United Brains for Complex Learning

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A cognitive-load approach to collaborative learning efficiency

The research reported here was carried out at the

OpenUniversiteitNederland

In the context of the research school

ico

Interuniversity Center for Educational Research

ISBN: 978 90 79447 35 0

Cover design: Femke Kirschner
Printed by Datawyse, Maastricht, The Netherlands

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A cognitive-load approach to collaborative learning efficiency

PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Open Universiteit Nederland
op gezag van de rector magnificus
prof. dr. ir. F. Mulder
ten overstaan van een door het
College voor promoties ingestelde commissie
in het openbaar te verdedigen

op vrijdag 11 december 2009 te Heerlen
om 13:30 uur precies

door

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geboren op 8 oktober 1979 te Groningen

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Voorwoord

Mijn proefschrift! Gelukkig geen optische illusie, maar het eindresultaat van vier belangrijke, leerzame, gezellige en spannende jaren. Ik had het niet alleen kunnen doen en wil daarom de volgende voor mij heel belangrijke personen kort maar KRACHTIG bedanken.

Dankjewel…

Fred, voor je vertrouwen en je geweldige ideeën!
Paul, dat je me het gevoel gaf dat het 'ons' project was en ik altijd bij je terecht kon. Het was je nooit teveel!

Mariëlle Rooduijn, zonder jou geen data en dus geen proefschrift.
Celstec collega's, waaronder alle (ex) AiO's, voor alle leerzame en gezellige momenten.

Sandra en Gemma, ik heb zo geboft met jullie als kamergenootjes.
Tamara, wat kan ik met jou lachen.
Fleurie, voor het mogen platlopen van je deur en je eeuwige oprechte interesse.

Anne, Sanne, Kim en Saskia, dat jullie alweer zo lang mijn superlieve vriendinnetjes zijn.
Frank, voor het zijn van een super goede vriend.

Paranimfen, Fleurie, Mara (en Tamara), wie wil er niet van die mooie en lieve meiden achter zich op het podium hebben staan.

Pap, Mam, Jesse, Mara en Aron, ik kan jullie niet genoeg voor ALLES bedanken. Ik ben zo blij dat ik in dit rijtje thuishoor en hou ontzettend veel van jullie!!

Femke

Heerlen, 2009

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General introduction

Contemporary thinking about learning – both initial and lifelong – has gravitated from individual learning towards learning in collaborative environments or situations. These collaborative environments take on a great variety of forms and often differ greatly along a number of dimensions. They can, for example, differ in size (e.g., dyads, small groups, learning communities), composition (e.g., gender based, based on prior knowledge or expertise, based on prior acquaintance with other members), pursued goal (e.g., recall and retention, solving a problem, carrying out a project), supporting tools (e.g., whiteboard and markers, shared writing spaces, social networking software), synchronicity (e.g., synchronous face-to-face, synchronous chat, asynchronous email and discussion boards), common knowledge distribution, division of tasks (e.g., roles, partitioning a process in phases or stages), and so forth. Despite these varieties, all approaches to collaborative learning require and ask for a certain mutual and shared effort of the members of the group. Teasley and Roschelle (1993) investigating the construction of shared meanings in model-building activities, showed the importance of individuals making a conscious and continued effort to solve a problem together. Just putting two or more individuals in the same room, and assigning them the same task does not guarantee for true collaboration. For collaboration to occur, group members must actively communicate and interact with each other with the intention of establishing a common focus and achieving a common goal (Akkerman et al., 2007; Beers, Boshuizen, Kirschner, & Gijselaers, 2006). To achieve this, valuable knowledge and information held by each group member must actively be shared (i.e., retrieving and explicating information), discussed (i.e., processing the information) and remembered (i.e., personalizing and storing the information).

There are several reasons why collaborative learning environments have emerged as a promising approach to education and learning. The first reason is an educational one and holds that acquiring many competencies that are important in today's world requires using authentic whole tasks carried out in teams. A second related reason is that acquiring the necessary 'soft' skills for such teamwork has become an explicit learning goal at many levels of education. The third reason is a social-philosophical one, which holds that learning and working are social activities where others are and must be involved. Although, these different arguments have been advanced to explain the need for collaborative learning, its potential and the justification of its use, this dissertation argues that the basic rationale for choosing collaborative learning as the preferred educational approach should be its relative effectiveness and efficiency in comparison with more traditional educational approaches in which learning takes place as an individual activity.

The results of studies comparing individual to collaborative learning are mixed at best and where positive results are found, it is often the case that for collaborative learning to be effective, educators have to implement extra measures to either ensure that the group members work together (e.g., by requiring that each member makes a specific number of contributions in electronic environments or by requiring compulsory attendance of face-to-face meetings) or to ensure that all learners effectively engage in the learning process (e.g., by assigning group members specific roles and implementing scripts or assessment schemes). Along with the positive findings showing the potential for positive benefits of collaborative learning (e.g., Cronjé, 1997; Gunawardena, 1995), mixed and negative findings have also been reported with respect to both the learning process itself (Gregor & Cuskelly 1994; Hallet & Cummings, 1997; Heath, 1998; Mason, 1991), and the processes surrounding group forming and group dynamics (Hiltz, 1998; Hobaugh, 1997; Hughes & Hewson 1998; Taha & Caldwell, 1993). This lack of unambiguous results brings with it the associated problem of identifying those factors that determine or promote the effectiveness and efficiency of collaborative learning. It is, therefore, argued that in order to better design, analyze, and understand effective instructional procedures for individual and group learning, the structures that constitute human cognitive architecture need to be taken into account.

Cognitive load theory (CLT: Paas, Renkl, & Sweller, 2003, 2004; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005) is a theoretical framework based upon human cognitive architecture. It maintains that any instructional procedure that ignores the structures making up human cognitive architecture is not likely to be effective. In the past two decades, cognitive load research has generated a substantial knowledge base on the design of instruction for individual learners. However, previous research on group-based learning has made clear that there is no one-to-one mapping of instructional design guidelines for individual learning and group-based learning. By applying CLT to collaborative learning environments, one can argue that if individuals are to work together and learn effectively and/or efficiently in groups, the architecture of their cognitive systems and the characteristics of the tasks to be carried out must be understood, accommodated, and aligned. Specifically, this means that the characteristics of the task must be such that the cognitive system of each individual is not capable of accommodating its solution alone and that the group communication and coordination activities necessary for effectively functioning as a team (i.e., the cognitive transaction costs) do not impede the learning process. In this light, it was considered important to use the cognitive load perspective to analyze collaborative learning environments to determine how and to what extent the insights that have arisen from CLT are applicable to learning in collaborative learning situations and what the conditions are that determine whether they may or may not be more effective than learning in individual learning environments. It should be noted that throughout this dissertation, the terms group learning and collaborative learning are used interchangeably and refer to the learning of each individual group member instead of on the learning of the group as a whole.

Cognitive load theory

Cognitive load theory assumes that individual learning from complex tasks is constrained by the limited processing capacity of the learner's cognitive architecture. This cognitive architecture consists of a long-term memory (LTM) and a working memory (WM). LTM is viewed as the central structure of human cognition containing a virtually unlimited number of knowledge structures in the form of hierarchically organized schemas that allow humans to categorize different problem states and decide the most appropriate solution moves. A stable change in the content and the structure of LTM is defined as learning. WM can be equated with consciousness. Humans are only conscious of the information currently being processed by them in WM and are oblivious to the far greater amount of information stored in LTM. When processing novel, yet to be learned information, WM is extremely limited both in its duration (Peterson & Peterson, 1959) and processing capacity (Baddeley, 1986; Miller, 1956). With regard to duration, almost all information stored in WM and not rehearsed is lost within 30 sec. With regard to processing capacity, WM is limited to only 4 ± 1 information element (Cowan, 2001). LTM provides humans with the ability to relatively expand WM's limited processing capacity in the sense that information stored in LTM can be retrieved from it and brought back to WM over indefinite periods of time. In this way, the temporal limits of WM become irrelevant. Therefore, when dealing with previously learned information which is stored in LTM, the limitations of WM disappear.

The cognitive load that learners experience when carrying out a learning task can be caused by the intrinsic nature of the task or by the manner in which the information within the task is presented to them (Sweller et al., 1998). 'Intrinsic' load is imposed by the number of information elements in a task and the degree to which those elements can, or cannot, be understood in isolation (i.e., element interactivity). From this point of view, learning a foreign language vocabulary is a low-element interactive task (i.e., simple task), because most often any single word can be learned independently of all other words in that language. Learning a foreign language grammar, however, is a high-element interactive task (i.e., complex task) because many elements must be considered simultaneously (e.g., all of the words in a sentence, their meanings, their gender, their tense, the sentence syntax et cetera). The more elements there are within a learning task and the more interactions there are between them, the higher the experienced intrinsic cognitive load will be. The manner in which the information is presented to learners can impose either 'extraneous' or 'germane' load. Extraneous load is the load that is imposed on the learner's WM by information and activities that do not directly contribute to learning while germane load is the load caused by information and activities that foster learning processes. Intrinsic load, extraneous load, and germane load are additive, thus for learning to occur (i.e., schema construction, elaboration and automation) it is important to take into account that the total cognitive load associated with an instructional design – the sum of the three separate loads – should stay within WM limits (P. A. Kirschner, 2002; Paas, Tuovinen, Tabbers, & Van Gerven, 2003). The relations between the three forms of cognitive load are asymmetric. Intrinsic load provides a 'base' or threshold load that is irreducible other than by constructing additional schemas and automating previously acquired schemas (i.e., learning); in other words, by an increase in expertise. Any available WM capacity remaining after cognitive resources have been allocated to deal with intrinsic load, can then be allocated to deal with extraneous and germane load. These loads can work in tandem in that, for example, a reduction in extraneous load by using a more effective instructional format can free processing capacity for an increase in germane load. This could mean that if learning is improved by an instructional design that reduces extraneous cognitive load, this improvement may have occurred because the freed up WM-capacity resulting from the reduction in extraneous cognitive load, has now been allocated to germane cognitive load. The newly acquired cognitive schemas, as a consequence of learning, reduce intrinsic load, again freeing up WM capacity which allows the learner to use the newly learned material in acquiring more advanced schemas. A new cycle commences and over many cycles, very advanced knowledge and skills may be acquired.

Collaborative learning as a means of overcoming working memory limitations

Overcoming individual WM limitations by instructional manipulations that are compatible with human cognitive architecture has been the central focus of CLT. Research has, therefore, mainly been concerned with developing techniques for managing WM load imposed by a learning task in order to facilitate the changes in LTM associated with schema construction and automation. To accomplish this, extraneous load first must be eliminated. Studying worked examples instead of, for example, solving conventional problems has been identified as an effective way of reducing extraneous load because the learner can devote all available WM capacity to studying a worked-out solution and constructing a schema in LTM for solving similar problems (e.g., Atkinson, Derry, Renkl, & Wortham, 2000; Sweller, 1988). Although, freeing up WM capacity by eliminating extraneous load has been identified as an effective instructional means to foster learning, its effectiveness can be further improved by managing the intrinsic load in such a way that the simultaneous processing of all interactive information elements leaves some spare cognitive capacity and that learners are encouraged to invest these available processing resources in schema construction and automation, evoking germane load. One way to manage intrinsic load is by applying a so called part-whole approach, in which the number of information elements and the interactions between the elements are initially reduced by simplifying the tasks, after which more and more elements and interactions are added (see e.g., Mayer & Moreno, 2003). An effective way to increase germane load is by increasing the variability of learning tasks (Paas & Van Merriënboer, 1994).

This dissertation argues that another way of overcoming individual WM-limitations is by using multiple working memories in groups of collaborating learners. When groups of collaborating learners are considered as information-processing systems (see e.g., Hinsz, Tindale, & Vollrath, 1997), the information necessary for carrying out a learning task and its associated intrinsic cognitive load can be divided across multiple collaborating working memories. On the one hand, this can result in lowering the risk of overloading each group member because individual WM capacity is freed up, while on the other hand, the group's reservoir of cognitive capacity is expanded.

Information processing in collaborative learning settings is characterized by active and conscious sharing (i.e., retrieving and explicating information), discussing (i.e., encoding and elaborating the information) and remembering (i.e., personalizing and storing the information) valuable task-relevant information and knowledge held by each group member (Hinsz et al., 1997; Tindale & Kameda, 2000; Tindale & Sheffy, 2002). For a group to carry out a learning task, not all group members need to possess all necessary knowledge, or process all available information by themselves and at the same time (Johnson, Johnson, & Stanne, 2001; Langfred, 2000; Ortiz, Johnson, & Johnson, 1996; Wegner, 1987, 1995). As long as there is communication and coordination between the group members, the information elements within the task and the associated cognitive load caused by the intrinsic nature of the task can be divided across a larger reservoir of cognitive capacity. In terms of CLT, this has two consequences. First, the distribution advantage causes collaborating individuals to invest less cognitive effort as compared to individuals learning alone. Second, the communication of information and the coordination of actions require group members to invest additional cognitive effort, an effort that individuals learning alone do not have to exert. These so called transaction costs (Ciborra & Olson, 1988;

Yamane, 1996) can be effective (i.e., by imposing germane cognitive load), or ineffective (i.e., by imposing extraneous cognitive load) on the learner depending on the situation. For example, if a collaborative task can be successfully solved by an individual alone, the communication and coordination processes will not be necessary for, or may even interfere with, learning, imposing extraneous cognitive load. In contrast, when the collaborative task needs more individuals working together for it to be solved successfully, the communication and coordination processes are necessary and facilitate learning, imposing a germane load.

Cognitive load as a determinant of collaborative and individual learning efficiency

It can be argued that because of the distribution advantage and the expanded processing capacity afforded by learning in a group, meaningful learning from learning tasks that impose a high cognitive load is more likely to occur in a group than in an individual setting. Based on this argument, the studies in this dissertation attempt to confirm the main crossover interaction hypothesis that for tasks imposing a high cognitive load, learning collaboratively would be more efficient than learning individually, while for tasks imposing a low cognitive load learning individually would be more efficient than learning collaboratively. Learning efficiency can be derived from the relationship between task performance and the amount of mental effort learners have to invest to attain the performance; the higher the performance and the lower the effort, the higher the efficiency.

With regard to learning from tasks imposing high cognitive load, it was expected that the load on the limited cognitive capacity of an individual learner would be too high for effective learning to commence. For learners in a group the benefits of distributing the cognitive load among each other would be higher than the costs of inter-individual integration and coordination of information. Group members would consequently be able to devote the freed up cognitive capacity to activities that foster schema construction and automation (i.e., germane load), materializing in a more favorable relationship between performance and mental effort on an individual transfer test (i.e., higher learning efficiency) for learners who carried out the learning tasks in groups than for learners who carried out the learning tasks individually.

With regard to learning from tasks imposing low cognitive load, it was expected that learners working individually or as a member of a group would have sufficient cognitive capacity to process all information by themselves. Hence, inter-individual communication and coordination of information would result in higher transaction costs than benefits of distributing the cognitive load across group members to the collaborative learning process. Consequently, qualitative differences in constructed schemas were expected between learners learning in a group and learners learning individually, materializing in a more favorable relationship between performance and mental effort on an individual transfer test for those who learned individually than for those who learned as a member of a group.

Overview of the dissertation

This dissertation consists of five studies investigating the differential effects of the cognitive load imposed by a learning task on the efficiency of learning individually or collaboratively, as indicated by the relationship between performance and mental effort on an individual transfer test. Chapter 2 begins with a review of research comparing the effectiveness and efficiency of individual learning environments with collaborative learning environments. Four characteristics of how research in this field has typically been designed and conducted, and which make it hard to draw unequivocal conclusions on the effectiveness and efficiency of collaborative learning, are identified. One of these characteristics, namely the differing complexities of the learning tasks used in the research and the concomitant load imposed on the learner's cognitive architecture, is subsequently discussed in the context of neuroscientific research on interhemispheric integration (e.g., Banich, Passarotti, & Chambers, 1994; Maertens & Pollmann, 2005). Based upon this research and CLT, it is argued that learning by an individual alone becomes less effective and efficient than learning by an individual in a group as the task complexity increases. Implications of these ideas for research on collaborative learning are discussed and addressed in Chapters 3, 4 and 5.

Chapter 3 presents an experiment investigating the effects of individual versus group learning (in triads) on efficiency of retention test and transfer test performance in the domain of biology (i.e., heredity). It was hypothesized that individuals in groups would have more processing capacity available for relating the information elements needed to carry out a learning task to each other and by doing so for constructing higher quality cognitive schemas than individuals carrying out the learning tasks alone if the high cognitive load imposed by complex learning tasks since some of the load could be shared among group members. In contrast, it was expected that individuals who learn from carrying out the same complex tasks alone would need all of their available processing capacity for remembering the interrelated information elements, and, consequently, would not be able to allocate sufficient resources to working with them and learn.

Chapter 4 presents an investigation into the efficiency of individual versus group learning as a function of low and high task complexity in the domain of mathematics. It was hypothesized that the learning processes and learning outcomes of groups would become more efficient than those of individuals as task complexity increases. Although, both individuals and groups would have no problem coping with the load imposed by low-complexity tasks, only groups would be able to deal with the high cognitive load imposed by high-complexity tasks by dividing it across their larger reservoir of cognitive capacity. In an appendix to this chapter, an alternative affective explanation for the results was investigated by analyzing the learners' expectations about the amount of invested mental effort. According to this affective explanation, which was inspired by research on group-efficacy, it was hypothesized that individuals working together in a group would have more confidence in their ability to solve a problem together and that there would, thus, be a greater willingness (i.e., motivation) by them to carry out the task than that which would be found in individuals working on their own.

Chapter 5 describes an investigation into the differential effects of the complexity of learning tasks on both learning process and outcome efficiency in the domain of biology. Whereas the studies presented in the previous chapters either focused solely on the learning process and outcome of high-complexity learning tasks (Chapter 3) or solely on the learning process while studying low and high-complexity learning tasks (Chapter 4), the study presented in Chapter 5 was designed to provide a more complete picture by investigating the effects of low- and high-complexity learning tasks on the efficiency of both the individual and group learning process and learning outcome. It was expected that for high-complexity tasks, group members would learn in a more efficient way than individual learners, while for low-complexity tasks, individual learning would be more efficient.

In addition to the previous studies into the effects of different levels of intrinsic load (i.e., task complexity) on the efficiency of individual and collaborative learning, the study presented in Chapter 6 kept the intrinsic load constant and investigated the differential effects of extraneous load as induced by instructional format. More specifically, individual and collaborative learning either from solving conventional problems or studying worked examples in the domain of biology was compared with respect to their effects on learning efficiency. It was hypothesized that for conventional problems, group members would learn in a more efficient way than individual learners, while for worked examples, learning individually would be more efficient.

The final chapter of this dissertation contains a general discussion of the findings. Special attention is paid to the theoretical, research and instructional implications of the results.

