en Organisatie klassen, binnen klassen, at random, toegewezen aan in totaal 34 teams. Alle teams voerden de opeenvolgende deeltaken uit, maar verschilden in de visualisatie tool(s) die zij dienden te gebruiken. Teams in de *gedeeltelijk matched* condities (enkel causal, n = 9; enkel simulatie, n = 9) ontvingen een causale of een simulatie visualisatie tool respectievelijk voor het uitvoeren van beide deeltaken. Teams in de *matched* (causaal-simulatie, n = 7) en de *mismatched* (simulatie-causaal, n = 9) condities ontvingen beide tools op een gefaseerde wijze. In tegenstelling tot teams in de simulatie-causaal conditie, ontvingen teams in de causaal-simulatie conditie visualisatie tools welke geschikt worden geacht voor het uitvoeren van beide deeltaken (causale tool voor probleemoplossing en simulatie tool voor oplossingevaluatie). De resultaten tonen aan dat teams in de matched conditie inderdaad meer deeltaakspecifieke representaties construeerden en kwalitatief betere discussies over het domein hadden. Dat wil zeggen, deze teams voerden meer cognitieve (b.v., discussiëren over het doel van de leertaak) en meta-cognitieve activiteiten (b.v., monitoren of de taken op tijd zijn afgerond) uit dan de teams in de andere condities. Daarnaast waren teams in de matched conditie ook beter in staat om hun probleemoplossingproces te coördineren. Deze verschillen in leerproces kunnen mogelijkerwijs verklaren dat deze teams tot een kwalitatief betere oplossing voor het gestelde probleem kwamen. Er werden geen significante verschillen gevonden tussen teams in de gedeeltelijk matched en teams in de mismatched condities. Alhoewel er individuele leerresultaten voor alle leerlingen werden gevonden, waren er geen verschillen tussen de condities.

De resultaten van de derde studie geven aan dat *het construeren van kwalitatieve en kwantitatieve representaties leerlingen kan ondersteunen bij het gezamenlijk oplossen van een complex bedrijfseconomisch probleem*. Deze resultaten verklaren echter nog niet hoe en op wat voor wijze:

- Het construeren van kwalitatieve en kwantitatieve representaties bijdraagt aan de begripsontwikkeling en de kwaliteit (i.e., correctheid) van de leerling-interactie.
- Teams informatie van verschillende representaties gebruiken en de representaties met elkaar combineren.

Synthese

Waar iedere studie inzicht geeft in hoe en waarom het scripten van domeinspecifieke representaties het uitvoeren van complexe leertaken kan ondersteunen, richt deze sectie zich op het integreren van de verschillende resultaten. Het algemene beeld van de uitkomsten van deze thesis ontstaat door het geleidelijk aan beantwoorden van de centrale vraagstelling, welke als volgt was geformuleerd:

> *Hoe en waarom beïnvloedt het visualiseren van de inhoud van het domein op deeltaakspecifieke wijze het samenwerkingsproces en de complexe leertaak prestatie van teams en het individuele leerresultaat?*

Het eerste deel van de centrale vraagstelling richt zich op de vraag *hoe* het visualiseren van de inhoud van het domein op deeltaakspecifieke wijze complex leren beïnvloedt. Het scripten van domeinspecifieke representaties bleek, zoals verwacht, *teams van lerenden te ondersteunen bij het uitvoeren van hun complexe leertaak*. Dat wil zeggen, deze teams formuleerden betere beslissingen voor de verschillende deeltaken en kwamen met betere eindoplossingen voor het gestelde probleem. Deze resultaten werden gevonden voor zowel het aanbieden (Studie 1) als het construeren (Studie 2) van deeltaakspecifieke representaties. Alhoewel beide typen niet direct met elkaar vergeleken zijn (b.v., niet dezelfde klas en verschillende in leertijd) en er dus geen specifieke verwachtingen waren, valt het op dat ongeveer gelijke team leerresultaten zijn behaald. Mogelijkerwijs leidt het aanbieden van geschikte representaties voor iedere deeltaak tot dezelfde uitkomsten dan het construeren van zo'n representatie (Scheiter, Gerjets, & Catrambone, 2006). Een andere verklaring zou kunnen zijn dat het scripten van domeinspecifieke representaties toegepast is binnen een digitale leeromgeving die samenwerkend leren ondersteunt. Aangezien binnen dit soort leeromgevingen de nadruk ligt op dialogen en discussies tussen de lerenden, is het mogelijk dat zowel het aanbieden als het construeren van de representaties hetzelfde effect op de interactie hebben (De Simone, Schmid, & McEwen, 2001).

In tegenstelling tot de verwachtingen zijn er ongeveer gelijke resultaten gevonden voor teams die enkel causale representaties ontvingen of konden construeren voor alle deeltaken. Dit resultaat benadrukt, aan de ene kant, het belang van causaal redeneren over de inhoud van het domein voor het uitvoeren van complexe leertaken (Jonssen & Ionas, 2008; McCrudden, Schraw, Lehman, & Poliquin, 2007). Aan de andere kant roept het ook de vraag op of het werken met meerdere representaties van het domein vereist is voor het succesvol kunnen uitvoeren van complexe leertaken (Ainsworth, 2006; Bodemer & Faust, 2006). In Studie 3 is daarom onderzocht of het combineren van kwalitatieve en kwantitatieve representaties van het domein effectiever is voor complex leren. De resultaten tonen aan dat het construeren van meerdere representaties op een deeltaakspecifieke wijze het uitvoeren van complexe leertaken beter ondersteunt dan wanneer met een enkele representatie of met meerdere representaties op een deeltaak incongruente wijze wordt gewerkt. Dit sluit aan bij eerder onderzoek waaruit blijkt dat het werken met kwalitatieve en

kwantitatieve representaties een goede manier kan zijn om het uitvoeren van complexe leertaken te ondersteunen (T. de Jong, Ainsworth, Dobson, Van der Hulst, Levonen *et al.*, 1998; Frederiksen & White, 2002; Jonassen, 2003).

Verder zijn er geen verschillen gevonden wat betreft de *individuele leerresultaten* (vergelijking van de score op de voortoets en de natoets) voor zowel het aanbieden als het construeren van deeltaakspecifieke representaties. Dit komt overeen met de bevindingen van anderen die onderzoek hebben gedaan naar de leereffecten van probleemoplossend leren (Dochy, Segers, Van den Bosche, & Gijbels, 2003; Mergendoller, Maxwell, & Bellisimo, 2006) en kan wellicht verklaard worden door de aard van de complexe leertaak. Een educatieve methode als probleemoplossend leren bestaat vaak uit verschillende deeltaken die vereisen dat leerlingen hun begrip van het domein toepassen om zodoende het probleem te analyseren, mogelijke oplossingen te bedenken en de geschiktheid hiervan evalueren. Dit kan deze methode minder geschikt maken voor het verwerven van meer domeinkennis aangezien het oproepen en begrijpen van concepten, principes en procedures vaak gezien wordt als een voorwaarde voor het toepassen er van (P.A. Kirschner *et al.*, 2006). Toch laten de resultaten van Studie 3 zien dat het gezamenlijk oplossen van een complex probleem tot individuele leerresultaten kan leiden. Aangezien er geen verschillen tussen de condities zijn gevonden, kan dit waarschijnlijk niet door het verschil in het educatieve ontwerp - scripting middels representaties - verklaard worden. Wellicht dat deze verschillen veroorzaakt zijn door het design van Studie 3. De teams die deelnamen aan Studie 3 voerden twee deeltaken uit in plaats van drie (Studie 1 en Studie 2), hetgeen sowieso één belangrijke consequentie had; de teams werkten met een causale kwalitatieve en/of een kwantitatieve representatie van het domein en niet meer met een conceptuele - meer abstracte - representatie. Aangezien conceptuele representaties soms lastiger te begrijpen en toe te passen zijn dan causale kwalitatieve en kwantitatieve representaties (Fredriksen, White, & Gutwill, 1999), zou dit kunnen verklaren dat er in Studie 3 wel individuele leerresultaten gevonden zijn. Dit stemt overeen met de bevinding dat de teams die enkel een conceptuele representatie ontvingen (Studie 1) of construeerden (Studie 2) de laagste scores ontvingen voor hun complexe leertaak prestatie.

Het tweede deel van de centrale vraagstelling richt zich op de vraag *waarom* het visualiseren van de inhoud van het domein op deeltaakspecifieke wijze complex leren beïnvloedt. Aangezien de studies plaatsvonden in een collaboratieve setting werden de aard en de kwaliteit van het samenwerkingsproces bestudeerd. De resultaten tonen aan dat het scripten van domeinspecifieke representaties het samenwerkingsproces op verschillende wijzen beïnvloedt.

Ten eerste, tonen de resultaten van Studie 2 en Studie 3, zoals verwacht, aan dat het *gebruik van deeltaakspecifieke visualisatie tools teams ondersteunt in het construeren van representaties die het uitvoeren van de complexe leertaak ondersteunen*. Dat wil zeggen, deze teams begonnen met het construeren van een globale representatie en werden gaandeweg meer selectief in het representeren van de concepten en het specificeren van de relaties (causaal of

mathematisch). Dit is de wijze waarop een probleem theoretisch gezien opgelost zou moeten worden (e.g., Van Merriënboer & Kirschner, 2007). Teams die slechts één van de tools konden gebruiken, representeerden min of meer dezelfde concepten en relaties en waren dus minder bezig met het afstemmen van hun representaties op de vereisten van de verschillende deeltaken. Dit stemt overeen met de resultaten van, bijvoorbeeld, Greene (1989) waaruit blijkt dat er een sterke positieve relatie is tussen de kwaliteit van de geconstrueerde representatie en de leertaak prestatie.

Ten tweede, tonen alle drie studies, zoals verwacht, aan dat het aanbieden en construeren van deeltaakspecifieke representaties lerenden ondersteunt in het coördineren van hun samenwerkingsproces. Het uitvoeren van deze zogenaamde *communicatieve activiteiten* zoals het (1) expliciteren van kennis en ideeën, (2) creëren en onderhouden van een gezamenlijk begrip hiervan en (3) discussiëren over de geschiktheid van dit begrip voor het uitvoeren van de taak bevordert de kwaliteit van het samenwerkingsproces en, dus, de leertaak prestatie (Barron, 2003; Erkens, Jaspers, Prangsma, & Kanselaar, 2005).

Ten slotte, zijn er enkele onverwachte resultaten gevonden voor de deeltaak gerelateerde activiteiten. Zo tonen Studie 1 en Studie 2 aan dat zowel het aanbieden als het construeren van deeltaakspecifieke representaties geen effect hebben op de uitgevoerde *cognitieve* (b.v., discussiëren over het doel van de leertaak) en *meta-cognitieve activiteiten* (b.v., monitoren of de deeltaken op tijd zijn afgerond). Een mogelijke verklaring hiervoor zou kunnen zijn dat het scripten van het probleemoplossingproces in deeltaken, met ieder hun eigen taakvereisten, de deeltaakgerelateerde activiteiten van alle teams op dezelfde wijze beïnvloedt (Beers, Boshuizen, Kirschner, & Gijselaers, 2005; Dillenbourg, 2002). In overeenstemming, maar tegenstrijdig met de resultaten van Studie 1 en Studie 2, tonen de resultaten van Studie 3 aan dat het construeren van deeltaakspecifieke kwalitatieve en kwantitatieve representaties wel tot meer cognitieve en meta-cognitieve activiteiten leidt. Zoals hierboven reeds beschreven kan het verschil in design tussen de studies dit mogelijkerwijs verklaren. Toch zijn hier, echter, wel verschillen tussen condities gevonden en kan wellicht het verschil in het educatieve ontwerp ook een verklaring voor de gevonden verschillen zijn. In Studie 3 voerden de teams twee deeltaken uit in plaats van drie deeltaken. Hiervoor werden de taakvereisten van de probleemoriëntatie fase (i.e., vaststellen van belangrijke concepten en deze relateren aan het probleem) geïntegreerd met die van de probleemoplossing fase (i.e., bedenken van meerdere oplossingen) in een 'nieuwe' deeltaak genaamd probleemoplossing. De belangrijkste reden hiervoor was dat de conceptuele visualisatie tool teams belemmerde bij het uitvoeren van hun complexe leertaak en ook niet geschikt lijkt voor het uitvoeren van de probleemoriëntatie taak. Het integreren van de beide deeltaken veranderde het educatieve ontwerp op twee manieren, (1) de deeltaken werden op een meer open wijze geformuleerd en (2) de 'nieuwe' deeltaak werd gekoppeld aan de causale visualisatie tool. Wellicht dat het afnemen van het scripten en het toenemen van het construeren van causale representaties van het domein in plaats van conceptuele representaties meer cognitieve en meta-cognitieve activiteiten ontlokt.