2

A cognitive-load approach to collaborative learning: United brains for complex tasks

This chapter presents a review of research comparing the effectiveness of individual learning environments with collaborative learning environments. In reviewing the literature, it was determined that there is no clear and unequivocal picture of how, when and why the effectiveness of these two approaches to learning differ, a result which may be due to differing complexities of the learning tasks used in the research and the concomitant load imposed on the learner's cognitive system. Based upon cognitive load theory, it is argued that learning by an individual becomes less effective and efficient than learning by a group of individuals as task complexity increases. Dividing the processing of information across individuals is useful when the cognitive load is high because it allows information to be divided across a larger reservoir of cognitive capacity. Although such division requires that information be recombined and that processing be coordinated, under high load conditions these costs are minimal compared to the gain achieved by this division of labor. In contrast, under low load conditions, an individual can adequately carry out the required processing activities, and the costs of recombination and coordination are relatively more substantial. Implications of these ideas for research and practice of collaborative learning are discussed.

This Chapter was published as:
Kirschner, F., Paas, F., & Kirschner, P. A. (2009a). A cognitive-load approach to collaborative learning: United brains for complex tasks. *Educational Psychology Review, 21*, 31-42.

Contemporary learning paradigms argue for the facilitation of lifelong learning in collaborative as opposed to individual environments. This is based upon the premise that the collaboration process will include discussion, argumentation and reflection upon the task at hand, thus leading to deeper processing of the information and richer and more meaningful learning. These environments can be either traditional collaborative ones, such as in face-to-face problem-based learning, or computer-mediated environments, which can be synchronous or asynchronous and/or distributed or non-distributed. Although, different educational, social, and economic arguments have been advanced to explain the potential of collaborative learning and justify its use, it is argued that the basic rationale for choosing collaborative learning as the preferred educational approach should be its relative effectiveness and efficiency for learning in comparison with more traditional educational approaches in which learning takes place as an individual activity.

This chapter presents a review of the available research on collaborative learning (i.e., learning in a group in which knowledge and/or information may be divided across individuals, but where the group as a whole carries out the task) to show that it is not possible to draw unequivocal conclusions about the superiority of collaborative learning above individual learning. The mixed results found are discussed in the context of the way research in this field is typically conducted, and the theoretical framework of cognitive load is used to identify factors that determine if and how collaborative learning can be effective and/or efficient for learning, especially, in comparison to individual learning. Group learning is considered to be more effective if the learning outcomes of n members of a group are higher than the sum of the learning outcomes of n comparable individual learners, and more efficient if those learning outcomes are obtained with the investment of less mental effort.

Collaborative learning research

Collaborative learning environments take on a great variety of forms. They can, for example, differ in size, composition, pursued goal, supporting tools, synchronicity, common knowledge distribution, division of tasks, and so forth. However, independent of this, they all ask for a certain mutual and shared effort of the members of the group. Teasley and Roschelle (1993) investigating the construction of shared meanings in model-building activities, showed the importance of individuals making a conscious and continued effort to solve a problem together. Just putting two or more individuals in the same room, and assigning them the same task is not a guarantee for true collaboration. For collaboration, group members must actively communicate and interact with each other with the intention of establishing a common focus and achieving a common goal (Akkerman et al., 2007; Beers, Boshuizen, Kirschner, & Gijselaers, 2006). To achieve this, valuable knowledge and information held by each group member must actively be shared (i.e., retrieving and explicating information), discussed (i.e., processing the information) and remembered (i.e., personalizing and storing the information). Although the processes occurring during group discussions, such as negotiating of meaning, including verbalizing explanations, justifications and reflections (Beers, Boshuizen, & Kirschner, 2007; P. A. Kirschner, Beers, Boshuizen, & Gijselaers, 2008), giving mutual support (Van Boxtel, Van der Linden, & Kanselaar, 2000), and developing arguments about complex problems or propositions (Munneke, Andriessen, Kanselaar, & Kirschner, 2007) are very important and often the subject of the research conducted, collaborative learning models should primarily be based on the premise that actual learning is best achieved – in terms of effectiveness, efficiency, or both – interactively rather than individually.

However, it is hard to find unequivocal support for this premise in the research because empirical evidence of actual learning in terms of knowledge increase is, on the one hand not straight forward, and on the other hand reveals mixed results. There is, for example, research showing the benefits of working in collaboration rather than in more traditional individual learning environments. With regard to the positive effects, students working collaboratively have been found to become more actively engaged in the learning process, to retain the information being learned for a longer period of time (e.g., Morgan, Whorton, & Gunsalus, 2000), to have their higher-order skills fostered more (e.g., Sloffer, Dueber, & Duffy, 1999), and are enabled to engage in activities valuable to the processes of learning such as self directed learning, negotiating meaning, verbalizing explanations, justifications and reflections, and giving mutual support (e.g., Van Boxtel et al., 2000). These results are primarily found in highly structured and/or highly scripted learning environments in which learning processes were bound to strict rules (Dillenbourg, 2002). But even when this was the case, beneficial effects on learning were not always found (Beers, 2005; De Westelinck, De Craene, & Kirschner, 2005; Makitalo et al., 2005; Van Bruggen, Kirschner, & Jochems, 2002; Van Drie, Van Boxtel, Jaspers, & Kanselaar, 2005). Along with the positive findings, however, there is also a body of research showing mixed and negative findings regarding both the learning process itself (Gregor & Cuskelly 1994; Hallet & Cummings, 1997; Heath, 1998; Mason, 1991) and group forming and their dynamics (Hiltz, 1998; Hobaugh, 1997; Hughes & Hewson, 1998; Taha & Caldwell, 1993). Groups appear to fall prey to information processing limitations such as underutilizing base-rate information (Tindale, 1993), committing additional resources to failing projects (i.e. the sunk cost effect: Smith, Tindale, & Steiner, 1998), ineffectively sharing information known only by individual group members (i.e., hidden profile paradigm), production blocking (Diehl & Stroebe, 1987) and social loafing (Latané, Williams, & Harkins, 1979). It has become clear that simply placing learners in a group and assigning them a task does not guarantee that they will work together (Hiltz, 1998; Hobaugh, 1997; Hughes & Hewson, 1998; Taha & Caldwell, 1993), engage in effective collaborative learning processes (Gregor & Cuskelly 1994; Hallet & Cummings, 1997; Heath, 1998; Mason, 1991), or lead to positive learning outcomes (Beers, 2005; De Westelinck et al., 2005; Mäkitalo, Weinberger, Häkkinen, Järvelä, & Fischer, 2005; Van Bruggen et al., 2002; Van Drie et al., 2005).

This inconclusiveness and the associated problem of identifying the factors that determine the effectiveness and efficiency of collaborative learning might be attributable to four characteristics of the way research in this field has typically been designed and conducted. The first characteristic is, that learning potentials and claims are often only indirectly tested by measuring performance, group processes, or both, in the learning phase (e.g., number of contributions, moves, types of contributions, etc.), instead of measuring them directly by appropriate measures of actual learning outcomes in a test phase specifically designed for testing learning and/or transfer (Kester & Paas, 2005). While problems in the learning phase might be successfully solved and group processes successfully stimulated, this does not necessarily mean that learners have effectively or efficiently learned (P. A. Kirschner, Sweller, & Clark, 2006; Sweller, Kirschner, & Clark, 2007). In addition, because of indirect testing, the measures used are often a determination of the quality of the group product or group processes rather than of the learning of the individual group members. The quality of group processes or products does not necessarily reflect the quality of learning of the individual group members, as the group product might, for example, be the result of the input of the most knowledgeable or diligent group member. The importance of collaborative learning and the superiority of groups above individuals could be best understood when assumptions of learning effectiveness are not primarily based on measurements of performance and/or group processes during the learning phase, but also on appropriate tests of learning outcomes and transfer.

The second characteristic is the dominant research focus on naturalistic studies in real-life contexts. P. A. Kirschner, Martens, and Strijbos (2004) argue that most systematic design process models center on designing effective conditions for the attainment of individual learning outcomes (Van Merriënboer, Kirschner, & Kester, 2003) and attempt to control instructional variables to create a learning environment that supports the acquisition of a specific skill (i.e., student A will acquire skill B through learning method C). This control of the instructional variables is complicated by the use of collaborative groups. In such groups, a multitude of individual and group-level variables affect the collaborative learning process making it practically impossible to both predefine the conditions of learning or instruction for a group-setting such that interaction processes and competency development are controlled and predict the processes that the group will carry out. P. A. Kirschner et al. (2004) refer to this as a shift from causal to probabilistic instructional designs. This approach leads to a complex pattern of interactions between cognitive, motivational, and social factors that are difficult to both predict and interpret. To be able to disentangle the contributions of each of these factors to the learning processes and outcomes of group-based learning, the different factors need to be studied within tightly constrained experimental environments, one at a time, keeping all other aspects constant.

Thirdly, computer supported collaborative learning research often focuses on surface level characteristics and/or variables (e.g., synchronicity or a synchronicity, 'optimal' group size, whether the task was a case, a problem or a project). For example, a group that could be considered 'small' for carrying out one type of task might be too 'large' to efficiently and/or effectively carry out a different task. This surface level approach cannot answer fundamental questions such as: Was collaboration really necessary? Did learners design (i.e., the goal being divergent and creative) or prove or diagnose something (i.e., the goal being convergent and specific)? Who determined the goal, how to reach it, and what is correct? Or under what circumstances do groups learn most effectively and efficiently? For research to provide a better understanding of the factors that determine if, and how, collaborative learning is effective/efficient, more fundamental aspects of the collaboration process need to be studied, such as the nature/characteristics of the task that is to be carried out and the nature/characteristics of the individual learners in a group (P. A. Kirschner, 2002).

The final characteristic of collaborative learning research that might be responsible for the inconclusive results is its focus on group performance instead of on the contribution of each group member. There are a substantial number of studies suggesting that collaborative learning improves students' achievements compared to working alone (Hartwick, Sheppard, & Davis, 1982; Johnson & Johnson, 1989). This suggestion is based on empirical data showing that collaborating groups outperform the 'average' individual working alone on a wide range of recall assignments in which groups and individuals are asked to recall as many facts of an event, story or film, or recall as many nonsense words as possible. (Brown, 2000; Hartwick et al., 1982; Kerr, MacCoun, & Kramer, 1996; Kerr & Tindale, 2004; Levine & Moreland, 1998; Lorge & Solomon, 1961; Stasser & Dietz-Uhler, 2001; Stasser, Kerr, & Davis, 1989; Vollrath, Sheppard, Hinsz, & Davis, 1989). The better performance and the assumption that in real life situations more recalled items could provide a better basis to make a decision or solve a problem would therefore make collaborating groups superior to individuals working alone. Superiority is attributed to a group interaction process in which specific information held by one member of the group is shared with and distributed among the other group members through a process of communication and coordination. However, only focusing on a group product instead of on the individual group member contributions can be considered to be a misinterpretation of the data.

Research taking a closer look at this presumed superiority argues (Laughlin, Bonner, & Andrew, 2002; Laughlin, Hatch, Silver, & Boh, 2006; Laughlin, Zander, Knievel, & Tan, 2003) that group performance should be compared to an expected performance of a nominal group (i.e., a fictitious group formed by pooling the non-redundant performances of individuals working alone) instead of to the individual performance. The performance of the nominal group is then used as a reference point for comparing the performance of the actual collaborating groups. This approach is similar to Lorge and Solomon's (1955) pooling of abilities model. The performance of the group can be at the level of what such pooling would predict, above this level or below. The first possibility holds that the collaboration or interaction process does not make individual group-member performance more effective. The latter two levels hold that collaboration either facilitates or inhibits performance of the individual group member. Facilitation, in this respect, means that the collaboration process causes the group performance to be better than the simple sum of the individual performances. Working in a group is then more efficient/effective (Laughlin, Bonner, & Miner, 2002; Laughlin et al., 2006). Inhibition implies the opposite in which collaboration is detrimental to the performance of the individual group member (Kerr & Brunn, 1981; Latané et al., 1979; Weldon & Bellinger, 1997). Although groups as a whole perform better than the individual who is working alone, they do not perform optimally. Working together causes a process loss (Steiner, 1972) due to poor coordination, which is considered to be a performance-limiting factor. Studies which have taken a critical look at the possible superiority of groups by comparing group performance with the expected performance of nominal groups, have shown that group recollection is either at or below the level that such pooling would predict (Hinsz, 1990; Hoppe, 1962; Meudell, Hitch, & Kirby, 1992; Perlmutter & De Montmollin, 1952; Stephenson, Clark, & Wade, 1986; Weldon & Bellinger, 1997). Collaboration appears to inhibit individual group member recall and therefore the superiority of learning in collaborating groups has not been proven. This misrepresentation shows that including the data of individual group members would be much more informative and straightforward than just basing conclusions on group performance.

Summing up, the way collaborative learning research is conducted and the inconclusive results obtained, make it impossible to draw sound conclusions as to the relative effectiveness and efficiency of collaborative learning environments compared to individual learning environments. To counter this, research should base its claims on direct measurements of learning in a test phase, should study one important or fundamental aspect of the learning environment at a time, and should focus on performance of the group members rather than on the group as a whole.

F. Kirschner, Paas, and Kirschner (2009a [Chapter 3]) have argued that to better design, analyze, and understand effective instructional procedures for individual and group learning, the structures that constitute human cognitive architecture need to be taken into account. A theoretical framework which states that any instructional procedure that ignores these structures is not likely to be effective, is cognitive load theory (CLT: Paas, Renkl, & Sweller, 2003, 2004; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005). By applying CLT to collaborative learning environments, one can argue that if individuals are to work together and learn effectively and/or efficiently in groups, the architecture of their cognitive system and the characteristics of the task to be carried out must be understood, accommodated, and aligned. This theoretical framework could provide a better understanding of the factors that determine if, when, and how collaborative learning will be effective and efficient for learning, especially when compared to an environment where individuals learn independently.

Cognitive load theory

Cognitive load theory is based on the cognitive architecture of individual learners. CLT is concerned with the learning of complex cognitive tasks, in which learners are often overwhelmed by the number of interactive information elements that need to be processed simultaneously before meaningful learning can commence. CLT distinguishes between three types of cognitive load (Sweller et al., 1998). The load is considered to be 'intrinsic' if it is imposed by the number of information elements in a task and the interactivity between those elements. The more elements there are within a task and the more interaction there is between them, the higher the intrinsic cognitive load. When the load is imposed by the manner in which the information is presented to learners and by the learning activities required of them, it is called either 'extraneous' or 'germane' cognitive load. Extraneous load is imposed by information and activities that do not directly contribute to learning, while germane load is caused by information and activities that foster learning processes. Intrinsic, extraneous, and germane cognitive load are considered additive in that, taken together, the total load cannot exceed the memory resources available to the learner if learning is to occur (see, Paas, Tuovinen, Tabbers, & Van Gerven, 2003).

The relations between the three forms of cognitive load are asymmetric. Intrinsic load provides a 'base' load that is irreducible other than by constructing additional schemas and automating previously acquired schemas; in other words, by an increase in expertise or by deconstructing the task so that less elements interact (see Ayres, 2006; Pollock, Chandler, & Sweller, 2002). Any available working memory (WM) capacity remaining after resources have been allocated to deal with intrinsic load can be allocated to deal with the extraneous and germane load. These can work in tandem in that, for example, a reduction in extraneous load by using a more effective instructional design can free capacity for an increase in germane load. If learning is improved by an instructional design that reduces extraneous cognitive load, that improvement may have occurred because the additional WM capacity freed-up by the reduction of extraneous cognitive load has now been allocated to germane cognitive load. Also, as a consequence of the acquisition of new cognitive schemas, intrinsic load is reduced. A reduction in intrinsic load reduces the total cognitive load, thus freeing-up WM capacity for information processing. The freed-up WM capacity allows the learner to use the newly learned material (i.e., the newly acquired cognitive schemas) in acquiring more advanced schemas. A new cycle, thus, commences and over many cycles, very advanced knowledge and skills may be acquired.

Instructional control of this (too) high cognitive load has become the focus of CLT. In the past two decades, cognitive load research has generated a substantial knowledge base on the design of instruction for individual learners. However, previous research on group-based learning has made clear that there is no one-to-one mapping of instructional design guidelines for individual learning onto group-based learning (Kreijns, Kirschner, & Jochems, 2003). As the instructional design for group-based learning environments might differ from those of individual learning environments, it is important to reconsider the cognitive load perspective to determine the conditions under which group-based learning environments may or may not be effective.

The group as information-processing system

When groups of collaborating learners are considered as information-processing systems in which the information within the task and the associated intrinsic cognitive load can be divided across multiple collaborating working memories, it can be argued that because of a combination of the expanded processing capacity and the distribution advantage, the more complex the task is, the more efficient it will become for individuals to cooperate with other individuals in a fashion that reduces this load. This distribution advantage for complex tasks has been shown at a more basic level in the domain of cognitive brain research. Research there has shown that the capacity of the brain was increased by dividing the processing of complex tasks between the two hemispheres of the brain (i.e., interhemispheric processing), instead of using one hemisphere (Maertens & Pollmann, 2005). By presenting stimuli to either the left visual field (i.e., processed by the right hemisphere), the right visual field (i.e., processed by the left hemisphere), or both (i.e., processed by both hemispheres), Banich and colleagues (Banich & Belger, 1990; Banich, Passarotti, & Chambers, 1994; Belger & Banich, 1992) have shown that processing within one hemisphere becomes less efficient than processing between the two hemispheres as task complexity increases. Thus, dividing processing across the hemispheres is useful when processing load is high because it allows information to be divided across a larger expanse of neural space. Although such division requires that information be recombined and that processing be coordinated, under high load conditions these costs are minimal compared to the gain afforded by a division of labor. In contrast, under low load conditions, a single hemisphere can adequately handle the processing requirements and the division of information does not add a significant amount of computational power and, thus, the costs caused by interhemispheric coordination are relatively more substantial. In the context of CLT and collaborative learning, this interhemispheric interaction effect could be explained in terms of a need for more working memory capacity when complex tasks need to be learned. If a task is of such a high complexity that two hemispheres (i.e., one individual) are not enough to process and relate all the interactive information elements, more processing capacity is needed. Therefore, it could be argued that assigning high complexity tasks to groups of learners allows information to be divided across a larger reservoir of cognitive capacity, and might result in more effective and efficient learning than assigning them to an individual learner.

It is, therefore, hypothesized that the more complex the learning task (i.e., the higher the intrinsic cognitive load), the more efficient and effective it will be for individuals to collaborate with other individuals in a manner that reduces this load. By contrast, less complex tasks that can easily be solved by a single individual will lead to less efficient learning in groups than in individuals alone, because the required group communication and coordination process (i.e., transaction costs) impose an additional cognitive load upon the group members, regardless of whether this communication and coordination is beneficial to learning or not (F. Kirschner et al., 2009a [Chapter 3]). Group communication is a process in which members of a group share and discuss the learning task, the relevant information elements and the task solution as well as communication intended to reach common ground. Group coordination is a process that manages the interdependencies between group members so that every group member knows exactly which activities other members are carrying out or will carry out, in order to effectively determine what one's own activities at the moment and in the future should entail (see, Malone & Crowston, 1990). Group coordination has to occur at both the group level (e.g., allocating resources among and defining workflow across the group members: Ellis, Gibbs, & Rein, 1991), and the task level (e.g., a shared text editor use requires that group members to know exactly where others are typing at any given moment: Dourish & Bellotti, 1992; Gutwin, 1997). According to CLT, these communication and coordination activities may either impose extraneous cognitive load with simple tasks because communication and coordination processes are not necessary for or interfere with learning, or a germane load with more complex tasks because communication and coordination processes are necessary for carrying out the learning task and, thus, for effective learning.

The CLT-based claim that individual learning will be more effective for simple cognitive tasks is supported by research on recall tasks (e.g., Vollrath et al., 1989; Stasser et al., 1989). Evidence for the claim that collaborative learning will be more effective in complex cognitive tasks has been found when more complex problem-solving tasks were used as a learning measure instead of recall tasks. When learners had to work with the information elements relevant for carrying out the task, relate them to each other, and by doing so come up with a solution to a problem, groups not only outperformed individuals but also the nominal group (Andersson & Rönnberg, 1995; F. Kirschner et al., 2009a [Chapter 3]; Kramer, 1999; Laughlin et al., 2002; Laughlin et al., 2006; Ohtsubo, 2005). Under these conditions, participating in a group facilitated the performance of the individual group member. The complexity of a task seems to be an important factor in determining whether collaboration is beneficial or not.

Conclusion and discussion

This chapter identified four possible causes for the mixed results of research on the effectiveness and efficiency of collaborative learning as compared to learning individually. The first is that learning is often only indirectly tested by measuring individual/group performance and/or group processes in the learning phase instead of through the use of appropriate measures of actual learning and/or transfer outcomes in a separate test phase. Van Gog and Paas (2008; see also Paas & Van Merriënboer, 1993) have argued that performance in a learning phase does not have to be predictive for what has been learned. Learning can only be reliably determined by measuring performance in a test phase. A second possible cause is that the dominant research focus of most collaborative learning research is the use of naturalistic studies in real-life contexts. This research, due to its probabilistic nature, involves complex patterns of interactions between cognitive, motivational, and social factors that are both difficult to predict and interpret. Thirdly, the majority of research tends to focus on surface level characteristics and variables of the learning environments used (e.g., group size, communication modes), which preclude the answering of fundamental questions regarding effective and efficient collaborative learning. An example of a non-surface level variable is task complexity. Finally, regardless of whether performance is adequately tested (see the first cause), most research focuses on group performance instead of on the contribution of each group member. This focus, when compared to individual performance, might lead to a misinterpretation of the data, in the sense that groups can be incorrectly considered superior. To this end, when comparing performance, group performance of collaborative groups should be compared with group performance of nominal groups.

The chapter then took a cognitive load approach to collaborative learning which was considered to provide the opportunity to re-study and re-interpret learning in groups. CLT, with its differentiation between intrinsic, extraneous, and germane cognitive load allows for a better understanding of the non-surface level aspects of collaborative learning such as task complexity (i.e., intrinsic load caused by the number of elements in a learning task and the interaction between those elements) and communication and coordination activities in collaborating groups (e.g., transaction costs that can cause either extraneous or germane cognitive load, depending on the situation).

The chapter also argued for studying new and different perspectives from other scientific disciplines as a way of understanding collaborative learning compared to individual learning. As an example, cognitive brain research on interhemispheric interaction was used as a source of inspiration for a cognitive-load perspective on collaborative learning. This perspective, in which groups are considered as information-processing systems consisting of multiple collaborating working memories, can be used to generate new hypotheses and study the effectiveness and efficiency of collaborative learning. It is expected that groups have an advantage above individual learners – as is the case in the research on information processing between two hemispheres or within one hemisphere – because this would allow for distributing cognitive effort among group members. From this point of view, the complexity of the task was identified as an important factor for determining whether collaborative learning will or will not be effective and/or efficient as compared to individual learning. Taken together, it was hypothesized that the more complex the learning task is (i.e., the higher the intrinsic cognitive load), the more efficient and effective it will be for individuals to collaborate with other individuals in a manner that reduces this load. The review of previous studies along with the empirical results of studies by the authors themselves testing this hypothesis are promising, in the sense that studies using simple recall tasks revealed that individuals seem to be more effective while groups seem to exhibit more effective learning when more complex problem solving tasks were used.

With regard to possible implications for educational practice it is important to know why and when collaborative learning will be superior to individual learning. This review suggests that the complexity of the task (i.e., the intrinsic cognitive load), should be a determining factor when deciding whether to employ a learning model or environment which is based upon an individual or a collaborative learning paradigm. The higher the complexity of the learning tasks, the more likely it is that collaborative learning will lead to better learning outcomes – either in terms of effectiveness, efficiency, or both – than individual learning. This means that if an institution chooses collaborative learning as an educational model, then the educational designers (most often the teachers) need to guarantee that the learning tasks given to the groups (e.g., problems, projects, et cetera) are complex in nature and thus cannot be easily carried out by an individual. This also suggests that practitioners should not make an exclusive choice for individual or collaborative learning, but rather that they vary the approach depending on the complexity of the tasks to be learned.

In conclusion, although the cognitive-load perspective appears to provide both an interesting and a fruitful supplement to the prevailing social and motivational perspectives of collaborative learning; it should be noted that ultimately, the complex interactions between cognitive, motivational, and social factors need to be investigated. For now, the presented cognitive-load perspective can broaden the horizon of researchers investigating collaborative learning and contribute both to the identification of those cognitive, non-surface level variables affecting collaborative learning and to the instructional design of effective and efficient collaborative learning.

3

Individual and group-based learning from complex cognitive tasks: Effects on retention and transfer efficiency

The effects of individual versus group learning (in triads) on efficiency of retention and transfer test performance in the domain of biology (heredity) among 70 high-school students were investigated. Applying cognitive load theory, the limitations of the working memory capacity at the individual level were considered an important reason to assign complex learning tasks to groups rather than to individuals. It was hypothesized that groups will have more processing capacity available for relating the information elements to each other and by doing so for constructing higher quality cognitive schemas than individuals if the high cognitive load imposed by complex learning tasks could be shared among group members. In contrast, it was expected that individuals who learn from carrying out the same complex tasks would need all available processing capacity for remembering the interrelated information elements, and, consequently, would not be able to allocate resources to working with them. This interaction hypothesis was confirmed by the data on efficiency of retention and transfer test performance; there was a favorable relationship between mental effort and retention test performance for the individual learners as opposed to a favorable relationship between transfer test performance and mental effort for the students who learned in groups.

This Chapter was published as:
Kirschner, F., Paas, F., & Kirschner, P. A. (2009b). Individual and group-based learning from complex cognitive tasks: Effects on retention and transfer efficiency. *Computers in Human Behavior, 25*, 306-314.

Collaborative learning models are based on the premise that certain types of learning are best achieved interactively rather than through a one-way transmission process (Johnston, James, Lye, & McDonald, 2000; Littleton & Häkkinen, 1999; Slavin, 1983, 1995; Veerman, 2000; Veerman & Veldhuis-Diermanse, 2001; Weigel, 2002). Although collaborative learning is emerging as a promising educational approach, research on its effects on learning has been highly inconclusive (Kester & Paas, 2005). We believe that these inconclusive results have, among other things, been caused by a lack of attention to the structures constituting human cognitive architecture (Sweller, 1988; Sweller & Sweller, 2006; Sweller, Van Merriënboer, & Paas, 1998) when designing collaborative learning environments.

Research stressing the potential of collaborative learning shows that collaborative learning environments can stimulate and/or enable learners to engage in activities that are valuable for learning. Activities such as self-directed learning, negotiating meaning (Beers, Boshuizen, & Kirschner, 2007; P. A. Kirschner, Beers, Boshuizen, & Gijselaers, 2008), verbalizing explanations, justifications and reflections, giving mutual support (Van Boxtel, Van der Linden, & Kanselaar, 2000), and developing arguments about complex problems or propositions (Munneke, Andriessen, Kanselaar, & Kirschner, 2007) have been found to facilitate the learning process. Collaborative learning has also been shown to help learners retain the learned information longer (Morgan, Whorton, & Gunsalus, 2000) and to foster their higher-order skills more than in more traditional lecture-based learning environments (Sloffer, Dueber, & Duffy, 1999). It is important to note that these positive results were found in studies that implemented 'extra' measures to ensure that participants engage in effective collaboration, primarily using highly constrained and scripted collaborative learning environments (Dillenbourg, 2002; Fischer, Bruhn, Gräsel, & Mandl, 1999, 2002; Kollar, Fischer, & Hesse, 2006); learning environments in which communication and coordination were bound to strict rules and formats to make sure that learners knew what they had to do, how they were supposed to do it, with whom they had to work and/or what they had to communicate about. Studies using less scripted or constrained environments show mixed and even negative findings regarding both learning process (Gregor & Cuskelly 1994; Hallet & Cummings, 1997; Heath, 1998; Mason, 1991), and group forming and group dynamics (Hiltz, 1998; Hobaugh, 1997; Hughes & Hewson 1998; Taha & Caldwell, 1993).

It has become clear that placing learners in a group and assigning them a task does not guarantee that they will work together, engage in effective collaborative learning processes, and show positive learning outcomes (Soller, 2001). However, a controlled collaborative learning environment is also not a guarantee for success. There is research on collaborative learning showing that, even when learners were engaged in collaborative learning in which groups were effectively formed and cognitive learning processes were successfully supported, beneficial effects were not always found (Beers, 2005; De Westelinck, Valcke, De Craene, & Kirschner, 2005; Makitalo, Weinberger, Häkkinen, Järvelä, & Fischer, 2005;

Van Bruggen, Kirschner, & Jochems, 2002; Van Drie, Van Boxtel, Jaspers, & Kanselaar, 2005).

Inconclusive results have also been found in studies comparing individual performance to group performance when subjects had to recall as many information elements as possible after studying them for a certain amount of time. In these scripted and constrained environments, groups outperformed individuals in the amount of items recalled. However, if group performance was compared to the sum of individual scores (i.e., the nominal score), in most cases group performance was inferior to that of the nominal group, meaning that when working together in a group to recall information, individuals recalled less than when they worked alone. The results of these recall studies suggest that the collaboration process is detrimental for group-member performance even though the environment was constrained and communication and coordination were bound to rules and kept to a minimum (Andersson & Rönnberg, 1995; Meudell, Hitch, & Kirby, 1992; Weldon & Bellinger, 1997).

Different results were found when the tasks used were problem-solving tasks instead of recall tasks. When learners had to work with the information elements, relate them to each other, and by doing so find the solution to a problem, groups again outperformed individuals but they also outperformed the nominal group (Laughlin, Bonner, & Miner, 2002; Laughlin, Hatch, Silver, & Boh, 2006). This time, participating in a group facilitated the performance of the individual group member. The type of the task seems to be an important factor in determining whether collaboration is beneficial or not.

Recall tasks in which remembering is the main goal can be seen as relatively simple tasks, whereas problem-solving tasks in which working with information is most important can be seen as relative complex tasks. The research in which individuals and groups are compared regarding their recall or problem-solving performance implies that individual learning is superior to group learning for relatively simple recall tasks, and that group learning is superior to individual learning for relatively complex problem-solving tasks. A possible explanation for this can be found in cognitive load theory (CLT: Paas, Renkl, & Sweller, 2003, 2004). CLT is mainly concerned with individual learning from complex cognitive tasks. It assumes that individuals cannot process an unlimited number of information elements in their working memory (WM). According to Cowan (2001), WM is limited to 4 ± 1 information element if the elements are interrelated and, consequently, have to be combined, contrasted or worked on for understanding to take place. According to CLT, a task can impose three kinds of load on an individual: intrinsic load, extraneous or ineffective load, and germane or effective load (Sweller et al., 1998). Intrinsic cognitive load caused by element interactivity is determined by a combination of the number of information elements and the interaction between the elements that have to be related to each other (the intrinsic nature of the material) and the expertise of the learners. Because this load is intrinsic to the task, it is assumed that it cannot be directly influenced by instructional designers. Extraneous cognitive load is the load resulting from poorly designed instruction that does not contribute to learning. An example of this is the cognitive load caused by the searching for relevant information during unguided discovery learning in problem-solving tasks (P. A. Kirschner, Sweller, & Clark, 2006; Sweller, Kirschner, & Clark, 2007). Germane cognitive load is the load related to the instruction that contributes to effective learning. Both extraneous and germane load are under the direct control of instructional designers. Because intrinsic load, extraneous load, and germane load are additive, from a cognitive load perspective, it is important to realize that the total cognitive load associated with an instructional design – the sum of the three loads – should stay within working memory limits (Paas, Tuovinen, Tabbers, & Van Gerven, 2003).

Applying the principles of CLT, this study considers groups as information-processing systems consisting of multiple (limited) WMs which can create a collective working space (F. C. Kirschner, Paas, & Kirschner, 2009a). From this theoretical point of view, multiple collaborating WMs always provide more processing capacity, but whether this capacity can be used effectively depends on the type of task. It can be argued that a group has more effectively available processing capacity than an individual information-processing system for tasks in which the relevant information needs to be shared among working memories for learning to commence. In a group, the cognitive load imposed by a task can be shared among group members, and by doing so free-up WM-capacity at the individual level that can be used to deal with more complex problems and construct higher quality cognitive schemas compared to an individual working alone. Therefore, the limitations of the WM-capacity at the individual level can be argued to be an important reason to assign complex learning tasks to groups rather than to individuals.

However, creating a collective working space is only possible if the relevant knowledge held by each individual group member is communicated and coordinated within the group (Salas, Simms, & Burke, 2005). Communication leads to shared cognition and the construction of shared mental models, which have been identified as key aspects of collaboration (Barron, 2003). Through social interaction within the team, a collective knowledge structure is formed, which is conditional for team success. Research shows that mutually shared cognition is the result of knowledge building in socio-cognitive processes and is directly linked to team effectiveness (Van Den Bossche, Gijselaers, Segers, & Kirschner, 2006). Communication is especially important when the information needed to successfully solve a problem is distributed among group members so that all members possess different but crucial information. Research on the hidden profile paradigm has shown that in complex decision making, collaborators do not effectively share the 'unshared' information (i.e., information that is only available to a group member). In such complex tasks, groups do not work well (Whyte, 1991). It is therefore important that when performing complex tasks that learners are stimulated to exchange knowledge and information. Making learners dependent on each other either for successfully carrying out and completing a task (i.e., task/goal interdependence) or for exchanging resources (i.e., positive resource interdependence) are ways of doing this. Task or goal interdependence refers to the interconnecting subtasks, such that the performance of one piece of work on a task or project depends on the completion of other pieces (Langfred, 2000). It involves members of a team depending on one another to accomplish both individual and team goals (Campion, Medsker, & Higgs, 1993). Wageman (1995) determined that reducing interdependency by dividing tasks into independent subtasks negatively influences team performance. Positive resource interdependence holds that learners working within a group receive only a part of the resources, information, or materials necessary for the task to be completed and, thus, that they need and access the other necessary resources through their partner or partners (Johnson, Johnson, & Stanne, 2001; Ortiz, Johnson, & Johnson, 1996). Research on resource interdependence shows that when learners are allocated only part of the resources necessary to achieve specific goals, effective information transmission, and positive interaction and cooperation is favored and performance enhanced (Buchs, Butera, & Mugny, 2004).

As shown, structure and control of knowledge communication and coordination are very important for collaborative learning environments to be effective. The beneficial effect of being able to share the cognitive load within a group could be annulled by the costs of communication and coordination between the group members, the so called cognitive and social transaction costs. This concept of transaction costs is more and more used in the field of learning and especially collaborative or cooperative learning (i.e., learning in groups: Ciborra & Olson, 1988; Yamane, 1996). It originates from the field of economics and concerns those costs, other than the money price, that are incurred in trading goods or services. Within a collaborative or cooperative learning environment these transaction costs are "the costs of setting up, enforcing, and maintaining the reciprocal obligations, or contracts, that keep the members of a team together [and]…represent the 'overhead' of the team…linked to the resources (time, skills, etc.) employed to allow a work team to produce more than the sum of its parts" (Ciborra & Olson, 1988, p. 95). In our situation, they refer to the specific cognitive load that has to be taken into account when learners are communicating with other learners and coordinating both the carrying out of the task and the communication between each other.

When communicating and exchanging information learners are forced to come up with and agree upon a common solution by combining and integrating their individual ideas into a shared and collective one. Group coordination manages the interdependencies between group members so that every group member knows exactly which activities other members are carrying out, or will carry out, in order to effectively determine what one's own activities at the moment and in the future should entail (for a general discussion about coordination theory see Malone & Crowston, 1990). Group coordination has to happen at both the group level (e.g., allocating resources and defining workflow, see Ellis, Gibbs, & Rein, 1991) and the task level (e.g., a shared editor use requires group members to know exactly where others are typing, see Dourish & Bellotti, 1992; Gutwin, 1997). Because CLT has exclusively focused on individual learners performing an individual task, the cognitive load associated with initiating and maintaining communication and coordination – the transaction costs – have not received specific attention. However, collaborative learning environments can only be effectively designed if those costs are taken into account. The transaction costs can be argued as imposing intrinsic, germane, or extraneous cognitive load on learners. Intrinsic load is imposed when communication and coordination are inherent to a collaborative learning situation and/or environment; one cannot exist without the other. Germane load is imposed when the transaction costs are effective for learning because they foster shared understanding, trust, mutual performance monitoring, common ground, argumentation, coordination, and positive cognitive conflicts (Leitão, 2000; Mercer, 1996; Munneke et al., 2007; Salas et al., 2005; Savery & Duffy, 1995) which have been shown to facilitate the learning process. Extraneous load is imposed when the transaction costs are ineffective for learning because it fosters errors, conflicts, unnecessary duplication, etc. (Bernard & Lundgren-Cayrol, 2001; Webb & Palincsar, 1996). Especially the extraneous or ineffective cognitive load should be minimized for collaborative learning to be effective. If these costs are not controlled and minimized, the freed-up WM-capacity at the individual level could be used for non-essential or non-learning related communication such as discussing who is going to fill in the answer, telling others what you bought yesterday, and fighting about the goal of the task, instead of constructing high quality cognitive schemas. The advantage of being able to share the cognitive load that a complex task causes could be annulled by too high transaction costs.

Taking both the complexity of the task and the transaction costs into account, a prerequisite for group-based learning being more effective than individual learning would be that the demands involved in carrying out the task alone exceed the sum of the cognitive resources that a single individual can supply and the resources needed to deal with the ineffective social transaction costs of communication and coordination of the knowledge between the group members. This is almost always the case in collaborative learning situations where the task that the learners must carry out demands simultaneous processing of the information that cannot be offloaded by the individual at any one time. In those situations, group members are expected to be more able to apply the knowledge and skills acquired in carrying out a cognitively complex learning task to tasks that differ from the ones trained, as indicated by more efficient and effective transfer performance. In contrast, individuals carrying out the same complex tasks do not have the possibility to distribute the load and, therefore, have less WM-capacity left to work with the interrelated information elements. Although the transaction costs do not exist here, the risk of the individual becoming cognitively overloaded is quite high. Consequently, they are minimally expected to be able to only focus on remembering the interrelated elements, as indicated by more efficient retention performance.