Verder tonen de resultaten van Studie 1 aan dat het aanbieden van deeltaakspecifieke representaties, zoals verwacht, tot *meer discussies over het domein (concepten, principes en oplossingen)* leidt. Deze verschillen werden echter niet gevonden wanneer de teams deeltaakspecifieke representaties construeerden (Studie 2 en Studie 3). Een mogelijke verklaring hiervoor kan zijn dat het aanbieden en construeren ieder zijn eigen specifieke voordelen en valkuilen voor de discussie van het domein heeft. Waar de aangeboden representaties geïnspecteerd en bediscussieerd dienen te worden, wordt de inhoud van de geconstrueerde representaties (1) soms beschouwd als gedeelde kennis die geen discussie behoeft en (2) niet als middel gezien wordt voor het genereren van nieuwe ideeën (Munneke, Andriessen, Kanselaar, & Kirschner, 2007).

Concluderend, de drie studies waarover gerapporteerd zijn in dit proefschrift, introduceren een educatief ontwerp - scripting middels representaties - als een mogelijke ondersteuning bij het uitvoeren van complexe leertaken. De gevonden resultaten ondersteunen de assumptie dat zowel het aanbieden als het construeren van deeltaakspecifieke representaties het gezamenlijk oplossen van een complex bedrijfseconomisch probleem kan ondersteunen. Om te voorkomen dat het uitvoeren van complexe leertaken als *another brick in the wall* (Pink Floyd, 1979) gezien wordt, wordt er in dit proefschrift voor gepleit dat lerenden (i.e., beginners) hierbij voldoende ondersteund worden. Onderwijzers en educatieve ontwerpers zouden daarom vormen van ondersteuning dienen te ontwerpen die gericht zijn op het:

- Ontwikkelen van een goed ontwikkeld begrip van het domein, de ondersteuning zou geleidelijk aan de complexiteit dienen te verhogen door kwalitatieve representaties voor kwantitatieve representaties te introduceren.
- Toepassen van dit begrip van het domein, de ondersteuning zou hiervoor gericht dienen te zijn op het werken met deeltaakspecifieke representaties.

Algemene Discussie

In dit proefschrift zijn op empirische wijze verkregen resultaten gevonden welke aantonen dat het educatieve ontwerp lerenden kan ondersteunen in het gezamenlijk oplossen van complexe bedrijfseconomische problemen. Waar dit interessant kan zijn voor de wetenschap en de onderwijspraktijk, blijven er toch een aantal zaken onderbelicht. Deze sectie sluit daarom af met het bespreken van, in ieder geval, een aantal van deze zaken.

Domeinspecifieke en argumentatieve tools

Dit proefschrift richt zich op het ondersteunen van complexe leertaken, zoals bijvoorbeeld het oplossen van complexe problemen, door het aanbieden (Studie 1) of construeren (Studie 2 en Studie 3) van deeltaakspecifieke representaties van het domein. Om dit te realiseren is per deeltaak een congruent perspectief op het domein gevisualiseerd door de onderhavige concepten op respectievelijk een conceptuele, causale of mathematische wijze aan elkaar te relateren. Waar de resultaten en die van andere onderzoeken

(Fischer *et al.*, 2002; Van Boxtel, Van der Linden, & Kanselaar, 2000) aantonen dat het gebruik van domeinspecifieke tools het uitvoeren van complexe leertaken kunnen ondersteunen, hoeft dit niet voor ieder aspect van de taak te gelden. Zoals beschreven in Hoofdstuk 1, zijn dit soort taken complex omdat ze (1) niet tot in detail omschreven kunnen worden, (2) er geen garantie voor de meest geschikte oplossing is en (3) meerdere perspectieven op het domein en de oplossingstrategie vereist zijn (Jonassen, 2003; Spector, 2008; Van Merriënboer & Kirschner, 2007).

Aangezien domeinspecifieke tools zich voornamelijk richten op het ondersteunen van het derde aspect, zou het wellicht effectief kunnen zijn om ondersteuning te bieden voor het komen tot een geschikte definitieve oplossing (i.e., tweede aspect). Het visualiseren van de voordelen, de nadelen en de criteria die aan bepaalde oplossingen verbonden zijn, kan het beslissingsproces en zodoende het uitvoeren van complexe leertaken ondersteunen (Jeong & Joung, 2007; P.A. Kirschner, Buckingham Shum, & Carr, 2003). Echter, net als bij domeinspecifieke tools vaak het geval is, worden er bij argumentatieve tools ook tegenstrijdige onderzoeksresultaten gerapporteerd (Buckingham Shum & Hammond, 1994; Veerman, 2000). Aan de ene kant kan dit verklaard worden door een gebrek aan domeinkennis en een gebrek aan argumentatieve vaardigheden van de gebruiker van de tool (Munneke *et al.*, 2007). Aan de andere kant kan het ook verklaard worden omdat het gebruik van argumentatieve tools niet goed aansluit bij de vereisten van een bepaalde fase uit het beslissingsproces (Buckingham Shum, 1996; Suthers, 2001). Bij de tweede verklaring wordt vaak gewezen op het verschil in ontologie (i.e., objecten, relaties en de regels voor het combineren van objecten en relaties) tussen Issue Based Information Systems (IBIS, see Conklin & Begeman, 1988) en Decision Representation Language (DRL, see Lee & Lai, 1991) notaties. *IBIS notaties* faciliteren de visualisatie van onderwerpen (i.e., vragen), posities (i.e., alternatieve antwoorden) waar argumenten (voor als tegen) aan gekoppeld kunnen worden. Zulke notaties zijn vaak niet heel erg precies en gestructureerd hetgeen het makkelijk maakt om mogelijke standpunten te onderzoeken en te noteren. *DRL notaties* zijn ontwikkeld om het beslissingproces te faciliteren door het visualiseren van de argumenten voor, argumenten tegen, tegenwerpingen en criteria voor bepaalde standpunten. Zulke notaties maken het makkelijker om de verschillende standpunten met elkaar te vergelijken, hun geschiktheid voor het probleem te bepalen en uiteindelijk tot een definitief besluit te komen.

Aangezien dezelfde problematiek als in dit proefschrift besproken wordt centraal staat (i.e., ontwerpen van deeltaakspecifieke ondersteuning) lijkt het interessant om te onderzoeken of een IBIS argumentatie tool geschikt is om de taakvereisten van de probleemoplossingstaak te ondersteunen en de DRL argumentatie tool wellicht meer geschikt is voor de taakvereisten van de oplossingevaluatie taak. Toekomstig onderzoek zou zich ook kunnen richten op het vaststellen van de effecten van het combineren van domeinspecifieke en argumentatieve tools tijdens het uitvoeren van complexe leertaken.