A drawback of many of the studies comparing individual learning with group learning has to do with the fact that the claims about the effects on learning are often only indirectly tested by measuring acquired skills, performance, and/or group processes in the learning phase (e.g., number of contributions, moves, types of contributions, etc.), and not directly by measures of actual learning performance. One can learn from complex cognitive tasks or can carry out complex cognitive tasks, through which it is assumed or hoped that learning also occurs. This need not be the case. Some criticism of problem-based learning is based upon findings that, while the problems are successfully solved, the learners do not effectively learn from working together (P. A. Kirschner et al., 2006; Sweller et al., 2007). In addition, because of indirect testing, measures are often a determination of the quality of the group product or group process rather than of individual learning. CLT takes these issues into account by incorporating specific claims concerning the role of cognitive load within an instructional context and its relation to individual learning (for an overview see Paas et al., 2003). Most importantly, it recognizes that a meaningful interpretation of a certain level of cognitive load can only be given in the context of its associated performance level, and vice versa. For instance, a performance score on a test does not provide any information about the cognitive costs at which this performance was attained. Therefore, taking both measures into account gives a better indication of the quality of the cognitive schemas participants have acquired than performance scores alone. This insight has led Paas and Van Merriënboer (1993; see also Tuovinen & Paas, 2004; Van Gog & Paas, 2008) to develop a computational approach for examining the observed relation between measures of test performance and measures of mental effort invested in completing the test. This approach enables cognitive load theorists and instructional designers to calculate and compare the efficiency of instructional conditions: high task performance associated with low mental effort is termed high performance efficiency, whereas low task performance with high mental effort is termed low performance efficiency. The value of the approach has been shown by revealing differential effects of varying instructional methods that would have been unnoticed with conventional performance measures (for an overview see Paas et al., 2003).

In this study, it is hypothesized that when performing complex tasks group members will be able to collaborate with one another in a fashion that reduces the high intrinsic cognitive load and therefore will be able to develop higher quality schemas than learners working individually. Higher quality schemas would allow those working in groups to attain higher performance on transfer tasks with less investment of mental effort than individual learners. By contrast, it was expected that those learning from carrying out the same complex tasks individually would need all of their processing capacity for remembering the interrelated information elements, and consequently, would not be able to allocate resources to working with and applying them. This would allow those working individually to attain higher performance on retention tasks with less investment of mental effort than group members. Group members will be able to solve a problem by collaboratively combining the information elements that are distributed across the multiple working memories in the group. Consequently, there will be no need for group members to remember all information elements.

Method

Participants

Participants where 70 fourth year Dutch high-school students (38 boys and 32 girls) with an average age of 15.4 years (*SD* = 0.70) who participated in the experiment as part of a biology course. Prior knowledge concerning biology-related topics was assumed to be approximately equal for all participants, because they had all followed the same courses using the same instructional materials in the preceding years. To assure comparability, they were randomly assigned to the different experimental conditions (i.e., individual vs. triadic group). They did not receive any financial or academic compensation for participation, but six tickets to an amusement park were raffled off.

Materials

All materials used in this experiment were in a domain of biology concerned with heredity, specifically the transfer of both genotypic and phenotypic biological characteristics from parents to their offspring through genes which carry biological information (e.g., eye color in humans, fur length in dogs, leaf shape in plants). The following topics are important when introducing hereditary characteristics: genes, genotype and phenotype of an organism, homozygosity or heterozygosity of an organism's dominant or recessive genes, and genealogical tree. In this domain, a general introduction and an instruction on how to solve inheritance problems, three problem-solving tasks, and six transfer tasks were designed. All tasks (i.e., learning and test), as well as the introduction and instruction where paper-based, however, a computer was used solely for time management.

The introduction. The general introduction and instruction on solving heredity problems discussed the relevant heredity characteristics, the basic terminology, the rules and theory underlying heredity, and the combination of this general instruction in a worked example of how to solve heredity problems. The worked example combined terminology, characteristics, rules, and theory.

Learning tasks. Learners were required to use the information and worked example presented in the introduction to carry out three similar problem-solving tasks. These problem-solving tasks required learners to combine a number of necessary information elements to give a correct answer to two questions concerning the proportion of possible genotypes of the offspring. Each piece of information was relevant but insufficient by itself for solving the problem, but when combined with the other information the problem could be solved. In the domain of heredity this, for instance, could mean that information element

1 is eye color of the mother: blue; information element 2 is eye color of the father: brown; and information element 3 is the dominance of brown eyes over blue eyes. Each element gives a certain amount of information, but to answer the question as to what the eye color of the offspring will be, the learner will have to combine all three pieces of information. All learners assigned to the individual or group condition received the learning tasks as a booklet. While learners in the individual condition received all information elements necessary for performing the task, these information elements were distributed in the group in such a way that every triadic group member only received one third of the information elements necessary for performing the task.

Test tasks. Three retention tasks and three transfer tasks were designed to determine how much was learnt. The first three tasks consisted of problems that were almost identical to the learning tasks that the learners received during the learning phase. Although the tasks differed on the organism used (e.g., a fruit fly was used instead of a guinea pig), the process of solving the problem was identical. To solve these problems, learners only had to remember the worked example that they had received in the introduction and remember what they practiced in the learning phase. The other three tasks consisted of problems that differed structurally from the training tasks. Although the same characteristics, basic terminology, rules, and underlying heredity-theory had to be used, the way it had to be used was structurally different from the learning tasks. The topics used in the transfer tasks were the genealogical tree, X-chromosome linked inheritance, and dihybrid crossings. To solve these problems, learners had to flexibly use the knowledge of heredity that they had acquired in the learning phase. All learners received the transfer tasks in a booklet.

Instruction. All learners received two non-content related instructions, one immediately before the learning tasks, and one before the transfer tasks. These instructions included the procedure, rules, and use of computer, pen, and paper when working on the learning or transfer tasks. The procedure in the learning phase was different for learners in the different conditions. Learners in the individual condition first had to read all information elements thoroughly, then had to individually read the questions, and finally had to try to answer the questions as correctly and quickly as possible using all information elements. Learners in the group condition did not have to read all information elements, but rather only the ones that where allotted to them, then had to read the questions, and finally had to answer the questions together as correctly and quickly as possible using their own as well as each other's allotted information elements. Every group member received one third of the total number of information elements necessary for answering the heredity questions on paper. No information elements were redundant and the number of information elements was the same for all group members. For all learners in all conditions, the rules on using pen and paper while solving the problem were the same, namely that its use was prohibited. It was important that all information elements were held in working memory and could not be offloaded onto the booklet. For learners in the group condition, it was stressed that working together was necessary for solving the problem. Face-to-face communication was very important here, but transaction costs had to be held to a minimum so as not to cause an overload from an extraneous load that is ineffective for learning. Therefore, learners were only permitted to communicate about task related topics, coordination tasks concerning computer use were assigned to group members at the beginning of the learning phase, and instructions on when to do what were written down before and after each task. Also, tasks were designed in such a way that information elements in the group condition were divided into three parts so that every group member received only one part of the information required to solve the problem. This forced distribution of information elements, or knowledge, and limited the coordination costs for the group members, because they did not have to do this division themselves. Learners in both conditions had a fixed amount of time that could be spent working on the task (i.e., 10 min on the first task and 12 on the second and third tasks).

The instruction preceding the transfer tasks was the same for all participants and almost identical to the instructions in the individual condition during the learning phase. Again, they first had to read all information elements thoroughly, then read the questions, and finally try to answer the questions as correctly and quickly as possible using all information elements. But this time, they had to use pen and paper to write down exactly what they were doing and there was a minimum time of 2 min and a maximum time of 10 min for solving each task.

Computer. The computer was solely used for time registration and time management. At the beginning of a task, when the learners started to read the first information elements, it was possible to click a start button. To register their time on task, they had to type their answer to a question and then click the 'save–button' on the screen with the mouse. After this, if still within the fixed amount of time given for a task, it was possible to change the answer and click the save-button again. The last answer saved was used to determine both time on task and correctness of response. The time management function of the computer consisted of a count-down in the learning phase, showing the participants the amount of time remaining for answering the questions or showing them – after they typed their answer – how much time was still available for thinking or talking about the task. In the test phase, the computer only showed the time remaining to complete a task. Working individually on learning or test tasks each learner had a private computer at his/her disposal. This was different in the group condition, where one of the group members was assigned the responsibility of typing in the final answer and clicking the save-button on the one computer per group. Although the group only used one computer, all group members were able to look at the computer screen to watch the count-down. The computers were not used for exchanging information.

Cognitive load measurement. After each task in the learning and test phase, the participants were required to indicate how much effort they had invested in answering the questions by rating this on a 9-point cognitive load rating scale (Paas, 1992; see also Paas & Van Merriënboer, 1994a), ranging from 'very very low effort' to 'very very high effort'.

Performance measurement. The retention test consisted of three complex problem-solving tasks in the domain of heredity, that were almost identical to the tasks received in the learning phase. Each task consisted of a number of information elements that had to be combined to solve the problem. Solving the problem meant answering four questions related to the genotypes, phenotypes, and proportion of both in a certain (fruit fly) family. A participant received one point for giving a correct answer to each of the four questions, thus the minimum score for a task was 0 points and the maximum 4 points. The maximum retention test score was 12 points.

The transfer test consisted of three complex problem-solving tasks in the domain of heredity that differed from the learning tasks on certain structural features. Each task consisted of a number of information elements that had to be combined to solve the problem, which meant answering two or three questions related to the genotypes of a certain family (e.g., dog, chicken, fruit fly). One point could be earned for a correct answer to every question, thus the minimum score for the transfer tasks was 0 points and the maximum score was 2 or 3 points depending on the number of questions in a task. The maximum transfer test score was 7 points. For the statistical analysis, the performance scores on retention and transfer were transformed into proportions. In other words, a participant's score on the three retention tasks and the three transfer tasks were divided by the maximum score of the retention test (i.e., 12) and the transfer test (i.e., 7), respectively.

Efficiency measurement. Performance efficiency was calculated for the retention and transfer tests using Paas and Van Merriënboer's (1993; see Van Gog & Paas, 2008) computational approach by standardizing each of the participants' scores for retention- and transfer-test performance, and mental effort invested in the retention and transfer tests, respectively. For this purpose, the grand mean was subtracted from each score and the result was divided by the overall standard deviation, which yielded z-scores for effort (R) and performance (P). Finally, a performance efficiency score, E, was computed for each participant using the formula: $E = [(P - R)/2^{1/2}]$. High efficiency was indicated by a relatively high test performance in combination with a relatively low mental-effort rating. In contrast, low efficiency was indicated by a relatively low test performance in combination with a relatively high mental-effort rating.

Design and procedure

Participants were randomly assigned to the individual or group learning condition in such a way that 16 participants worked individually on the three learning tasks and 54 participants worked in 3-person groups (i.e., triads). All participants had to individually study a general introduction to heredity concepts and problems. They received this introduction on paper and had to hand it in after 20 min. The participants were then randomly assigned to the individual or group condition to work on the first learning task which took 10 min. After the task, each learner had to rate the amount of invested mental effort on the 9-point rating scale. Next, they worked on the second learning task for which they had 12 min. After this task, they had to again rate the amount of mental effort invested. Finally, they worked on the third learning task, also for 12 min, and rated the amount of invested mental effort. After this learning phase, participants in the group condition were set apart and all (i.e., individuals and groups) had 1 hr to individually solve three retention problems requiring them to individually apply the newly learned principles in familiar situations, and three transfer problems requiring them to use the principles in new, unfamiliar situations. During the test phase, the amount of invested mental effort was measured after each transfer task using the same cognitive load scale used in the learning phase.

Results

Learning Phase

Table 3.1 shows the means and standard deviations of the dependent variables in the learning phase as a function of learning condition. A significance level of .05 was used for all analyses. Cohen's d was used as a measure of effect size, where d-values of .20, .50, and .80, correspond to small, medium, and large effects, respectively (Cohen, 1988). Individual mental-effort scores and individual performance scores are an average of the scores of the three learning tasks. For the group mental-effort scores, an intermediate calculation was necessary. The three group member scores were averaged into one group score. These group scores were then used to calculate the average mental effort of the three tasks. For the performance score, this intermediate calculation was not necessary because groups gave a group answer to the questions.

Table 3.1. Means and standard deviations of the dependent variables in the learning and test phase as a function of learning condition

	Learning condition			
	Individual		Group	
	M	*SD*	*M*	*SD*
Learning phase				
Performance (0-1)[a]	0.70*	0.29	0.94*	0.12
Mental effort	4.48*	1.31	3.65*	0.98
Time	297.58	110.54	306.30	113.40
Test phase				
Performance				
Retention tasks	0.95	0.08	0.84	0.14
Transfer tasks	0.47	0.26	0.54	0.20
Mental effort (1-9)				
Retention tasks	3.96	1.62	3.60	1.16
Transfer tasks	5.17	1.41	4.86	1.28
Efficiency[b]				
Retention tasks	0.18	1.22	-0.17	0.97
Transfer tasks	-0.23	1.33	0.26	0.94
Time (sec)				
Retention tasks	252.73	75.58	260.02	27.41
Transfer tasks	242.02	66.73	248.94	39.72

[a] Performance is the proportion of correct answers on the learning tasks.
[b] Based on z-scores of mental effort and performance.
* $p < .05$

An independent sample t-test revealed that group members invested significantly less mental effort than participants who learned individually, $t(32) = 2.03$, $p < .05$ (one-tailed), $d = 0.74$. An independent sample t-test revealed that group members performed significantly better on the learning tasks than participants who learned individually, $t(32) = -3.01$, $p < .05$ (one-tailed), $d = 1.15$. There was no significant difference between group members and individuals on the amount of time invested in solving the problem, $t(32) = -0.22$, *ns*.

Test Phase

A 2 (learning condition: individual vs. group) × 2 (type of test: retention vs. transfer) ANOVA with repeated measures on the latter factor was used to analyze the data obtained during the test phase. For all analyses, the first factor – learning condition – was a between-subjects factor, and type of test was a within-subjects factor. Means and standard deviations per condition for the dependent variables – performance, mental effort, efficiency, and time for both retention and transfer test – are provided in Table 3.1. Cohen's f^2 statistic was used as an effect size index, where f^2 values of .02, .15, and .35 correspond to small, medium, and large effects, respectively (Cohen, 1988). Mental effort scores and performance scores of the learners assigned to the individual condition in the learning phase are an average of the scores of the three retention tasks and three transfer tasks. For learners assigned to group condition in the learning phase, an intermediate calculation was necessary. The group member scores were averaged into one group-score. These group scores were used to calculate the average of the three retention tasks and three transfer tasks. With regard to efficiency, the ANOVA revealed no main effects of learning condition, $F(1, 32) < 1$, *ns*, and type of test, $F(1, 32) < 1$, *ns*, but did reveal a significant interaction between learning condition and type of test, $F(1, 32) = 6.79$, $MSE = 0.42$, $p < .05$, $f^2 = 0.25$, indicating that participants who had learned individually exhibited more efficient retention performance, and participants who had learned in a group exhibited more efficient transfer performance. The interaction is depicted in Figure 3.1.

With regard to mental effort, an ANOVA revealed a significant main effect of test performance $F(1, 32) = 52.02$, $MSE = 0.48$, $p < .001$, $f^2 = 0.68$, indicating that retention problems caused a lower mental effort than transfer problems. With regard to test performance, there was a main effect for type of test $F(1, 32) = 90.41$, $MSE = 0.03$, $p < .001$, $f^2 = 1.32$, indicating that learners performed better on the retention tests than on the transfer test. For learning condition, no significant results were found $F(1, 32) < 1$, *ns*. The learning condition × test-type interaction approached significance, $F(1, 32) = 4.10$, $MSE = 0.03$, $p = .052$, $f^2 = 1.32$, suggesting that participants who learned individually performed better on retention problems, while participants who learned in a group performed better on transfer problems. The ANOVA performed on the time on task revealed neither significant main effects, $F(1, 32) < 1$, *ns*, nor an interaction $F(1, 22) < 1$, *ns*.

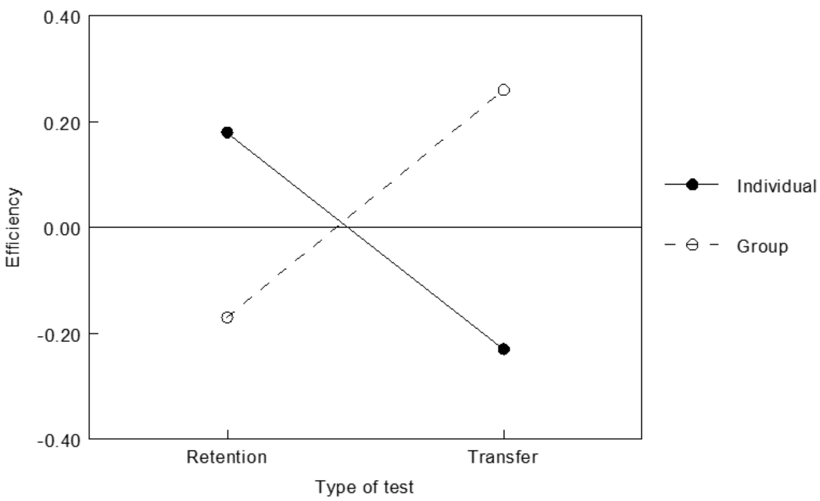


Figure 3.1. Interaction between learning condition and type of test.

Discussion

In this study, it was hypothesized that group members would be able to collaborate with each other in a way that the cognitive load imposed by a complex task would be reduced.

Due to this reduction, group members were expected to develop higher quality schemas than individual learners carrying out the same task. Consequently, it was predicted that group members would have to invest less mental effort to apply acquired knowledge and skills to tasks that differ from the ones trained, as indicated by more efficient transfer performance. In contrast, it was expected that learners carrying out the same complex tasks individually would not have the advantage of the collective workspace and thus would have less WM-capacity left to work with the interrelated information elements. This means that they were expected to be able to only focus on what is initially necessary to work with the elements (i.e., remembering them) and consequently would have to invest less mental effort remembering the information elements, as indicated by more efficient performance on a retention task.

This interaction hypothesis was confirmed. While those learning individually performed more efficiently on a retention task in the test phase than learners who had learned in a group, group learners performed more efficiently on transfer tasks than did individual learners. In other words, by making use of each others processing capacity through sharing the cognitive load imposed by the task, it was possible for group members to more deeply process the information elements and work with them by relating them to each other, and construct higher quality schemas in their long-term memory. For individual learners who could only rely on their own WM and, thus, had to process all of the information elements themselves, the experienced mental effort in the learning phase was significantly higher than that of the group members. The limited processing capacity of the individual combined with the complexity of the learning tasks meant that it was only possible for them to focus on remembering the information elements instead of relating them to each other so as to construct higher quality schemas. The conclusion here is clear, namely that collaborative learning can have a positive effect on deep learning of complex cognitive tasks.

A second conclusion, based on the significantly lower metal effort scores of the group members during the learning phase and their more efficient performance on the transfer tasks during the test phase, is that the transaction costs caused by communication and coordination in the groups were not excessively high. For groups, excessive transaction costs could annul the benefit of the possibility of groups to divide the cognitive load among its members.