Methodologie

De studies waarover gerapporteerd is in dit proefschrift maken allemaal gebruik van dezelfde complexe leertaak en bestudeerden de effecten van het educatieve ontwerp - scripting middels representaties - met dezelfde product en proces georiënteerde methode. Zo'n aanpak wordt vaak bepleit voor het onderzoeken van de effecten van het ondersteunen van het gezamenlijk uitvoeren van complexe leertaken (Dennen, 2008; De Wever, Van Keer, Schellens, & Valcke, 2007; Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010; Sweller, Kirschner, & Clark, 2007). Toch leiden de resultaten en de tijdens de studies opgedane ervaringen toch tot een aantal methodologische vraagstukken.

Validiteit en betrouwbaarheid

Het uitvoeren van onderzoek binnen scholen en gedurende een aantal lessen heeft als voordeel dat het ecologisch een meer valide onderzoekssetting is dan een laboratorium onderzoek. Daarnaast werd de leertaak geïntegreerd in het curriculum en telden de scores op de team prestatie en natoets mee voor het rapportcijfer dat de lerenden kregen. Helaas had deze werkwijze ook tot gevolg dat er acceptabele, althans voor Studie 1, maar lage betrouwbaarheidsscores op zowel de voortoets als de natoets geconstateerd werden. Wanneer de meetinstrumenten ook geschikt moeten zijn om als toetsinstrument voor het curriculum te kunnen fungeren, zijn vaak geen gestandaardiseerde instrumenten beschikbaar. Deze instrumenten zijn daarom in samenwerking met de deelnemende docenten ontwikkeld wat de meetinstrumenten ecologisch valide maakte voor het meten van de team en de individuele leerresultaten. Alhoewel dit is hoe docenten normaliter met hun lerenden werken en hun beoordelen, kan deze werkwijze de betrouwbaarheid van de meetinstrumenten schaden en zodoende de generaliseerbaarheid van de gevonden resultaten belemmeren. Aangezien de studies bij, in totaal, 18 verschillende klassen verdeeld over vier verschillende scholen uitgevoerd zijn, wordt er vanuit gegaan dat dit geen substantiële invloed heeft op de generaliseerbaarheid, maar niet compleet uitgesloten kan worden. Verder viel het tijdens de lessen op dat veel lerenden de chat tool als hinderlijk ervoeren en daarom de neiging hadden om verbaal te communiceren met hun teamgenoten. De docent heeft uitgelegd dat het communiceren hoorde bij de taak en nodig was voor het onderzoek, maar toch kon niet voorkomen worden dat er ook op verbale wijze gecommuniceerd is en dat dus niet alle interactie gelogd konden worden. Aangezien alle lerenden deze neiging hadden, wordt aangenomen dat er geen verschillen tussen de onderzoekscondities waren. Op basis van deze ervaringen moet wel afgevraagd worden of het ecologisch valide is leerlingen binnen dezelfde ruimte op deze wijze te laten samenwerken (Elen & Clarebout, 2007). Wellicht dat toekomstig onderzoek over de grens van de klas heen kan gaan en lerenden van verschillende scholen met elkaar kan laten samenwerken.

Meten van de leereffecten van het uitvoeren van complexe leertaken

Zoals ook het geval is bij eerder onderzoek naar de leereffecten van het uitvoeren van complexe leertaken (Dochy *et al.*, 2003; Mergendoller *et al.*, 2006)

worden in Studie 1 en Studie 2 geen individuele leeropbrengsten in termen van verworven declaratieve kennis van het domein gevonden. In Studie 3 worden deze wel gevonden voor alle lerenden, maar worden er geen verschillen tussen de condities geconstateerd. Wellicht dat het educatieve ontwerp in Studie 3 het meest geschikte is voor zowel team als individueel leren. Een meer plausibele verklaring lijkt te zijn dat dit op toeval gebaseerd is en er andere meetinstrumenten nodig zijn om de eventuele leereffecten voor individuele lerenden vast te kunnen stellen. Toekomstig onderzoek zou zich mogelijkerwijs kunnen richten op het meten van een diepere verwerking van de inhoud van het domein, het aanleren van samenwerkings- en probleemoplossingvaardigheden, motivatie om te leren en de mate waarin lerenden in staat zijn om het geleerde toe te passen binnen een andere context (i.e., transfer). Meer specifiek, in plaats van het afnemen van een natoets gericht op het meten van de reproductie van concepten, principes en procedures, kunnen ook andere toetsingsvormen gebruikt worden welke gericht zijn op het meten van de toepassing (i.e., productie) van de inhoud van het kennisdomein. Zo zou er ook voor gekozen kunnen worden om de lerenden een ander, maar gerelateerd, probleem op te laten lossen en, bijvoorbeeld, te meten of de lerenden dit probleem op een andere manier benaderen, het probleem sneller of beter oplossen, hun eerder verworven kennis toepassen en/of beter in staat zijn om samen te werken.

Meten van de kwaliteit van het samenwerkingsproces

Door enkel en alleen het type uitingen (b.v., cognitief) en het gebruik van de concepten en hun onderlinge relaties te coderen en te kwantificeren, wordt wellicht geen volledig inzicht in de dynamiek van het samenwerkingsproces verkregen (Bromme, Hesse, & Spada, 2005; Hmelo-Silver, Chernobilsky, & Jordan, 2008; Suthers, 2006). Zo geeft dit, bijvoorbeeld, weinig inzicht in de (1) ontwikkeling van het begrip van het domein en de correctheid van de discussie over de inhoud van het domein en (2) wijze waarop lerenden informatie uit externe bronnen en representaties gebruiken en aan elkaar relateren.

Een eerste manier om hier meer inzicht in te kunnen verkrijgen, zou het vergelijken van de interactie in de verschillende fases van het probleemoplossingproces kunnen zijn. Door per fase te bestuderen welke concepten, principes en relaties gebruikt zijn en of dit op correcte wijze plaatsvindt, kan onderzocht worden of de lerenden een beter begrip van het domein ontwikkeld hebben. Vanwege tijdsbeperkingen zijn deze analyses nog niet uitgevoerd voor de studies die in dit proefschrift staan beschreven, maar de verzamelde data maakt dit wel mogelijk. Naast deze inhoudelijke analyse zou ook gekeken kunnen worden of er sprake is van een kennisconstructie binnen een team door na te gaan wat voor type leeractiviteiten teamleden hebben uitgevoerd. Als in de interactie bijvoorbeeld alleen maar definities gegeven worden van de concepten dan is er geen sprake van constructie maar van reproductie. Het gezamenlijk construeren van kennis gaat verder dan enkel het bespreken van definities, hetgeen vaak lastig in een codeerschema te vatten is. Diverse onderzoekers hebben zich hier mee bezig gehouden (Gunawardena, Lowe, & Anderson, 1997; Schellens & Valcke, 2005; Veerman & Veldhuis-

Diermanse, 2001). De codeerschema's hebben vaak met elkaar gemeen dat er een bepaalde fasering aangebracht wordt in de gebruikte cognitieve activiteiten en welk niveau van kennisconstructie hiermee bereikt wordt. Om een indicatie te geven van de fasering en de activiteiten is hieronder de operationalisering van Schellens en Valcke weergegeven (vertaald vanuit het Engels):

Fase 1: delen en vergelijken
- Cognitieve activiteiten: observeren, verduidelijken, geven van definities,

Fase 2: vaststellen van inconsistenties
- Cognitieve activiteiten: identificeren en benoemen, vragen en verklaren, herformuleren en ondersteunen van eerdere beweringen,

Fase 3: argumenteren over waar overeenstemming over is
- Cognitieve activiteiten: voorstellen doen voor nieuwe gezamenlijke kennis welke de bediscussieerde overeenkomsten van de verschillen uit de vorige fase bevat,

Fase 4: testen van nog niet volledig ontwikkelde inzichten
- Cognitieve activiteiten: testen van de nieuwe gezamenlijke kennis aan externe informatiebronnen en het persoonlijke begrip van de teamleden,

Fase 5: vaststellen en toepassen van de nieuw geconstrueerde kennis
- Cognitieve activiteiten: definitieve herziening en delen van de nieuwe kennis die door het team geconstrueerd is.

Generalisatie van het educatieve ontwerp

Aangezien gunstige effecten voor het leren zijn gevonden in alle drie studies, zouden docenten en educatieve ontwerpers wellicht het educatieve ontwerp - scripting middels representaties - willen gebruiken in hun dagelijkse educatieve praktijken. Deze sectie gaat daarom in op de mogelijkheden hiervoor en de beperkingen die hierbij in acht dienen te worden genomen.

Domein- en taakspecificiteit

De studies vonden allemaal plaats in het bedrijfseconomische domein. Alhoewel er meerdere domeinen zijn (b.v., scheikunde, biologie, meteorologie) waarin kwalitatieve en kwantitatieve presentaties vereist zijn, hangt het effect van een specifiek ontwerp af van de kenmerken van zowel de leertaak als het kennisdomein (De Vries, 2003; Elen & Clarebout, 2007). Bij het ontwerpen van tools/leeromgevingen dient hier dan ook zorgvuldig rekening mee te worden gehouden. De in dit proefschrift gerapporteerde effecten kunnen daarom niet automatisch gegeneraliseerd worden naar andere leertaken en domeinen. Om te verifiëren of het scripten van domeinspecifieke representaties een geschikte manier is om het leerproces te ondersteunen, is het raadzaam om een leertaakanalyse uit te voeren (Gagné, Briggs, & Wagner, 1992). Pas wanneer uit de analyse blijkt dat de gehele leertaak uit meerdere deeltaken bestaat die ieder hun eigen perspectief op het domein vereisen, is het nodig om de aard van de perspectieven te bepalen. Op basis van deze inzichten kunnen de (1) fasering en de taakvereisten van de deeltaken gespecificeerd en (2) deeltaakspecifieke visualisatie tools ontworpen worden.

Visualiseren en discussiëren

Het educatieve ontwerp is er op gericht om het cognitieve gedrag van lerenden te sturen zodat zij beter in staat zijn om een complexe leertaak uit te voeren. Alhoewel de resultaten van de drie studies aantonen dat met name de team prestatie hierdoor kan worden bevorderd, is niet met zekerheid te zeggen waarom dit het geval is. De reden hiervoor is dat de onderzoeken plaats hebben gevonden in een collaboratieve setting (i.e., samenwerkend leren). Met andere woorden, naast het visualiseren van de inhoud van het domein op een deeltaak congruente wijze hebben de lerenden ook met elkaar hierover gediscussieerd. De gevonden resultaten kunnen daarom niet enkel en alleen verklaard worden door het educatieve ontwerp, maar dienen te worden toegeschreven aan de combinatie visualiseren en discussiëren. Aangezien andere studies hebben aangetoond dat de leerprestatie van een lerende ook bevorderd kan worden door het aanbieden of construeren van een representatie (Larkin & Simon, 1987; Vekiri, 2002; Zhang, 1997), lijkt het aannemelijk dat het scripten van domeinspecifieke representaties ook in deze (individuele) setting ondersteuning kan bieden. Toekomstig onderzoek zou zich op deze vraag kunnen richten, maar ook op de vraag of het wellicht beter is om eerst individueel een representatie te bekijken of te construeren alvorens dit met teamgenoten te doen.

In dezelfde lijn van redeneren zou het ook beargumenteerd kunnen worden dat het bekijken en het construeren van deeltaakspecifieke representaties wellicht gecombineerd dient te worden. Uit de impliciete vergelijking van Studie 1 en Studie 2 kwam naar voren dat het bekijken van een representatie tot meer discussie over de inhoud van het domein leidt. Dit is mogelijkerwijs meer geschikt voor het uitvoeren van de probleemoriëntatie taak omdat lerenden zo een breder perspectief van het domein creëren. Wanneer lerenden nieuwe ideeën dienen te genereren en specifieke oplossingen dienen te formuleren (i.e., probleemoplossing) zou het construeren een betere ondersteuningsvorm kunnen zijn. Het construeren dwingt lerenden om specifieker te worden en dit zou wellicht belemmerd kunnen worden door het bekijken van een representatie waarin alle concepten, mogelijke oplossingen en hun onderlinge relaties al zijn uitgewerkt.