It should be noted that the learning conditions in this study can be considered rather artificial, for example, as a result of the very strict division of information and roles within groups and the fact that learners were not allowed to use pen and paper. In that sense, it is not clear to what extent the present results can be generalized to a real classroom setting. It can be assumed that the complex pattern of interactions between cognitive, motivational, and social factors that characterize such a real life context would add a lot of 'noise' to the data and cause the effects to be less pronounced than in this experimental study. We acknowledge that, ultimately, the research on group-based learning requires an interrelated perspective integrating cognitive, motivational, and social aspects. However, to be able to disentangle the contributions of each of these factors to the learning processes and outcomes of group-based learning, they need to be studied within tightly constrained experimental environments, one at a time, keeping all other aspects constant.

Although we have shown that learning-task complexity is an important factor that helps determine the effectiveness of group learning, it should be clear that it is not merely complexity of the tasks that determines if group learning, other than individual learning, is favorable in a certain context. Recent research has identified a number of other task characteristics relevant when considering group learning as a good option. This would, for example, be the case when positive cognitive conflict is necessary or desirable when solving a problem or creating a product (Munneke et al., 2007), when diversity in expertise or a multidisciplinary approach is necessary for carrying out a task or solving a problem (P. A. Kirschner et al., 2008), or when specific cognitive or metacognitive skills (e.g., reflection: King, 2007) or socio-cognitive skills (e.g., negotiation: Beers et al., 2007 or debating: Leitão, 2000; Veerman, Andriessen, & Kanselaar, 2000) are the required products of learning.

In this study, the type of communication and coordination activities that took place within the groups was not recorded or analyzed. Therefore, we do not know what topics were discussed, whether the discussions that were carried out were mostly content related, whether social talk was part of those discussions and, if so, to what extent, whether learners actually engaged in discussions at all, or whether every group member participated in the communication and coordination equally or whether there were roles or patterns of communication. We concentrated here on the transaction costs that would be detrimental for learning and therefore cause extraneous cognitive load. It could, however, also be possible that the communication among the group members was such that it fostered learning instead of hampered it and by doing so caused germane cognitive load. Carrying out such an analysis would add a useful and interesting new dimension to this study and would be interesting to analyze in further studies.

Another interesting topic for further research is determining how to measure a group's cognitive load. In this study, group load was considered to be the average of the individual mental-effort scores. However, group cognitive load could also be defined as the sum of the individual scores (i.e., the nominal score), in which case group cognitive load will be higher than an individual's cognitive load and a scale would need to be developed to determine what a relatively high and low group cognitive load is and how this could be compared to an individual cognitive load score, Another way of defining group cognitive load would be to ask the group as a whole to score their group mental effort on the 9-point rating scale that is also used for individuals. This way the experienced mental effort of the individual group members is lost, but the 9-point rating scale can still be used and because of this a comparison to an individual score is still possible. It might even be the case that it could be better to use two rating scales, one that measures the mental effort a group member experiences while solving a problem (i.e., the rating scale used in this experiment: Paas, 1992), and another that measures how much effort it took the group member to be a member of the group as a whole. These scores could be combined (e.g., either averaged or summed) to give an indication of the experienced cognitive load on two subjects, namely task complexity and transaction costs.

Finally, further research could be carried out to determine at which level of task complexity it becomes more effective and/or efficient to assign learning tasks to groups rather than to individuals. In such research, the optimal trade-off between task complexity, learner characteristics (e.g., expertise, age) and group characteristics (i.e., group size, group homogeneity with respect to learner characteristics) for the effectiveness of collaborative learning environments could be determined. We often see in both research and education that learners involved in collaborative learning or problem solving are required to send a minimal number of emails to each other or to add a minimal number of messages to a discussion board when working collaboratively via computer mediated communication (i.e., computer-supported collaborative learning). These requirements could be due to the fact that the learning tasks that the learners must carry out or the problems that the learners collaboratively must solve are not sufficiently complex to warrant the requested or required collaboration.

In summary, this study showed that group learning is superior to individual learning of a complex cognitive task if the transaction costs are kept to a minimum and if performance is measured on transfer problems. In contrast, individual learning is superior to group learning if performance is measured on retention problems.

4

Efficiency of individual versus group learning as a function of task complexity

This study investigated the efficiency of individual versus group learning as a function of task complexity among 53 high school students in the domain of mathematics. Based upon cognitive load theory it was hypothesized that learning processes and outcomes of groups would become more efficient than those of individuals as task complexity increases. Although, both individuals and groups would have no problem coping with the load imposed by low-complexity tasks, only groups would be able to deal with the high cognitive load imposed by high-complexity tasks by dividing it across their larger reservoir of cognitive capacity. The results confirmed this hypothesis, indicating a more favorable relationship between effort and performance (i.e., higher learning efficiency) for groups in the learning phase on high-complexity tasks, but not on low-complexity tasks. In addition, on a transfer test participants performed better and invested less mental effort (i.e., higher test efficiency) and time on topics that were learned in a group than on topics that were learned individually. Results are discussed with regard to their implications for the design of individual and group learning environments.

This Chapter is submitted for publication as:
Kirschner, F., Paas. F., & Kirschner, P. A. (2009c). *Efficiency of individual versus group learning as a function of task complexity.*

The popularity of collaborative learning is among others based upon the premise that the collaboration process will lead to deeper processing of information and richer and more meaningful learning as a result of discussion, argumentation and reflection processes coming from the interactions in the group (e.g., Marttunen & Laurinen, 2001; Van Boxtel, Kanselaar, & Van der Linden, 2000). Although different educational, social, and economic arguments have been advanced to explain the potential of collaborative learning and justify its use, F. Kirschner, Paas, and Kirschner (2009a [Chapter 3], 2009b [Chapter 2]) have argued that the basic rationale for choosing collaborative learning as the preferred educational approach should be its relative effectiveness and efficiency for learning in comparison with individual learning.

Based on a review of research comparing the effectiveness of individual learning approaches to collaborative learning approaches, F. Kirschner et al. (2009b [Chapter 2]) concluded that there is no clear and unequivocal picture of how, when and why the effectiveness of these two approaches to learning differ. They argued that one possible cause for the inconclusive results may be the fact that this research has not systematically considered the structures that constitute human cognitive architecture (see also, P. A. Kirschner, Sweller, & Clark, 2006). In particular, the differing complexities of the learning tasks used and the concomitant load imposed on the learner's cognitive system was identified as a potentially important factor affecting the effectiveness of individual and group learning. More specifically, the research in which individuals and groups are compared regarding their recall or problem-solving performance implies that individual learning is superior to group learning for relatively simple recall tasks (e.g., Andersson & Rönnberg, 1995; Meudell, Hitch, & Kirby, 1992; Weldon & Bellinger, 1997), and that group learning is superior to individual learning for relatively complex problem-solving tasks (e.g., F. Kirschner et al., 2009a [Chapter 3]; Laughlin, Bonner, & Miner, 2002; Laughlin, Hatch, Silver, & Boh, 2006).

In this study we used a cognitive load perspective to analyze how the complexity of a task can inform the design of effective group-based learning settings. In this perspective, groups of collaborating learners are considered as information-processing systems (Hinsz, Tindale, & Vollrath, 1997; Tindale & Kameda, 2000), in which knowledge and information may be divided across individuals, but where the group as a whole makes a conscious and continued effort to carry out the task. Processing of information within a collaborative learning setting involves activities that occur within as well as among the minds of group members (Hinsz et al., 1997; Ickes & Gonzalez, 1994) and therefore affect performance and learning, both at the individual-level and group-level.

A theoretical framework dealing with individual information processing and learning is cognitive load theory (CLT: Paas, Renkl, & Sweller, 2003; Sweller, 1988; Sweller, Van Merriënboer, & Paas, 1998). The central notion of CLT is that if individuals are to learn effectively in a learning environment, the architecture of their cognitive system, the learning environment, and interactions between both must be understood, accommodated and aligned. The theory focuses on complex cognitive tasks, in which instructional control of cognitive load is critically important to meaningful learning. To realize this control, CLT uses current knowledge about the human cognitive architecture to generate instructional techniques. This architecture consists of an effectively unlimited long-term memory (LTM), which interacts with a working memory (WM) that is very limited in both capacity (Baddeley, 19786; Miller, 1956) and duration (Peterson & Peterson, 1959). For new, yet to be learned information, the processing capacity is limited to only 4 ± 1 element, and if not rehearsed, the information is lost within 30 seconds (Cowan, 2001). Long-term memory (LTM) provides humans with the ability to relatively expand WM's limited capacity, as it contains cognitive schemas that are used to store and organize knowledge by incorporating multiple elements of information into a single element with a specific function. Skilled performance develops through the building of increasing numbers of ever more complex schemas by combining elements consisting of lower level schemas into higher level schemas. If the learning process has occurred over a long period of time, the schema may incorporate a huge amount of information. Because a schema can be treated by working memory as a single element, the limitations of WM disappear for more knowledgeable learners when dealing with previously learned information stored in LTM.

The cognitive load learners experience when working on a learning task can be caused by the intrinsic nature of the task or by the manner in which the information within the task is presented to them. 'Intrinsic' load is imposed by the number of interactive information elements in a task. The more elements there are within a learning task and the more interaction there is between them, the higher the experienced intrinsic cognitive load will be. The manner in which the information is presented to learners can either impose an 'extraneous' or 'germane' load. Extraneous load is imposed by information and activities that do not directly contribute to learning, while germane load is caused by information and activities that foster learning processes. The three loads are additive and it is important to realize that the total cognitive load associated with an instructional design should not exceed the available WM processing capacity (Paas, Tuovinen, Tabbers, & Van Gerven, 2003; Sweller et al., 1998).

Overcoming individual WM limitations by instructional manipulations that are compatible with human cognitive architecture has been the central focus of CLT. Research is therefore mainly concerned with the development of techniques for managing WM load, imposed by a learning task, in order to facilitate the changes in LTM associated with schema construction and automation. To accomplish this, first of all, extraneous load must be eliminated. Studying worked examples (instead of solving conventional problems) has been identified as an effective way of reducing extraneous load, because the learner can devote all available WM capacity to studying a worked-out solution and constructing a schema for solving similar problems in LTM (e.g., Atkinson, Derry, Renkl, & Wortham, 2000; Sweller, 1988). However, freeing WM capacity by eliminating extraneous load is not a sufficient technique for instructional conditions to be effective. Therefore, as a next step, a balance must be found between intrinsic load and germane load. This means that intrinsic load must be managed in such a way that the simultaneous processing of all interactive information elements leaves some spare cognitive capacity and that learners are encouraged to invest free processing resources in schema construction and automation, evoking germane load. One way to manage intrinsic load is by applying a so called part-whole approach, in which the number of information elements and interactions between elements is initially reduced by simplifying the tasks, after which more and more elements and interactions are added (e.g., Mayer & Moreno, 2003). An effective way to increase germane load is by increasing the variability of learning tasks (Paas & Van Merriënboer, 1994).

In this chapter it is argued that another way of overcoming individual WM-limitations is by using multiple working memories in groups of collaborating learners. When groups of collaborating learners are considered as information-processing systems, the information necessary for carrying out the learning task and the associated intrinsic cognitive load can be divided across multiple collaborating working memories. On the one hand this can result in lowering the risk of overloading each group member because individual WM capacity is freed up, on the other hand the groups reservoir of cognitive capacity is expanded. Information processing in collaborative learning settings is characterized by active and conscious sharing (i.e., retrieving and explicating information), discussing (i.e., encoding and elaborating the information) and remembering (i.e., personalizing and storing the information) of valuable task-relevant information and knowledge held by each group member (Hinsz et al., 1997; Tindale & Kameda, 2000; Tindale & Sheffy, 2002). For a group to carry out a learning task not all group members need to posses all necessary knowledge, or process all available information by themselves and at the same time (Johnson, Johnson, & Stanne, 2001; Langfred, 2000; Ortiz, Johnson, & Johnson, 1996; Wegner, 1987, 1995). As long as there is communication and coordination between the group members, the information elements within the task and the associated cognitive load caused by the intrinsic nature of the task can be divided across a larger reservoir of cognitive capacity (F. Kirschner et al., 2009a [Chapter 2], 2009b [Chapter 3]). In terms of CLT, this has two consequences. First, the distribution advantage causes collaborating individuals to invest less cognitive effort as compared to individuals learning alone. Second, the communication of information and coordination of actions require the group members to invest an additional cognitive effort, an effort that individuals do not have to exert. These, so called, transaction costs (Ciborra & Olson, 1988; F. Kirschner et al, 2009a [Chapter 3]; Yamane, 1996) can be effective (i.e., by imposing germane cognitive load), or ineffective (i.e., by imposing extraneous cognitive load) for learning. Whereas effective transaction costs such as negotiation of common ground should be stimulated, ineffective transaction costs such as discussing ways to share information should be kept to a minimum.

It can be argued that because of the distribution advantage and expanded processing capacity, meaningful learning from complex cognitive tasks that impose a high intrinsic cognitive load, is more likely to occur in a group than in an individual setting. This was confirmed in an experiment comparing the effects of group and individual learning of complex cognitive tasks on test efficiency (F. Kirschner et al., 2009a [Chapter 3]). By making use of each others' processing capacity through sharing of cognitive load imposed by a task, it was possible for group members to process information elements more deeply and construct higher quality schemas in their long term memories than learners working individually. Although within groups there is a cognitive load caused by communication and coordination processes that have to be taken into account (i.e., transaction costs), in case of complex cognitive tasks this load can be considered relatively low compared to the advantage of being able to share the high cognitive load of the complex task among group members. Evidence for the claim that collaborative learning will be more effective in complex cognitive tasks has generally been found when more complex problem-solving tasks were used as a learning measure instead of relatively simple recall tasks. When learners had to work with the information elements relevant for carrying out the task, relate them to each other, and by doing so come up with a solution to a problem, groups performed better than individuals or nominal groups (i.e., fictitious groups formed by pooling the non-redundant performances of individuals) (Andersson & Rönnberg, 1995; Laughlin, Bonner, & Andrew, 2002; Laughlin et al., 2006; Laughlin, Zander, Knievel, & Tan, 2003; Ohtsubo, 2005). Under such conditions, participating in a group facilitated the performance of individual group members.

However, based on the theoretical framework of CLT and the specific characteristics of collaborative learning, the complexity of a task seems an important factor determining whether collaborative learning is more effective than individual learning. Whereas learning from high-complexity tasks can benefit from working in groups, for low-complexity tasks there might be no advantage of collaboration because individual learners have sufficient capacity to solve the problem by themselves. Although, in this case, the cognitive load caused by the task can also be distributed among the group members, the load imposed by the transaction costs is relatively high in comparison with the advantages accrued by working together. As a result, group learning is expected to be as efficient as individual learning when the transaction costs are kept to a minimum or even less efficient than individual learning when the transaction costs are high and consist primarily of load that is not effective for learning. This expectation is supported by research on relatively simple recall tasks, which showed that collaborative learning was detrimental to the performance of individual group members, that is, groups performed worse than nominal groups (e.g., Hinsz, 1990; Hoppe, 1962; Meudell et al., 1992; Perlmutter & De Montmollin, 1952; Stephenson, Clark, & Wade, 1986; Weldon & Bellinger, 1997).

In this study we attempted to determine the differential effects of task complexity on individual and group learning. It was hypothesized that the process of learning by a group of individuals would be more efficient (i.e., they would show higher learning performance with lower mental effort) than the process of learning by an individual with high-complexity tasks, but not with low-complexity tasks. With low-complexity tasks and minimal transaction costs, group members would have to invest the same amount of mental effort in learning to achieve the same performance than individual learners. With high-complexity learning tasks and minimal transaction costs, group members would have to invest less mental effort in learning to achieve higher performance (i.e., higher learning efficiency) than individuals. In addition, it was expected that on a transfer test participants would show higher performance and invest less mental effort (i.e., higher test efficiency) and time for topics that were learned in a group than for topics that were learned individually.

Method

Participants

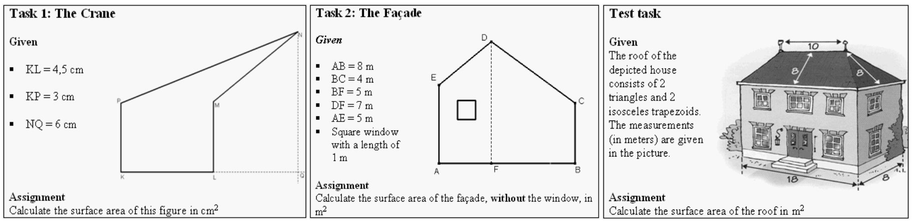
Participants were 53 second year Dutch high school students (17 boys, 36 girls) with an average age of 13.3 years (*SD* = 0.47). They participated in the experiment as part of their regular mathematics curriculum and did not receive any academic or financial compensation. Prior knowledge on mathematics-related subjects was assumed to be the same for all participants, since all students had followed exactly the same math courses during the previous two years and in that period they did not have any prior experience in or exposure to learning tasks like the ones used in the experiment (i.e., calculation of surface areas, which were a combination of rectangles with triangles and rectangles with circles).

Materials

All materials were in the domain of mathematics concerned with the calculation of geometrical surface areas (i.e., the area of rectangles, triangles and circles). An introduction on how to calculate geometrical surface areas, high and low complexity learning tasks, and transfer test tasks were designed. The materials were approved by two mathematics teachers as suitable for the learners. All materials were paper-based.

Introduction. The introduction was based on the calculation of the surface area of one already known geometrical figure: the rectangle, and two new to be learned geometrical figures: the circle and triangle. For every geometrical figure, the method for calculating the surface area, together with a worked example of how to use this method when solving a surface calculation problem, was the core of the introduction. The three instructions gave insight into the relevant formulas and shapes of the geometrical figures and were treated separately in the order of rectangle, triangle, and circle. Participants' prior knowledge was activated by first presenting them with the instruction of the already known information about rectangles before presenting them the unknown information about triangles and circles. The introduction was paper-based, but was also discussed in class by the math teacher.

Learning tasks. Learning tasks were of low and high complexity. For each of these two levels of task complexity, two tasks were developed, one based on a combination of a rectangle and circles and the other on a combination of a rectangle and triangles (for an example see Figure 4.1). Task complexity or intrinsic cognitive load was determined by using Sweller and Chandler's (1994) method based on the number of interactive elements in a task and the insight necessary for solving the problem. Low-complexity tasks contained three information elements that needed to be combined to calculate the surface area. High-complexity tasks not only contained six information elements that needed to be combined to calculate the surface area, but also required more insight into the geometrical figure than in the low-complexity task. All tasks consisted of a geometrical figure, a certain number of information elements concerning the figure (i.e., length, proportion, width, shape), and a calculation question on either the whole surface area or a part of the surface area (see Figure 4.1a. for an example of a low-complexity task, and Figure 4.1b. for an example of a high-complexity task). For groups the tasks were structured in such a way that task interdependence was high (Saavedra, Early, &Van Dyne, 1993), that is, group members had to rely on each other and interact with each other to obtain resources and to perform the task effectively. This was managed by assigning every group member one third of the total number of information elements necessary for solving the problem. To stimulate collaboration, the distribution of cognitive load (i.e., the distribution advantage), and the communication of information none of the information elements was redundant and the number of information elements was the same for all group members. Because group members did not have to divide the information elements among themselves, ineffective transaction costs were kept to a minimum. Individuals received all information elements at the same time. Because the main hypothesis of this study is focused on WM load, it was important that participants could not offload their WM during the learning phase, and therefore were not allowed to use pencil and paper.



a. b. c.

Figure 4.1. A low (a) and high (b) complexity learning task, as well as a transfer test task (c) on surface calculation of the rectangle-triangle combination.

Transfer test tasks. Eight test tasks were designed to determine how much students had learned and to see if they were able to apply the acquired knowledge and skills to problems that differed from the ones that they learned. Although the same underlying rationale on surface calculation had to be used to solve these problems, compared to the tasks in the learning phase they differed in shape, structure and question asked. Four transfer test tasks about rectangle-circle combinations and four about rectangle-triangle combinations were designed. For example, participants were required to calculate the surface area of an unknown shape, calculate the length of one of the sides of a figure while the surface area was given, or calculate the surface area of a 3-dimensional instead of a 2-dimensional figure (see Figure 4.1.c for an example). The transfer test tasks were designed pair wise, which meant that except for the geometrical figure used (i.e., rectangle-circle combination or rectangle-triangle combination), task one and two, three and four, five and six, seven and eight where identical with regard to the amount of information elements and the kind of problem. The geometrical figure used in the first task was a rectangle-triangle combination, in the second task the geometrical figure was therefore a rectangle-circle combination, the third geometrical figure was again a rectangle-triangle combination, and so forth.

Cognitive-load measurement. To measure the participants' cognitive load after each task in the learning and test phase, the subjective 9-point cognitive-load rating scale developed by Paas (1992) was used. Participant are asked to rate how much effort it took them to solve a problem, on a scale ranging from very, very low effort (1) to very, very high effort (9). This cognitive load measure has been used in numerous studies dealing with cognitive load and proven to be non intrusive, valid and reliable (Paas, Van Merriënboer, & Adam, 1994). In addition, participants, both learning in groups or individually, were asked prior to solving the learning task how much effort they thought they would have to invest to successfully perform the task. Participants were asked, prior to working on the task, to rate how much effort it would take them to solve the problem. The rating scale used was based on the 9-point cognitive load rating scale. Results on the pre-measurement of expected mental effort will be discussed in the Appendix to this chapter.

Performance measurement. Correctly carrying out the learning and test tasks meant correctly calculating the surface area of a geometrical figure, with 1 point for a correct answer and 0 points for an incorrect answer. In the learning phase a minimum score of 0 and a maximum score of 2 points could be earned, in the test phase the minimum score was 0 and the maximum 8 points. For the statistical analyses, the performance scores on the test tasks were transformed into proportions. In other words, participants' scores on the eight test tasks were divided by the maximum score of 8.

Design and procedure

Two days prior to receiving the learning tasks, all participants received a written instruction on how to calculate the surface areas of rectangles, circles, and triangles. They had 7 min to study each geometrical figure individually, after which the teacher had 7 min to discuss both the theory and a worked example in class and give clarification answers to questions asked by the participants. The total instruction took 50 min after which the participants had to hand in the written instructions to the teacher.

In the learning phase, because of the within subject design of this study, every participant at one point, worked on the learning tasks individually as well as in a 3-person group (i.e., triad). For each participant, the order of individual and group work, as well as task subject with which a participant started (i.e., rectangle-circle combination or rectangle-triangle combination) was counterbalanced. Therefore, at the beginning of the learning phase, participants were randomly assigned to the individual or group condition, in such a way that half of the participants started to work individually on two tasks at two different complexity levels and then worked in triads on two other tasks at these two complexity levels. The other half of the participants started to work in triads on these problems and then worked individually. With regard to counterbalancing of task subjects, if a participant first, individually or in a group, worked on the calculation of the surface area of a rectangle-triangle combination, the second time, being in the individual or group condition, the geometrical figure was a rectangle-circle combination. If a participant first, individually or in a group, worked on the calculation of the surface area of a rectangle-circle combination, the second time, being in the individual or group condition, the geometrical figure was a rectangle-triangle combination. After the participants knew whether they had to work in a group or individually they were presented with a low-complexity task and asked to rate how much mental effort they expected to invest in performing that task successfully (i.e., pre-measurement). They worked on the task for 7 min, and afterwards they were asked to rate how much mental effort they had invested in performing the task. The sequence was then repeated with a high-complexity task. Working in groups differed from working individually in that group members had to communicate with each other during the problem solving process while individuals had to solve the problem by themselves. To prevent participants from offloading their WM, in the learning phase it was not allowed to use a pen or pencil to write anything down.

One day after the learning phase, the test phase required participants to work individually for 50 min on eight transfer tasks. After each task, participants were required to indicate how much mental effort they had invested in working on that task.

Results

A significance level of .05 was used for all analyses. Because of registration problems in the learning phase there were incomplete data for performance, mental effort, or both, from 6 participants. More specifically, the performance data of 5 participants, the mental effort data of 3 participants, and the learning efficiency data of 6 participants were missing. In the test phase 5 participants did not show up and the time on task data for 2 participants were missing. Case-wise deletion of participants was used to analyze the data. Table 4.1 shows the means and standard deviations for the performance, mental effort and efficiency data in the learning phase as a function of learning condition and task complexity, and performance, mental effort, efficiency, and time on task data in the test phase as a function of learning condition. In the following analyses, Cohen's d was used as measure of effect size when conducting dependent samples t-tests, where d-values of .20, .50, and .80, correspond to small, medium, and large effects, respectively. Cohen's f^2 statistic was used as an effect size index when conducting repeated measures ANOVA's, where f^2 values of .02, .15, and .35 correspond to small, medium, and large effects, respectively (Cohen, 1988).

Table 4.1. The means and standard deviations of the dependent variables in the learning phase as a function of task complexity and learning condition, and in the test phase as a function of learning condition

	Learning condition			
	Individual		Group	
Dependent variable	*M*	*SD*	*M*	*SD*
Learning performance (0-1)[a]				
Low complexity	0.54	0.50	0.54	0.50
High complexity	0.40	0.49	0.71	0.46
Learning mental effort (1-9)				
Low complexity	3.92	1.94	3.18	1.77
High complexity	5.36	2.18	4.36	1.88
Learning efficiency[b]				
Low complexity	0.10	1.16	0.31	0.84
High complexity	-0.60	1.24	0.14	0.95
Test performance (1-0)[a]	0.26	0.25	0.36	0.32
Test mental effort (1-9)	5.56	1.77	5.47	1.66
Test efficiency[c]	-0.12	1.13	0.16	1.25
Time on test task (min)	17.26	4.18	15.65	3.78

[a] Performance is the proportion of rorrect answers on the learning tasks or test tasks.
[b] Based on z-scores of mental and performance in the learning phase.
[c] Based on z-scores of mental effort and performance in the test phase.

Learning Phase

The data of the learning phase were analyzed with 2 (learning condition: individual vs. group) × 2 (task complexity: low and high) analyses of variance (ANOVA) with repeated measures on both factors. Performance, mental effort and efficiency were used as dependent variables.

With regard to performance, the ANOVA revealed a main effect for learning condition, $F(1, 47) = 4.76$, $MSE = 0.25$, $p < .05$, $f^2 = 0.04$. The main effect of task complexity did not yield significant differences between conditions, $F(1, 47) = 0.04$, $MSE = .05$, *ns*. As predicted, a significant interaction between learning condition and task complexity was found, $F(1, 47) = 6.42$, $MSE = 0.18$, $p < .05$, $f^2 = 0.05$. To determine the nature of this interaction, dependent samples t-tests (one-tailed) were conducted. A Bonferroni correction was applied by multiplying the p value calculated by the total number of analyses. This analysis indicated that groups and individuals performed equally well on the low-complexity tasks, $t(47) = 0.00$, *ns*, but that groups outperformed individuals on the high-complexity tasks, $t(47) = -3.29$, $p < .05$ (one-tailed), $d = 0.65$. With regard to mental effort, the ANOVA revealed main effects for learning condition, $F(1, 49) = 10.00$, *MSE* = 3.78, $p < .01$, $f^2 = 0.07$, and task complexity, $F(1, 49) = 32.99$, *MSE* = 2.60, $p < .001$, $f^2 = 0.18$. The interaction between learning condition and task complexity was not significant, $F(1, 49) = 0.61$, *MSE* = 1.38, *ns*. These results indicate that group members at both complexity levels experienced a lower mean mental effort than did individuals.

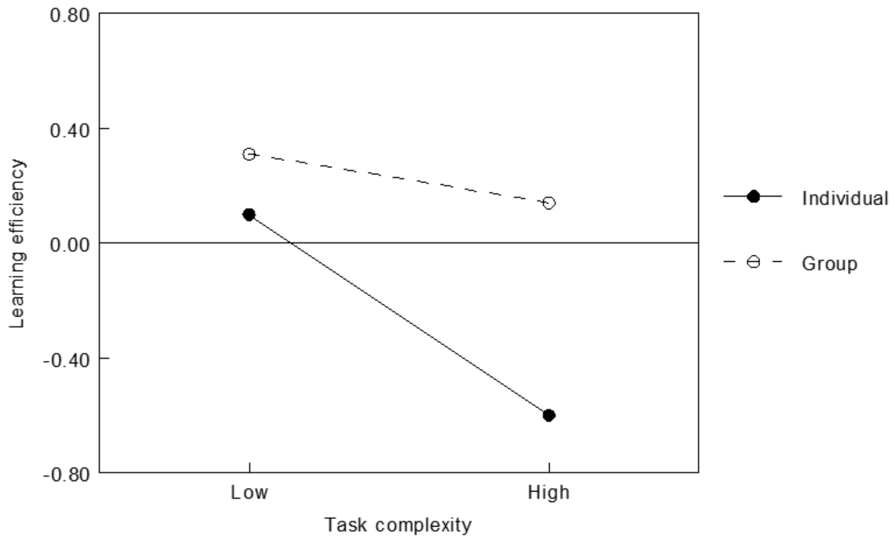


Figure 4.2. Interaction between learning condition and task complexity in the learning phase.

The efficiency in the learning phase was calculated using Paas and Van Merriënboer's (1993; see Van Gog & Paas, 2008) computational approach by standardizing each of the participant's scores for learning task performance and mental effort invested. The basic idea of this approach is that instructional conditions that require less learning effort and that lead to the same or higher performance are more efficient than instructional conditions that require more learning effort and that lead to the same or lower performance. For this purpose, the grand mean was subtracted from each score and the result was divided by the overall standard deviation, which yielded z-scores for effort (*R*) and performance (*P*). Finally, a learning efficiency score, *E*, was computed for each participant using the formula: $E = [(P - R)/2^{1/2}]$. High learning efficiency was indicated by a relatively high performance in combination with a relatively low mental-effort rating. In contrast, low learning efficiency was indicated by a relatively low performance in combination with a relatively high mental-effort rating. With regard to learning efficiency, the ANOVA showed main effects for learning condition, $F(1, 46) = 9.42$, *MSE* = 1.15, $p < .01$, $f^2 = 0.07$, and task complexity, $F(1, 46) = 11.74$, *MSE* = 0.73, $p = .001$, $f^2 = 0.07$, as well as a significant interaction between learning condition and task complexity, $F(1, 46) = 5.00$, *MSE* = 0.63, $p < .05$, $f^2 = 0.03$. To determine the nature of this interaction (see Figure 4.2), dependent samples t-tests (one-tailed) were conducted. Using a Bonferroni correction this analysis indicated that learning in a group was more efficient than learning individually – as indicated by a more favorable relationship between learning effort and learning task performance – with high-complexity tasks, $t(46) = -3.70$, $p < .05$ (one-tailed), $d = .70$, but not with low-complexity tasks, $t(46) = 1.17$, *ns*.

Test phase

To test the hypothesis that participants would show higher performance and invest less mental effort (i.e., higher efficiency) and less time on the transfer test for topics that were learned in a group than for topics that were learned individually, the data of the test phase were analyzed using dependent samples *t*-tests (one-tailed), with performance, mental effort, test efficiency, and time on task as dependent variables. Because all participants learned both individually and as part of a 3-person group, the geometrical figures of the transfer tasks (i.e., being a rectangle-circle combination or a rectangle-triangle combination) was used to determine how the learning conditions affected performance, mental effort, test efficiency and time on the transfer tasks. Every participant, in the learning phase, had a geometrical figure-condition match, meaning that if a participant worked individually on the geometrical figure of a rectangle-triangle combination, he/she worked within a triad on the geometrical figure of a rectangle-circle combination. By mapping the transfer tasks to being about rectangle-circles or rectangle-triangles, and then mapping this to whether the participant learned the geometrical figure of the rectangle-circle in a group or individually it was determined how the learning conditions affected the dependent variables in the test phase.

With regard to test performance there was a significant effect for learning condition, $t(47) = -2.37$, $p < .05$ (one-tailed), $d = .36$, indicating that group learning lead to higher test performance than individual learning. There was no significant difference between group members and individuals on the amount of mental effort invested in solving the problems, $t(47) = .42$, *ns*. The efficiency in the test phase, calculated using Paas and van Merriënboer's (1993) approach, this time by standardizing each of the participant's scores for performance and mental effort on the test tasks. With regard to test efficiency, the dependent samples *t*-test yielded a significant effect, $t(1, 47) = -1.72$, $p < .05$ (one-tailed), $d = .24$., which indicates that participants who learned in groups learned more efficiently than the participants who learned individually. Analysis of the data of time on test task revealed a significant effect, $t(45) = 2.04$, $p < .05$ (one-tailed), $d = .40$, indicating that participants who learned as a member of a group were significantly faster in solving the test tasks than participants who learned individually.

Discussion

The present data are consistent with a cognitive load perspective on collaborative learning, which argues that although the limited WM capacity of an individual learner is equally effective for working with low-complexity tasks than the expanded WM capacity of a group of collaborating individuals, for high-complexity tasks the limited individual WM capacity can be effectively expanded by using multiple WM in groups of collaborating learners. As we hypothesized, learning of low-complexity tasks in a group was as efficient as learning individually, whereas learning of high-complexity tasks in a group was more efficient than learning individually. In addition, learners in groups invested the same amount of mental effort and achieved the same performance as individual learners on the low-complexity learning tasks that imposed low cognitive load. On the high-complexity learning tasks, which imposed a high cognitive load, a more favorable relationship between performance and mental effort was found for learners in groups than individual learners. Furthermore, on the transfer test, participants invested less time and less mental effort and performed better on topics that they had learned in a group than on topics that they had learned individually. This more favorable relationship between performance and mental effort has been argued to reflect the efficiency of cognitive schemas that are acquired in the learning phase (Van Gog & Paas, 2008). Although it is not possible to draw direct conclusions on the cause of the better test score for topics that were learned in a group because all participants had to learn tasks of low and high complexity, as learning performance on low-complexity tasks did not differ between groups and individuals, the better test scores are most likely caused by the superior learning performance of groups on complex tasks.

Within the context of CLT, the results of the present study have strong implications for the design of collaborative learning environments, such as problem-based learning (Schmidt, Loyens, Van Gog, & Paas, 2007). Human cognitive architecture, and in particular the limitations of WM capacity at the individual level (Cowan, 2001), has been argued to be an important reason to assign learning tasks to groups rather than to individuals. It is believed that the more complex the task (i.e., the higher the intrinsic cognitive load), the more efficient it will become for individuals to collaborate with other individuals in a fashion that will distribute and share this load (F. Kirschner et al, 2009b [Chapter 2]). Indeed, the results of this study reveal that the more complex the tasks, the more efficient it is to learn in a collaborative learning setting. Learners in groups individually invested less mental effort to achieve a higher learning performance than individual learners learning alone. In addition, this group superiority in learning efficiency was evidenced by better test performance that could be achieved within less time and with less mental effort on the topics that were learned in a group. Although it is clear that the results need further experimental confirmation with tasks at more complexity levels, under different experimental conditions, and in more realistic complex domains, task complexity seems to be an essential factor in determining the efficiency of collaborative learning environments.

Future research should attempt to identify the level of task complexity at which it becomes more efficient to assign tasks to groups rather than to individuals. However, such recommendations cannot be given in absolute terms since task complexity, which is defined as the number of interacting elements in a task, is relative to the quality and quantity of the schemas in the learner's long term memory (i.e., expertise; Paas et al., 2003). Therefore, comparable to the expertise-reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003), it can be expected that the task-complexity threshold at which group learning becomes more efficient than individual learning will vary as a function of learner expertise. An interesting hypothesis for future research would be that for group learning to become efficient, task complexity needs to be higher for more advanced learners and experts than for novices.

With regard to the learning setting used in the present study, it should be noted that rather optimal conditions were created for collaboration. First, participants received unique information elements and, consequently, were forced to exchange information to solve the problems in the group learning conditions. Second, participants were not allowed to offload their WM by using pencil and paper, which also stimulated them to collaborate. Finally, the learning setting was highly structured and scripted, which resulted in minimal transaction costs and made collaboration more attractive as compared to conditions in which the transaction costs are high. Although these specific conditions were created to focus solely on the factor task-complexity, it could be expected that under conditions of shared information (i.e., where each individual has access to all information elements), with the possibility to offload WM, and with high transaction costs, different results could have been obtained. Future research should investigate the contribution of these aspects to the effects of task complexity on the effectiveness of learning in a group.

In conclusion, task complexity appears to be an important factor determining the efficiency of collaborative learning. However, to be able to provide specific guidelines for the design of group learning environments, more research is needed into the relationship between task complexity and learning in groups.

Appendix

An alternative affective explanation for the superiority of group over individual learning with complex tasks

When collaborating learners are considered as information-processing systems (Hinsz, Tindale, & Vollrath, 1997; Tindale & Kameda, 2000), it can be argued that the information necessary for carrying out a learning task and the associated cognitive load can be distributed across multiple collaborating working memories, creating a larger reservoir of cognitive capacity. Based on cognitive load theory (Paas, Renkl, & Sweller, 2003; Sweller, 1988) this distribution advantage has been used as a cognitive explanation for the findings that the process of learning by a group of collaborating individuals was more efficient (i.e., higher learning performance with lower mental effort) than the process of learning individually with high-complexity tasks, but not with low-complexity tasks (F. Kirschner, Paas, & Kirschner, 2009a [Chapter 3], 2009c [Chapter 4]).

In this study we investigated an alternative affective explanation for this interaction effect that was inspired by research on group-efficacy. According to this affective explanation it can be argued that individuals working together in a group have more confidence in their ability to solve a problem together and that there will, thus, be a greater willingness (i.e., motivation) by them to carry out the task than that which will be found in individuals working on their own. Group-efficacy (also referred to as collective efficacy) is an extension of Bandura's (1997) concept of self-efficacy to groups, and refers to a person's belief in the capacity of the group to perform a specific task (Bandura, 1986, 1997). Bandura (2000) states that

> [t]he growing interdependence of human functioning is placing a premium on the exercise of collective agency through shared beliefs in the power to produce effects by collective action…Perceived collective efficacy fosters groups' motivational commitment to their missions, resilience to adversity, and performance accomplishments. (p. 75)

These collective efficacy beliefs refer to the aggregate or sum of individual group members' perceptions of group capability. They are the perceptions of members of a team that the team as a whole can organize and execute the courses of action necessary for the successful completion of a task.