Ontwikkeling van expertise

Het ontwerp principe achter het educatieve ontwerp is dat het begrip dat de lerenden van het domein hebben op gefaseerde wijze wordt verfijnd en dit hen in staat zou moeten stellen om de complexe leertaak op een efficiënte en effectieve wijze uit te voeren (e.g., Frederiksen & White, 2002; Quintana, Reiser, Davis, Krajcik, Fretz *et al.*, 2004; Van Merriënboer & Kirschner, 2007). Dit wordt geconcretiseerd door de lerenden verschillende perspectieven (i.e., kwalitatief en kwantitatief) op het domein op een deeltaakspecifieke wijze aan te bieden of te laten construeren. Zo doende, wordt de ontwikkeling van expertise gezien als het geleidelijk aan verhogen van de complexiteit van de relaties tussen de verschillende concepten (i.e., model order progressie, Frederiksen & White). Dit is, echter niet de enige wijze waarop de ontwikkeling van expertise plaats zou kunnen vinden. Zo beschrijven Frederiksen & White, onder andere, ook model elaboratie progressie; het gefaseerd introduceren van meerdere concepten en

(verschillende typen) relaties. In tegenstelling tot order progressie worden alle mogelijke concepten niet op hetzelfde moment geïntroduceerd en is er een minder strikt onderscheid tussen kwalitatieve en kwantitatieve relaties aangezien deze, binnen hetzelfde perspectief, met elkaar gecombineerd worden. De gevonden leereffecten van model elaboratie progressie zijn echter vaak teleurstellend (Swaak, Van Joolingen, & De Jong, 1998). Toekomstig onderzoek zou zich daarom kunnen richten op de vergelijking van model order progressie en model elaboratie progressie voor het ondersteunen van complexe leertaken. Alhoewel deze vergelijking nog niet vaak gemaakt is, tonen Mulder, Lazonder en De Jong (submitted) aan dat, binnen het natuurkunde onderwijs, order progressie beter aansloot bij de ondersteuningsbehoefte van de lerenden en tot betere leerresultaten leidde. Toch dient hierbij vermeld te worden dat de 'betere leerprestatie', gemiddeld gezien slechts een derde van de maximaal te behalen score betrof. Vervolgonderzoek zou moeten uitwijzen of dezelfde resultaten ook binnen andere domeinen dan natuurkunde gevonden worden. Een tweede onderzoekslijn zou zich kunnen richten op de vraag wanneer lerenden in staat zijn om progressie naar een ander model te maken. In het educatieve ontwerp dat centraal staat binnen dit proefschrift vindt dit plaats op basis van de verandering in taakvereisten. Alhoewel dit is gebaseerd op eerder onderzoek naar het ontwerpen en gebruiken van visualisaties (Ainsworth, 2006; Cox, 1999; Schnotz & Kürschner, 2008; Van Bruggen, Boshuizen, & Kirschner, 2003), wil dit nog niet zeggen dat lerenden ook in staat zijn om een ander perspectief op het domein te begrijpen en te construeren. In dit licht, zou in de toekomst ook onderzocht kunnen worden welke factoren van belang zijn bij de progressie naar een ander model (Mulder *et al.*).

Cursus en curriculum niveau

Waar dit proefschrift aantoont dat het gezamenlijk uitvoeren van complexe leertaken ondersteund kan worden door het educatieve ontwerp, dient in acht genomen te worden dat dit binnen één vak en één module heeft plaatsgevonden. Men kan zich daarom afvragen of het wenselijk is om binnen het curriculum op deze wijze het uitvoeren van complexe leertaken te ondersteunen. Aan de ene kant dienen lerenden (i.e., beginners) ondersteund te worden, maar aan de andere kant is één van de einddoelen van het curriculum vaak ook dat lerenden zelfstandig dit soort taken succesvol uit kunnen voeren. Kortom, er lijkt een delicate balans te zijn tussen het structureren en het problematiseren van het leerproces (Reiser, 2004). Wellicht dat docenten en educatieve ontwerpers dit kunnen bereiken door gaandeweg de hoeveelheid ondersteuning te laten afnemen (*fading*; Kollar, Fischer, & Slotta, 2007). Wat betreft het scripten van domeinspecifieke representaties zou dit mogelijkerwijs gerealiseerd kunnen worden door lerenden meerdere maar vergelijkbare probleemoplossingtaken uit te laten voeren en de mate van ondersteuning stapsgewijs te laten afnemen. Een interessant toekomstig vraagstuk zou kunnen zijn welk aspect van het educatieve ontwerp eerst af dient te nemen, de fasering in het probleemoplossingproces of de deeltaakspecifieke ondersteuning?

Samenvattend, het implementeren van het educatieve ontwerp - scripting middels representaties - kan het gezamenlijk oplossen van een complex bedrijfseconomisch probleem ondersteunen. Er zijn, echter, verschillende redenen aan te dragen dat deze effecten niet automatisch te generaliseren zijn naar andere domeinen en leertaken. Toekomstig onderzoek, gericht op deze generaliseerbaarheid, zou zich daarom, onder andere, dienen te richten op de vraagstukken die in dit hoofdstuk zijn besproken.

Dankwoord (Acknowledgement)

Wêrmei komst yn 't libben 't fierste? Wês dysels en kom sa 'st biste!
(Waarmee kom je in het leven het verst? Blijf jezelf en kom zoals je bent)

Dat een geboren Amerikaan, een Amsterdammer, en een getogen Fries toch succesvol een promotietraject af kunnen ronden, geeft aan dat er een kern van waarheid in bovenstaande spreuk zit. Paul, jouw tomeloze inzet stimuleerde mij om steeds weer nieuwe stukken op te sturen wat uiteindelijk tot dit proefschrift heeft geleid. Gijsbert, jij zorgde ervoor dat mijn wildste ideeën ingeperkt werden, zodat het onderzoek transparant en, met name, behapbaar bleef voor mij. Dit proefschrift was ook niet tot stand gekomen zonder al het programmeerwerk van Jos Japers. Het aanpassen van de VCRI-omgeving was vaak een tijdrovende klus, zo zal de periode rond de kerstdagen van 2007 ons allebei ongetwijfeld nog lang bij blijven staan.... Paul, Gijsbert en Jos, bedankt voor alle ondersteuning die jullie mij hebben geboden.