Although not as straightforward as self-efficacy, group-efficacy has been shown to be a determinant of the effectiveness of group performance (e.g., Bandura, 1993; Campion, Medsker, & Higgs, 1993; Gibson, 1995; Gist & Mitchell, 1992; Goddard, 2002; Guzzo, Yost, Campbell, & Shea, 1993; Parker, 1994; Pescosolido, 2001; Peterson, Mitchell, Thompson, & Burr, 1996; Silver & Bufiano, 1996). Pescosolido (2001), for example, found that group efficacy has a beneficial effect on group dynamics and on the overall group effectiveness. Goddard, Hoy, and Hoy (2004) speak of the "link between collective efficacy beliefs and group goal attainment" (p. 7). Another interesting finding of group learning research is that working in a group can have positive effects on the confidence of the group members in their successful task completion (Lent, Schmidt, & Schmidt, 2006; Puncochar & Fox, 2004).

Therefore, the prospect of being able to successfully work together at the group level (i.e., high confidence), as compared to the prospect of having to rely on ones own effort at the individual level (i.e., low confidence), could explain the finding of F. Kirschner et al. (2009a [Chapter 3], 2009c [Chapter 4]) as to why a group of individuals working on high complexity tasks performs better and experiences less mental effort than individuals working alone. With low complexity tasks, which can be completed successfully by each individual, groups and individuals experience the same amount of confidence and perform equally well while investing the same amounts of mental effort (i.e., equal learning efficiency).

Learners' beliefs in their capacity to perform low and high complexity tasks as individuals within a group or on their own are expected to become visible in the amount of mental effort they think they will have to invest to successfully carry out the task. It was hypothesized that individuals working on complex tasks in a group would have more confidence in solving the problem and therefore expect to invest less mental effort than individuals working alone. With low task-complexity, individuals working in groups and individuals working alone would both have high confidence in their ability to carry out a task successfully and would therefore rate the amount of mental effort they expect to invest equally. These expectations are similar to the efficiency results obtained during the learning process, which indicated that learning from carrying out low-complexity tasks in a group was as efficient as learning individually, whereas learning from carrying out high-complexity tasks in a group was more efficient than learning from them individually.

To get more insight into the alternative affective explanation, this study used a pre-measurement of cognitive load to determine the mental effort individuals expect to invest when they worked and learned either in a group or individually.

Results[1]

For all analyses a significance level of .05 was used. Registration problems resulted in incomplete data from 3 participants who were excluded from the analysis. Cohen's f^2 statistic was used as an effect size index when conducting repeated measures ANOVA's, where f^2 values of .02, .15, and .35 corresponded to small, medium, and large effects respectively (Cohen, 1988).

Table 4.2. Means and standard deviations of the pre mental effort rating in the learning phase as a function of learning condition and task complexity

	Learning condition			
	Individual		Group	
Dependent variable	*M*	*SD*	*M*	*SD*
Pre mental effort (0-9)				
Low complexity	4.64	1.60	4.60	1.55
High complexity	6.10	1.61	5.30	1.63

Results on the pre-measurement of expected mental effort as a function of task complexity were analyzed using a 2 (learning condition: individual vs. group) × 2 (task complexity: low vs. high) ANOVA with repeated measures on both factors. The pre-mental effort scores

[1] The methods section for this appendix can be found in Chapter 4.

reported by the participants were used as dependent variable (for means and standard deviations see Table 4.2). With regard to the pre-mental effort scores, the ANOVA revealed a significant main effect for task complexity, $F(1, 49) = 61.88$, $MSE = 0.95$, $p < .001$, $f^2 = 0.46$, indicating participants expected having to invest higher amounts of mental effort before working on high complexity tasks than before working on low complexity tasks. The main effect of learning condition was significant, $F(1, 49) = 5.10$, $MSE = 1.73$, $p < .05$, $f^2 = 0.05$, indicating that group members expected having to invest lower amounts of mental effort than individuals. In addition, the interaction between task complexity and learning condition was significant, $F(1, 98) = 8.37$, $MSE = 0.86$, $p < .05$, $f^2 = 0.06$. To determine the nature of this interaction (see Figure 4.3), dependent samples t-tests (one-tailed) were conducted. Using a Bonferroni correction this analysis indicated that those who were to learn in a group and those who were to learn individually expected that the same amount of mental effort would be needed to carry out the low-complexity task, $t(49) = 0.19$, *ns*, but when predicting the amount of mental effort needed to carry out the high-complexity tasks, those learning in a group expected that they would need a significantly lower amount than those learning individually, $t(50) = 3.49$, $p < .02$ (one-tailed).

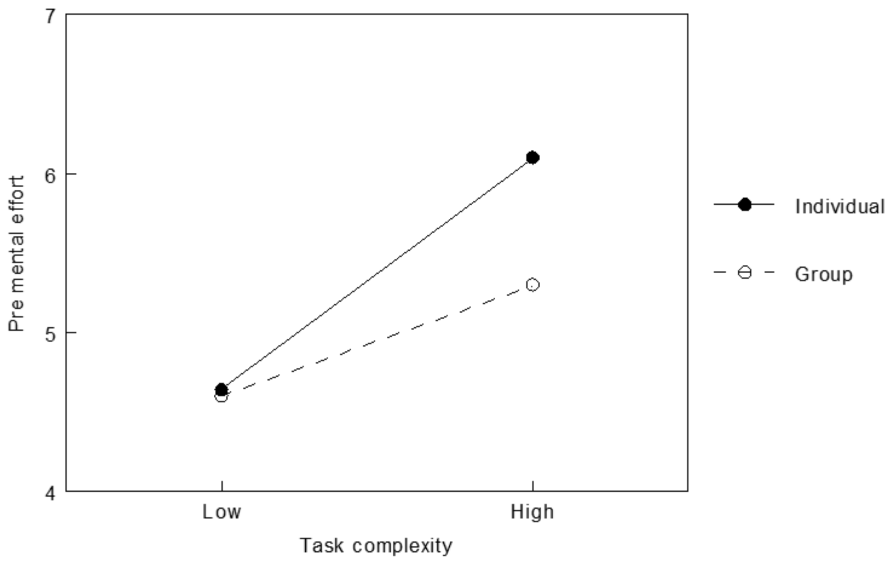


Figure 4.3. Interaction between learning condition and task complexity in the learning phase.

Discussion

F. Kirschner et al. (2009c [Chapter 4]) have shown that collaborative learning is more efficient (i.e., higher performance with lower invested mental effort) than individual learning if the load imposed by the learning task exceeds the limited processing capacity of an individual. Based on cognitive load theory (Paas et al., 2003; Sweller, 1988), they argued that with complex learning-tasks, collaboration increases the processing efficiency, as the load can be distributed across individuals and hence inter-individual integration and coordination produces more benefits than costs of processing. In this study, we showed that in addition to this cognitive explanation, the results could also be explained by an alternative affective explanation based on perceptions of efficacy. By measuring the invested mental effort not only after learning task performance, but also before carrying out the task by asking learners how much mental effort they expected to invest in the task, we were able to show that learners who had to solve a complex problem within a group expected to invest less mental effort than learners who had to solve the problem by themselves. When confronted with low complexity tasks, this expectation did not differ between learners who had to solve the problems within a group and those who had to solve it individually. Moreover, independent of the prospect of being able to work on a problem in a group or individually, learners expected to invest more mental effort in solving the high complexity tasks than in solving the low complexity tasks.

Task complexity seems to be an important factor determining the expected amount of mental effort to be invested for successful task performance. From this efficacy point of view, the prospect of collaboration leads to learners feeling more confident about successful task completion with high-complexity tasks that are difficult to solve by a single learner. In contrast, with low-complexity tasks which can be completed successfully by a single learner, the prospect of collaboration does not differentially affect the confidence of group and individual learners in successful task completion.

Perceptions of efficacy for various individual and collective pursuits arise from cognitive and metacognitive processing of the sources of efficacy belief-shaping information (Bandura, 1997, 2000). One important source of information is the prospect of being able to jointly bundle efforts to perform the task. This bundling of effort links both the affective and cognitive explanations to each other. With high complexity tasks, groups feel more confident because there is the possibility of using the processing capacity, expertise and knowledge of others while working on the task. Which of the two explanation, the cognitive or the affective, is strongest for explaining the efficiency of the learning process depends not only on task characteristics such as task complexity, but might also depend on the characteristics of the learners, such as level of expertise, and characteristics of the group such as group composition. Future research could be directed at how those characteristics contribute to the cognitive and the affective explanations and how they affect learning efficiency of groups and individuals.

5

Task complexity as a driver for collaborative learning efficiency

Collaborative learning, while touted as an important approach to learning, often does not meet the expectations of its proponents. One reason might be that the tasks that groups are given to work together on are not complex enough to deliver the benefits of working together. This study investigated the differential effects of the complexity of learning tasks on both learning process and outcome efficiency of 83 individual and group learners in the domain of biology. Based upon cognitive load theory, it was expected that for high-complexity tasks, group members would learn in a more efficient way than individual learners, while for low-complexity tasks, individual learning would be more efficient. This interaction hypothesis was confirmed, supporting our premise that the learning efficiency of group members and individuals is determined by a trade-off between the possibility to divide information processing amongst team members and the associated costs of information communication and action coordination.

This Chapter is submitted for publication as:
Kirschner, F., Paas. F., & Kirschner, P. A. (2009e). *Task complexity as a driver for collaborative learning efficiency.*

Although collaborative learning is a popular and widely used educational approach, research on its effects on learning has been inconclusive (Kester & Paas, 2005). In a review of research comparing the effectiveness of individual learning approaches to collaborative learning approaches, F. Kirschner, Paas and Kirschner (2009b [Chapter 2]) argued that one possible cause for these inconclusive results may be that the structures constituting cognitive architecture have not been systematically considered (see also, P. A. Kirschner, Sweller, & Clark, 2006) when designing and carrying out research on collaborative learning. Specifically, the differing complexities of learning tasks used and the concomitant load imposed by these tasks on the learner's cognitive architecture could be an important factor affecting individual and group learning, especially with respect to the *efficiency of learning*, defined here as the amount of mental effort invested by a learner to reach a certain level of performance.

Two recent studies were conducted to investigate the efficiency of individual versus group learning as a function of task complexity. F. Kirschner, Paas, and Kirschner (2009a [Chapter 3]) investigated the hypothesis that in contrast to individual learners, group members would be able to share the high cognitive load imposed by complex learning tasks, leaving more processing capacity available for constructing high quality cognitive schemas. This hypothesis was confirmed by results showing a more favorable relationship between mental effort and performance on a transfer test for students who learned in groups than for students who learned individually. In another study, F. Kirschner, Paas, and Kirschner (2009c [Chapter 4]) found a more favorable relationship between effort and performance in the learning phase for students who worked in a group than for students who worked individually with high-complexity tasks, but not with low-complexity tasks. The former study focused solely on the learning process and outcome of high-complexity learning tasks and consequently *did not allow conclusions about the effects of low-complexity learning tasks*. The latter study focused solely on the learning process while studying low and high-complexity learning tasks and consequently *did not allow conclusions about the effects of task complexity on learning outcomes.* The present study was designed to provide a more complete picture by investigating the effects of low- and high-complexity learning tasks on the efficiency of both the individual and group learning process and learning outcome.

The theoretical framework of cognitive load theory (CLT: P. A. Kirschner, 2002; Paas, Renkl, & Sweller, 2003, 2004; Sweller, 1988; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005) can be used to analyze how the complexity of a task can inform the design of efficient group-based learning environments. According to CLT, individual learning depends on the limited processing capacity of the learner's cognitive architecture and the cognitive load imposed by a task. The cognitive architecture consists of an effectively unlimited long-term memory (LTM), which interacts with a working memory (WM) that is very limited in both capacity (Baddeley & Hitch, 1974; Miller, 1956) and duration (Peterson & Peterson, 1959). For new, yet to be learned information, the processing capacity is limited to only 4 ± 1 information element, and if not rehearsed, the information is lost within 30 seconds (Cowan, 2001). LTM contains cognitive schemas that are used to store and organize knowledge by incorporating multiple elements of information into a single element (also referred to as chunking; Chase & Simon, 1973; Miller, 1956; Simon, 1974) with a specific function. According to Van Merriënboer and Kirschner (2007) learning can, thus, be seen as the process of (1) creating new schemas (i.e., schema construction); (2) incorporating new elements of information into consisting schemas (i.e., assimilation); (3) combining elements consisting of lower level schemas into higher level schemas, building increasing numbers of ever more complex schemas (i.e., schema elaboration); and (4) adapting existing schemas based upon recurring new information which is in incongruous or inconsistent with existing schemas (i.e., accommodation). If the learning process has occurred over a long period of time, the eventual schema may consist of a huge amount of information. Empirical evidence of this can be found in the study of chess grandmasters (De Groot, 1946; 1978; Simon & Gilmartin, 1973) who stored enormous amounts of board of chess pieces taken from real games in their LTM, making them the experts they are. Because a schema can be treated by WM as a single element or even bypass WM if a schema has become sufficiently automated after long and consistent practice, the limitations of WM disappear for more knowledgeable learners when dealing with previously learned information stored in LTM.

The cognitive load that learners experience when working on a learning task can be caused by the intrinsic nature of the task or by the manner in which the information within the task is presented (Sweller et al., 1998). *Intrinsic* load is imposed by the *number* of interactive information elements in a task and the interactions between the elements. The more elements there are within a learning task and the more interactions there are between them, the higher the experienced intrinsic cognitive load will be. The *manner* in which the information is presented to learners can impose either 'extraneous' or 'germane' load. *Extraneous* load is the load imposed on the learner's WM by information and activities that do not directly contribute to learning, while *germane* load is the load caused by information and activities that foster learning processes. Intrinsic load, extraneous load, and germane load are additive, thus for learning to occur (i.e., schema construction, elaboration and automation) it is important to take into account that the total cognitive load associated with an instructional design (i.e., the sum of the three separate loads) should stay within WM limits (Paas, Tuovinen, Tabbers, & Van Gerven, 2003).

To facilitate changes in LTM associated with learning, the focus of CLT has been on overcoming individual WM-limitations by introducing instructional manipulations compatible with the human cognitive architecture. Research has, therefore, been concerned mainly with designing, developing and researching instructional techniques for managing the cognitive load imposed by complex cognitive learning tasks in individual learning settings. Recently, group or collaborative learning has become recognized as an alternative way of overcoming individual WM limitations (F. Kirschner et al., 2009a [Chapter 3], 2009b [Chapter 2], 2009c [Chapter 4]), in the sense that groups of collaborative learners can be considered as information-processing systems (Hinsz, Tindale, & Vollrath, 1997; Tindale & Kameda, 2000; Ickes & Gonzalez, 1994), consisting of multiple limited WMs which can create a collective working space. Within these systems, valuable task-relevant information and knowledge held by each group member is consciously and actively shared (i.e., retrieving and explicating information), discussed (i.e., encoding and elaborating information) and remembered (i.e., personalizing and storing information) (Hinsz et al., 1997; Tindale & Kameda, 2000; Tindale & Sheffy, 2002). Therefore, to carry out a learning task not all group members need to *possess* all necessary knowledge, or *process* all available information individually and at the same time (Johnson, Johnson, & Stanne, 2001; P. A. Kirschner, Beers, Boshuizen, & Gijselaers, 2008; Langfred, 2000; Ortiz, Johnson, & Johnson, 1996; Wegner, 1987, 1995). As long as the information is communicated between the group members and their actions are coordinated, the information elements within the task and the associated cognitive load caused by the intrinsic nature of the task can be divided across a larger reservoir of cognitive capacity (F. Kirschner et al., 2009b [Chapter 2]; Ohtsubo, 2005). In terms of CLT, this has two conflicting consequences. First, the collaborating individuals can invest less cognitive effort as compared to individual learners, because of a *distribution advantage*. Second, collaborating individuals need to invest cognitive effort that individuals working alone do not have to exert for communicating information with each other and the coordination of their actions. These, so called, *transaction costs* (Ciborra & Olson, 1988; F. Kirschner et al, 2009a [Chapter 3]; Yamane, 1996) can positively or negatively affect learning. While positive transaction costs such as negotiation of common ground should be stimulated because they positively affect learning (Akkerman et al., 2007), negative transaction costs such as discussing ways to share information should be kept to a minimum since they increase cognitive load without positively affecting learning.

Previous research comparing collaborative learning to individual learning provides some support for the idea that the complexity of a task and the associated cognitive load are important factors for determining learning efficiency. More specifically, the research suggests that group learning is superior to individual learning for relatively complex problem-solving tasks (e.g., F. Kirschner et al., 2009a [Chapter 3], 2009c [Chapter 4]; Laughlin, Bonner, & Miner, 2002; Laughlin, Hatch, Silver, & Boh, 2006), and that individual learning is superior to group learning for relatively simple recall tasks (e.g., Andersson & Rönnberg, 1995; Meudell, Hitch, & Kirby, 1992; Weldon & Bellinger, 1997).

With regard to high-complexity tasks, research has shown that when learners have to work with the information elements relevant for carrying out the task, relate them to each other, and by doing so come up with a solution to a problem, groups perform better than individuals or nominal groups (i.e., fictitious groups formed by pooling the non-redundant performances of individuals) (Andersson & Rönnberg, 1995; Laughlin et al., 2002; Laughlin et al., 2006; Laughlin, Zander, Knievel, & Tan, 2003; Ohtsubo, 2005). Under such conditions, participating in a group facilitates the performance of individual group members. Based on CLT, it can be argued that by dividing the high intrinsic cognitive load imposed by the complex learning task across learners, the risk of exceeding the limits of the WMs of the individual group members is reduced. We call this the *distribution advantage*. Although the additional cognitive load imposed by the communication of information and coordination of actions has to be taken into account, this load can be considered to be relatively low compared to the distribution advantage for complex tasks. Consequently, the process of learning will be more efficient for these group members, allowing them to construct higher quality schemas than individual learners who have to process all of the information individually. This was confirmed in an experiment comparing the effects of group learning and individual learning from complex cognitive tasks on the efficiency of cognitive schema construction (F. Kirschner et al., 2009a [Chapter 3]). By making use of each others' processing capacity through sharing of cognitive load imposed by a task, it was possible for group members to process information elements more deeply and construct higher quality schemas in their LTMs than learners working individually.

With regard to low-complexity tasks, individual learners have sufficient capacity to carry out the tasks by themselves and no advantage of learning together is expected. Dividing the information among the group members means that they have to communicate information and coordinate their actions, which in the case of low-complexity tasks imposes a relatively high load (in relation to the benefits that will be accrued) thereby negating the distribution advantage. If the transaction costs can be kept to a minimum, the learning process for groups will be as efficient as that of individuals while if the transaction costs are high, groups can be expected to learn less efficiently than individuals. This was confirmed in an experiment comparing the effects of group and individual learning from low-complexity and high-complexity learning tasks on the efficiency of the learning process (F. Kirschner et al., 2009c [Chapter 4]). For low-complexity tasks, the limited WM capacity of the individual learner and the expanded processing capacity of the group were equally effective for learning from low-complexity tasks, as indicated by the equivalent performance scores and mental effort investment of groups and individuals during the learning process. For high-complexity tasks the group members could profit from distributing the high intrinsic cognitive load, as indicated by lower mental effort and higher learning performance (i.e., more efficient learning process) than individuals. Although the results on transfer-test efficiency showed a significant advantage of learning in a group over individual learning, the results did not allow the drawing of unequivocal conclusions about the differential effect of task complexity. The outcomes regarding low-complexity tasks are supported by research on relatively simple recall tasks which has shown that collaborative learning was detrimental to the performance of individual group members; that is, groups performed worse than nominal groups (e.g., Hinsz, 1990; Hoppe, 1962; Meudell et al., 1992; Perlmutter & De Montmollin, 1952; Stephenson, Clark, & Wade, 1986; Weldon & Bellinger, 1997).