Morele steun werd gegeven door de sociale context van de Afdeling Onderwijskunde. De praatjes op de wandelgang, bij 'de jongens' in H056 en tijdens de wandelingen zorgden voor de nodige afleiding en inspiratie. Agaath, Anna, Anouschka, Bert (V.), Casper, Crina, Daniëlle, Ellie, Elly, Femmy, Frieda, Gerdine, Havva, Hein, Heleen, Hendrien, Hesther, Jan, Janneke, Jeroen, Karel, Lennart, Liesbeth, Luce, Marieke (J.), Marieke (v/d S.), Mieke, Patrick, Sandy, Theo en Tim, ik zal deze context en jullie gaan missen. Mijn nieuwe collega's bij het Universitair Onderwijscentrum Groningen hebben deze rol echter goed overgenomen gedurende de laatste periode van het promotietraject. Niet alleen de sociale context maar zeker ook de tijd en de ruimte die jullie mij geboden hebben, maakten het mij mogelijk om het promotietraject af te ronden.

Zonder docenten en studenten geen data en dus niets om over te schrijven. David, Dirk, Folkert, Geke, Gerard, Jan, Jeannet en Pier bedankt voor alle lesuren die jullie ter beschikking stelden en het meedenken over de materialen, de planning en de toetsing. Gelukkig heb ik bij de verwerking van de data ondersteuning gehad van verschillende studenten en student-assistenten. Annick, Aron, Magali en Mara, hartelijk dank voor het invoeren en coderen van de data, zonder jullie was het mij niet gelukt om alle analyses uit te voeren en deze in het proefschrift te verwerken.

Verder nog een woord van dank voor degenen die mij en mijn gedrag zowel in positieve als in negatieve zin van dichtbij hebben meegemaakt. De afgelopen vier jaren heb ik zowel ups als downs meegemaakt, welke ik met jullie deelde, waar wij vrolijk van werden, maar ook waar wij samen weer boven op moesten zien te komen. Yvonne, jij bent één van de grote voordelen die het netwerk van de ICO onderzoeksschool mij heeft geboden. Tijdens de introductiecursus kwamen wij er achter dat we zowat hetzelfde onderzoek deden, maar dat we het alleen anders benoemden. Bedankt voor de inhoudelijke discussies die wij over modelprogressie (ik gebruik jouw term maar even) hebben gehad, maar ook voor de steun en vriendschap die hieruit voortvloeide. Chris en Harmen, mijn *Brothers in Arms* (Dire Straits, 1985), we hebben letterlijk en figuurlijk vele

hoogtepunten (b.v., fietsen van Elfstedentochten, beklimmen van de Mount Ventoux en alle geaccepteerde artikelen), maar ook enkele dieptepunten (b.v., onderkoelingsverschijnselen, zoveelste minor revision en het 'boompje knuffelen') meegemaakt. Ik ben erg blij dat wij elkaar hebben leren kennen en dat jullie vanaf het begin tot aan het einde aan mijn zijde hebben gestaan. Over jullie en over al ons ervaringen zou ik een boek kunnen schijven, maar dat valt buiten het bestek van dit proefschrift..... Piebes, bedankt voor alles, wij gaan ook zeker na ons AiO-schap nog wel het één en ander met elkaar beleven! Tot slot, heit (vader), mem (moeder) en Kirsten, jullie stonden altijd voor mij klaar en ondersteunden mij op alle (on)mogelijke momenten. Tijdens alle drukke, moeilijke en onzekere periodes die wij al hebben meegemaakt, is er altijd gestreden en vooruit gekeken. Ook dit proefschrift is daar weer een voorbeeld van. Daarnaast zorgden jullie voor de nodige relativering en ontspanning door o.a. de vele uren op de tennisbaan, het vervoer van en naar Bolsward en de gezamenlijke etentjes. Het proefschrift is klaar! Nu is er weer meer tijd voor jullie en kan na Zeist ook Groningen worden verkend!

Bert Slof
Groningen, December 2010

List of Publications

Submitted journal articles

Phielix, C., Prins, F. J., Kirschner, P. A., Janssen, J., & Slof, B. (submitted). Using reflection to increase reliability of peer assessments on social and cognitive behavior: Do we need to reflect?

Slof, B., Erkens, G., Kirschner, P. A., Janssen, J., & Jaspers, J. G. M. (submitted). Representational Scripting: Fostering complex learning-task performance through guiding teams' qualitative and quantitative reasoning.

Journal articles, refereed

Slof, B., Erkens, G., Kirschner, P. A., Janssen, J., & Phielix, C. (2010). Fostering complex learning-task performance through scripting student use of computer supported representational tools. *Computers and Education, 55,* 1707–1720.

Slof, B., Erkens, G., Kirschner, P. A., & Jaspers, J. G. M. (2010). Design and effects of representational scripting on group performance. *Educational Technology Research and Development, 58,* 589–608.

Slof, B., Erkens, G., Kirschner, P. A., Jaspers, J. G. M., & Janssen, J. (2010). Guiding learners' online complex learning-task behavior through representational scripting. *Computers in Human Behavior, 26,* 927–939.

Journal articles, non-refereed

Slof, B., Erkens, G., & Kirschner, P. A. (2010). Leren bedrijfseconomische problemen op te lossen door het maken van vakspecifieke schema's [Learning to solve business-economics problems through constructing domainspecific diagrams]. *Tijdschrift voor het Economisch Onderwijs (TEO), 110*(4), 226–230.

Books

Harskamp, E. G., & Slof, B. (2006). *Invoering van individuele ontwikkelingsplannen in het praktijkonderwijs.* [Implementing personal development plans in special vocational education]. Groningen, The Netherlands: RijksUniversiteit Groningen, GION.

Conference presentations

Individual papers

Slof, B., Erkens, G., & Kirschner, P. A. (2009a, June). Representational scripting effects on group performance. In O'Malley, C., Suthers D. D., Reimann P., Dimitracopoulou A. (Eds.). *Proceedings of the Eight International Conference on Computer Supported Collaborative Learning: Vol. 2* (pp. 532-541). New Brunswick, NJ: International Society of the Learning Sciences.

Slof, B., Erkens, G., & Kirschner, P. A. (2009b, August). *Representational effects on individual learning gains*. Paper presented at the Junior researchers pre-conference (JURE) of the 13th Biennial Conference of the European Association for Research on Learning and Instruction, Amsterdam, The Netherlands.

Slof, B., Erkens, G., & Kirschner, P. A. (2009c, November). *Guiding learners' online problem-solving performance through evoking proper part-task related Student interaction.* Paper presented at the 5th Interuniversity Centre for Educational Research (ICO) Toogdag, Utrecht, The Netherlands.

Slof, B., Erkens, G., Kirschner, P. A. (2010a, June). Succesvol probleemoplossen door deeltaakspecifieke ondersteuning [Succesfull problem-solving through providing part-task congruent support]. *In De lerende leraar als onderzoeker en ontwerper. Proceedings van de 37e Onderwijs Research Dagen 2010,* Enschede: Universiteit Twente, The Netherlands.

Slof, B., Erkens, G., & Kirschner, P. A. (2010b, July). Coordinating collaborative problem-solving processes by providing part-task congruent representations. In Gomez, K., Lyons, L., & Radinsky, J. (Eds.), *Learning in the Disciplines. Proceedings of the Ninth International Conference for the Learning Sciences: Vol. 1* (pp. 675-682). Chicago, IL: International Society of the Learning Sciences, Inc.

Slof, B., Erkens, G., & Kirschner, P. A. (2010c, July). Representational scripting to support learners' online problem-solving performance. In Gomez, K., Lyons, L., & Radinsky, J. (Eds.), *Learning in the Disciplines. Proceedings of the Ninth International Conference for the Learning Sciences: Vol. 1* (pp. 476-483). Chicago, IL: International Society of the Learning Sciences, Inc.

Posters

Slof, B., Erkens, G., & Kirschner, P. A. (2008a, June). Modelprogressie: Kunnen modellen het probleemoplossing-proces ondersteunen? [Can model representations support problem-solving processes?]. In W. M. G. Jochems, P. den Brok, Th. Bergen, & M. van Eijck (Eds.), *Licht op Leren. Proceedings van de 35e Onderwijs Research Dagen 2008,* (pp. 292-293), Eindhoven: Eindhoven School of Education, Technische Universiteit Eindhoven.

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Slof, B., Erkens, G., & Kirschner, P. A. (2009, May). Leren probleem oplossen door het faseren van deeltaken en schema's: De leereffecten. [Learning problem-solving problems through structuring part-tasks and visualizations: The learning gains]. *In Onderwijs: Een kwestie van emancipatie en (on)gelijkheid. Proceedings van de 36e Onderwijs Research Dagen 2009* (pp. 189). Leuven: Katholieke Universiteit Leuven, Belgium.

Symposia

Slof, B., Erkens, G., Kirschner, P. A. (2010a, June). Ondersteuning van gezamenlijk probleemoplossen door gefaseerd construeren van domeinspecifieke representaties. [Supporting collaborative problem-solving through constructing phase-related domain-specific representations]. *In De lerende leraar als onderzoeker en ontwerper. Proceedings van de 37e Onderwijs Research Dagen 2010,* Enschede: Universiteit Twente, The Netherlands.

Slof, B., Erkens, G., & Kirschner, P. A. (2010b, July). Matching representational tools' ontology to part-task demands to foster problem-solving in business-economics. In Gomez, K., Lyons, L., & Radinsky, J. (Eds.), *Learning in the Disciplines. Proceedings of the Ninth International Conference for the Learning Sciences: Vol. 2* (pp. 16-18). Chicago, IL: International Society of the Learning Sciences, Inc.

Curriculum Vitae

Bert Slof was born on February 5th 1981 in Haarlem, the Netherlands. After completing secondary school in 1998, he attended the Teacher Education Program for Economics at a school for higher professional education (NHL). In July 2002 he earned a Bachelor's degree in Economics that qualified him to teach in secondary schools. He taught Economics in a school for senior vocational education from September 2002 to January 2003. In the same period he began studying Educational Sciences at the University of Groningen. In the third and final year of this study he focused primarily on writing his Master's thesis *(Teaching economics through multimedia instruction).* In addition, he worked as a graduate assistant on a project researching the implementation of individual development plans in special vocational education, which resulted in the publication of a book entitled 'Implementing personal development plans in special vocational education'. In August 2005 he received his Master's degree in Educational Sciences at the University of Groningen and, from December 2005 to October 2006, he taught Economics at a secondary school.

Slof began his PhD project *Embedding External Representations in Design-based Learning* in 2006 at the Research Centre Learning in Interaction (RCLI) at Utrecht University, part of the research group led by Prof. Paul A. Kirschner. Alongside his PhD project, he also lectured at the Department of Social and Behavioral Sciences, expecting to earn his educational degree for lecturing at universities in 2011. He has been a member of the ICO Educational Committee (2009-2010), organized the election of the PhD supervisor of the year on behalf of the Netherlands PhD Association in 2009, and assisted the organizing committee of the International Conference for the Learning Sciences (ICLS) in 2008.

In October 2010 Slof completed his PhD project, having presented aspects of this study at several national and international conferences. In October 2010, he joined the University Centre for Learning & Teaching, the educational centre of expertise at the University of Groningen, where he works as a lecturer and researcher in the research group led by Prof. Wim J.C.M. van de Grift.

List of ICO-Dissertations 2009

194. Radstake, H. (14-05-2009). *Teaching in diversity: Teachers and pupils about tense situations in ethnically heterogeneous classes*. Amsterdam: University of Amsterdam.
195. Du Chatenier, E. (09-09-2009). *Open innovation competence: Towards a competence profile for inter-organizational collaboration in innovation teams*. Wageningen: Wageningen University.
196. Van Borkulo, S. P. (26-06-2009). *The assessment of learning outcomes of computer modelling in secondary science education*. Enschede: University of Twente.
197. Handelzalts, A. (17-09-2009). *Collaborative curriculum development in teacher design teams*. Enschede: University of Twente.
198. Nievelstein, F. E. R. M. (18-09-2009). *Learning law: Expertise differences and the effect of instructional support*. Heerlen: Open University of the Netherlands.
199. Visser-Wijnveen, G. J. (23-09-2009). *The research-teaching nexus in the humanities: Variations among academics*. Leiden: Leiden University.
200. Van der Rijst, R. M. (23-09-2009). *The research-teaching nexus in the sciences: Scientific research dispositions and teaching practice*. Leiden: Leiden University.
201. Mainhard, M. T. (25-09-2009). *Time consistency in teacher-class relationships*. Utrecht: Utrecht University.
202. Van Ewijk, R. (20-10-2009). *Empirical essays on education and health*. Amsterdam: University of Amsterdam.
203. Seezink, A. (18-11-2009). *Continuing teacher development for competence-based teaching*. Tilburg: Tilburg University.
204. Rohaan, E. J. (09-12-2009). *Testing teacher knowledge for technology teaching in primary schools*. Eindhoven: Eindhoven University of Technology.
205. Kirschner, F. C. (11-12-2009). *United brains for complex learning*. Heerlen: Open University of the Netherlands.
206. Wetzels, S. A. J. (18-12-2009). *Individualized strategies for prior knowledge activation*. Heerlen: Open University of the Netherlands.