In this study, we attempted to determine the effects of low-complexity and high-complexity learning tasks on the efficiency of the process and outcome of learning individually and learning in a group. With regard to learning from high-complexity tasks, the advantage of being able to divide the processing of information among group members is expected to be relatively larger than the disadvantage of having to invest the additional effort related to the transaction costs. Therefore, the learning process was hypothesized to be more efficient (i.e., higher learning performance with lower mental effort) for participants who learn in a group than for participants who learn individually. Consequently, group members were expected to be able to develop higher quality schemas than individual learners, which would be manifested in more efficient learning outcome (i.e., higher transfer performance with lower mental effort) for those who learn in a group.

With regard to learning from low-complexity tasks, learners are expected to have sufficient cognitive capacity to process the information individually. Therefore, both groups and individuals are expected to perform equally well, but the advantage of being able to divide the processing of information among group members is expected to be relatively smaller than the disadvantage of having to invest the additional effort associated with information communication and action coordination. Therefore, the learning process was hypothesized to be more efficient for individuals than for group members (i.e., equal learning performance with lower mental effort). Consequently, individual learners were expected to be able to develop higher quality schemas than group members, which would manifest itself in a more efficient learning outcome for those who learned individually (i.e., higher transfer performance with lower mental effort).

Method

Participants

Participants were 83 Dutch fourth year high school students (46 girls, 37 boys) with an average age of 15.52 years (*SD* = 0.67). They participated in the study as part of their biology curriculum. No differences in prior knowledge were expected because all participants had followed the same biology courses in the previous three years and the topic of this study (i.e., heredity) was new to them. In addition, participants were randomly assigned to the different experimental conditions to exclude possible differences in prior knowledge. Participants did not receive any academic or financial compensation for their participation.

Materials

Materials were in a domain of biology concerned with heredity, specifically the passing of both genotypic and phenotypic biological traits from parents to offspring through genes which carry biological information (e.g., eye color in humans, fur length in dogs, leaf shape in plants). In this domain a general introduction containing necessary concepts and instruction on how to solve a cross breeding problem in the form of a worked example, simple and complex problem-solving tasks, and transfer tasks were designed. The materials were approved by two biology teachers as suitable for the participants. All materials were paper based.

General Introduction. Relevant terminology, rules and theory underlying heredity, as well as a worked example on solving heredity problems were presented in the introduction. More specifically, it provided participants with the definition of genes, and information on the genotype and phenotype of an organism, homozygosity or heterozygosity of an organism's dominant or recessive genes, the pedigree chart, and the rules concerning the Punnett square (i.e., a diagram used to predict the outcome of a particular cross or breeding experiment). The worked example demonstrated the procedure involved in solving a heredity problem by combining relevant terminology, rules, and theory.

Learning tasks. Low-complexity and high-complexity learning tasks were used, both consisting of a certain number of information elements concerning a biological trait in a family (i.e., ear shape of a guinea pig family, thumb length of a human family, and fur color of a rabbit family) and two questions about the proportion of possible genotypes of the offspring and/or the specific genotype and phenotype of a family member. Participants were required to use the definitions, rules and theory underlying the topic of heredity to combine the information elements that they were given and solve the problem (i.e., correctly answer the questions). Each piece of information provided in a learning task was relevant but insufficient by itself for solving the problem. Only by combining it with the other information elements could the problem be successfully solved. In the domain of heredity this, for instance, could mean that information element 1 is eye color of the mother: blue; information element 2 is eye color of the father: brown; and information element 3 is the dominance of brown eyes over blue eyes. Each element gives a certain amount of information, but to answer the question as to what the eye color of the offspring will be, the participant will have to combine all three pieces of information.

Task complexity or intrinsic cognitive load was determined by using Sweller and Chandler's (1994) method based on the number of interactive elements in a task. Low-complexity learning tasks contained three information elements and high-complexity learning tasks contained nine information elements that needed to be combined to solve a heredity problem (see Figure 5.1a for an example of a low-complexity task, and Figure 5.1b for an example of a high-complexity task). The low-complexity and high-complexity learning tasks consisted of three series of tasks which were connected to three main family-trait combinations (i.e., ear shape of a guinea pig family, thumb length of a human family, and fur color of a rabbit family). To keep the amount of practice of terminology, rules and theory concerning heredity equal in both the low-complexity and the high-complexity condition, the number of learning tasks in a series differed. In the low-complexity condition, each series consisted of four learning tasks which were identical except for the names of the family members. In the high-complexity condition, each series consisted of two learning tasks which were identical except for the names of the family members. Consequently, there were a total of 12 low-complexity learning tasks consisting of 3 information elements per learning task and 6 high-complexity learning tasks consisting of 9 information elements per learning task.

Transfer-test tasks. To determine how much the participants had learned and to determine whether they were able to apply the knowledge and skills acquired in the learning phase to different problems, six transfer-test tasks were designed. Although the same basic terminology, rules, and underlying heredity-theory had to be used to solve these problems, the transfer tasks differed from the tasks in the learning phase with respect to the families and traits used, the kind of information elements given, the structure and the questions asked (e.g., genealogical tree, X-chromosome linked inheritance, dihybrid crossings, etcetera; see Figure 5.1c for an example).

Cognitive-load measurement. To measure the participants' cognitive load after each task in the learning and test phase, the subjective 9-point cognitive-load rating scale developed by Paas (1992) was used. Participants were asked to rate how much effort it took them to solve a problem on a scale ranging from very, very low effort (1) to very, very high effort (9). This cognitive load measure has been used in numerous studies dealing with cognitive load and has proven to be non intrusive, valid and reliable (Paas, Van Merriënboer, & Adam, 1994).

Performance measurement. Successfully completing the learning and test tasks meant correctly answering two questions per task on the heredity characteristics of a certain trait in a family. Every question could be scored on multiple elements, with 1 point for a correct element and 0 points for an incorrect or not included element. This resulted in a maximum score of 40 points that could be earned for the 12 low-complexity learning tasks, 32 points for the 6 high-complexity learning tasks, and 24 points for the 6 transfer-test tasks. The minimum score for all tasks was zero. For the statistical analysis, the performance scores on learning and test tasks were transformed into proportions. In other words, a participant's score on the 12 low-complexity learning tasks, the 6 high-complexity learning tasks, and the 6 test tasks were divided by the maximum score of the low-complexity learning tasks (i.e., 40), high-complexity learning tasks (i.e., 32) and the test tasks (i.e., 24) respectively.

a.

GUINEA PIG GERARD AND FIEN

Study the information, read the questions and write down the answer in the answer box provided.

GIVEN

- Guinea pig female Fien has at least 1 gene that is recessive.
- Guinea pig male Gerard has genotype Hh for ear shape.
- The gene for straight ears (H) is dominant over the gene for curled ears (h).
- Guinea pig Fien has straight ears.

QUESTION

1. What could be the genotypes of the offspring of guinea pig Gerard and Fien? And what are their proportions?
2. What could be the phenotypes of the offspring of guinea pig Gerard and Fien? And what are their proportions?

ANSWER TO

Question 1:

Write down the genotypes and proportion (in percentages) here

Question 2:

Write down the phenotypes and proportion (in percentages) here

b.

THE GUINEA PIG FAMILY OF GERARD AND FIEN

Study the information, read the questions and write down the answer in the answer box provided.

GIVEN

- The gene for straight ears (H) is dominant over the gene for curled ears (h).
- One of the offspring of guinea pig female Gemma and guinea pig male Marco: guinea pig female Fien, starts a family with guinea pig male Gerard.
- The mother of guinea pig female Gemma has genotype Hh for ear shape.
- Guinea pig female Gemma has straight ears.
- Guinea pig male Marco is homozygotic for ear shape.
- Guinea pig male Marco has at least 1 gene that is recessive.
- The father of guinea pig female Gemma has at least one gene that is recessive.
- 75% of the offspring of guinea pig female Fien and guinea pig male Gerard have straight ears.
- The father of guinea pig female Gemma was homozygotic for ear shape.

QUESTION

1. What could be the genotypes and phenotypes of guinea pig Fien? And what are their proportions?
2. What is the genotype and phenotype of guinea pig Gerard?

ANSWER TO

Question 1:

Write down the genotypes and proportion (in percentages) here

Question 2:

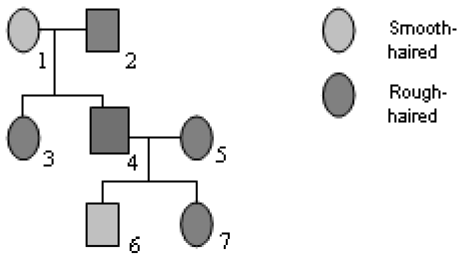
Write down the genotype and phenotype here

c.

THE FAMILY TREE

A family tree displays all phenotypes of a family in one glance. In a family tree the males are depicted by a square and females by a circle. In a dog family both rough-haired and smooth-haired dogs can be found. The figure below shows a specific dog family tree with information about their hair characteristic.

GIVEN



QUESTION

1. Which of the genes, smooth-haired or rough-haired is dominant and which is recessive?
2. What are the genotypes of dog number 4, 5 and 6 concerning their hair characteristic (use capital letter 'H' for the dominant gene and the lower case 'h' for the recessive gene)?

ANSWER TO

Question 1:

Write down all of the steps needed to the answer this question

Question 2:

Write down all of the steps needed to the answer this question

Figure 5.1. A low (a) and high (b) complexity learning task, as well as a transfer-test task (c).

Efficiency measurement. The combination of performance and cognitive load measures can provide a reliable estimate of the efficiency of instructional methods, both in terms of the learning process and learning outcomes. Paas and van Merriënboer's (1993; see Van Gog & Paas, 2008) computational approach was used to calculate efficiency as a function of task complexity. The basic idea underlying this approach is that instructional conditions that require less learning effort with equal or higher performance are more efficient than instructional conditions requiring more learning effort with equal or lower performance.

With regard to the learning process, efficiency while learning (i.e., the mental efficiency while learning) was calculated by standardizing each of the participants' scores for the low and high learning task performance and mental effort invested. For this purpose, the grand mean was subtracted from each score and the result was divided by the overall standard deviation, which yielded *z*-scores for effort (*R)* and performance (*P).* Finally, a performance efficiency score, *E*, was computed for each participant using the formula: $E = [(P - R)/2^{1/2}]$. High learning efficiency was indicated by relatively high learning task performance in combination with relatively low mental-effort rating. In contrast, low learning efficiency was indicated by relatively low learning task performance in combination with relatively high mental-effort rating. With regard to the efficiency of learning outcomes, the same computational approach was used, although this time by standardizing each of the participant's scores for performance and mental effort on the transfer-test tasks. High learning efficiency was indicated by relatively high test task performance in combination with relatively low mental-effort rating. In contrast, low test efficiency was indicated by relatively low test task performance in combination with relatively high mental-effort rating.

Time-on-task. During the learning phase, time on task was fixed and managed by a proctor. All tasks within a series (i.e., four tasks per series in the low-complexity condition and of two tasks per series in the high-complexity condition) had to be performed and studied for 10 min. The test phase had to be finalized within a maximum of 90 min. The specific time spent on each test task was recorded by the participants themselves with the aid of a digital clock.

Design and procedure

Participants were randomly assigned to the four conditions in such way that 21 had to learn individually from low-complexity learning tasks, 20 had to learn individually from high-complexity learning tasks, 21 had to learn in 3-person groups (i.e., triads) from low-complexity learning tasks, and 21 had to learn in 3-person groups from high-complexity learning tasks. Participants in all conditions were guided through the learning and test phase by a proctor who read the instructions out loud. These instructions included the procedure and rules when working on the learning or transfer-test tasks. At the start of the learning phase, all participants had to individually study the general introduction on heredity-related concepts and the worked example. They received this on paper and had to return it to the proctor after 15 min. Participants were then assigned to one of the four conditions to carry out the first series of problem-solving tasks in a fixed amount of time (i.e., 10 min). After each task in the series, independent of being in the group or individual condition, all participants had to rate the amount of invested mental effort on the 9-point cognitive load rating scale. The second and third series of learning tasks followed the same procedure. The instructions given to all participants preceding the series of learning tasks consisted of reading all information elements thoroughly, reading the questions, and finally trying to answer the questions as correctly as possible using all information elements. For participants in the group condition, it was also stressed that working together was necessary for solving the problem. Face-to-face communication was very important, but transaction costs were held to a minimum so as not to cause an overload from extraneous load. Therefore, participants were only permitted to communicate about task related topics. To prevent participants from offloading information in their WM (Scaife & Rogers, 1996), both individuals and group members were not allowed to write anything down. After this learning phase, the test phase required all participants to work individually for a maximum of 90 min on six transfer tasks. The amount of invested mental effort was measured after each transfer task using the same 9-point cognitive load rating scale as in the learning phase. Time on task was recorded by asking participants to note begin and end time of each task with the aid of a digital clock. Use of pen and paper was permitted in this phase.

Results

The data were analyzed with 2 (learning condition: individual vs. group) by 2 (task complexity: low vs. high) between-subjects multivariate analyses of variance (MANOVAs). The results for the learning and test phases are described separately. Dependent variables for the learning phase were performance, mental effort and learning efficiency. For the test phase, performance, mental effort, test efficiency and time-on-test-task were used as dependent variables. A significance level of .05 was used for all analyses. There were incomplete data from two participants due to registration problems in the test phase. Case-wise deletion of those participants was used to analyze the data. Table 5.1 shows the means and standard deviations for performance, mental effort, learning efficiency, test efficiency and time-on-test-task in the learning and test phase as a function of learning condition and task complexity. Cohen's f is provided as a measure of effect size, with f-values of .10, .25, and .40, corresponding to small, medium, and large effects, respectively (Cohen, 1988).

Learning phase

The omnibus MANOVA comparing learning condition (individual vs. group) and task complexity (low vs. high) indicated a main effect for learning condition, multivariate Wilks' Lambda = .71, $F(2, 78) = 16.02$, $p < .001$, and task complexity, multivariate Wilks' Lambda = .23, $F(2, 78) = 129.42$, $p < .001$. In addition there was a significant interaction between learning condition and complexity, multivariate Wilks' Lambda = .91, $F(2, 78) = 3.99$, $p < .05$. Univariate ANOVAs were conducted to further examine these significant effects.

The ANOVA for learning performance revealed a significant main effect for learning condition, such that participants learning in groups outperformed participants learning individually, $F(1, 79) = 17.69$, $MSE = 0.03$, $p < .001$, $f = 2.15$. The main effect for task complexity was significant, such that participants had a higher performance score on low-complexity tasks than on high-complexity tasks, $F(1, 79) = 111.06$, $MSE = 0.03$, $p < .001$, $f = 1.03$. In addition, it revealed a significant interaction between learning condition and task complexity, $F(1, 79) = 6.93$, $MSE = 0.03$, $p < .02$, $f = 0.18$. To determine the nature of this ordinal interaction, a post hoc analysis of simple effects was conducted using Tukey-Kramers method of multiple comparisons with unequal sample sizes (honestly significant difference [HSD] = 0.15, α = .05). This analysis indicated that on the low-complexity learning tasks participants learning in groups and participants learning individually performed equally well, but that on the high-complexity tasks participants learning in groups significantly outperformed participants learning individually.

Table 5.1. Means and standard deviations of the dependent variables in the learning and test phase as a function of learning condition and task complexity

	Learning condition			
	Individual		Group	
Dependent variable	*M*	*SD*	*M*	*SD*
Learning performance (0-1) [a]				
Low complexity	0.87	0.21	0.93	0.09
High complexity	0.34	0.18	0.61	0.22
Learning mental effort (1-9)				
Low complexity	2.35	0.85	1.64	0.61
High complexity	6.27	1.14	4.64	1.32
Learning efficiency [c]				
Low complexity	0.88	0.65	1.27	0.33
High complexity	-1.72	0.71	-0.51	0.83
Test performance (0-1) [a]				
Low complexity	0.64	0.21	0.63	0.19
High complexity	0.41	0.20	0.52	0.21
Test mental effort (1-9)				
Low complexity	4.06	1.39	4.73	1.69
High complexity	5.77	1.28	4.78	1.54
Test efficiency [c]				
Low complexity	0.66	1.08	0.33	1.18
High complexity	-0.84	1.01	-0.06	1.18
Time on test (min)				
Low complexity	24.25	8.12	29.00	5.85
High complexity	24.20	7.16	22.65	5.42

[a] Performance is the proportion of correct answers on the learning or test tasks.
[b] Based on the z-scores of mental effort and performance in the learning phase.
[c] Based on z-scores of mental effort and performance in the test phase.

The ANOVA performed on the perceived amount of mental effort invested in solving the learning tasks revealed a main effect for learning condition, $F(1, 79) = 27.28$, $MSE = 1.03$, $p < .001$, $f = 0.29$, thus indicating that participants learning in groups invested lower amounts of mental effort than participants learning individually. The main effect of task complexity was significant, $F(1, 79) = 240.96$, $MSE = 1.03$, $p < .001$, $f = 1.48$, thus indicating that participants rated a lower investment of mental effort on low-complexity tasks than on high-complexity tasks. In addition, it revealed a significant ordinal interaction between learning condition and task complexity, $F(1, 79) = 4.23$, $MSE = 1.03$, $p < .05$, $f = 0.11$. To determine the nature of this ordinal interaction, a post hoc analysis of simple effects was conducted using Tukey-Kramers method of multiple comparisons with unequal sample sizes (honestly significant difference [HSD] = 0.84, = .05). Whereas there was no difference in perceived amount of invested mental effort in learning from low-complexity tasks between participants that learned in groups and those who learned individually, group members reported investing significantly less mental effort than individuals in learning from high-complexity problems.

For learning efficiency, the ANOVA revealed a main effect for learning condition, $F(1, 79) = 30.54$, $MSE = 0.43$, $p < .001$, $f = 0.31$, indicating that participants learning in a group had a higher efficiency score than participants learning individually. The main effect for task-complexity was significant, $F(1, 79) = 228.53$, $MSE = 0.43$, $p < .001$, $f = 1.39$, indicating that participants performing low-complexity tasks learned more efficient than participants performing high-complexity tasks. As expected, the learning condition × task complexity interaction was significant, $F(1, 79) = 7.99$, $MSE = 0.43$, $p < .02$, $f = 0.15$. To determine the nature of this ordinal interaction, a post hoc analysis of simple effects was conducted using Tukey-Kramers method of multiple comparisons with unequal sample sizes (honestly significant difference [HSD] = 0.56,   = .05). While learning efficiency for low-complexity tasks did not differ between participants learning in groups and participants learning individually, a significantly more favorable relationship between invested mental effort and performance was found for participants learning in groups than for participants learning individually for high-complexity tasks (see Figure 5.2).

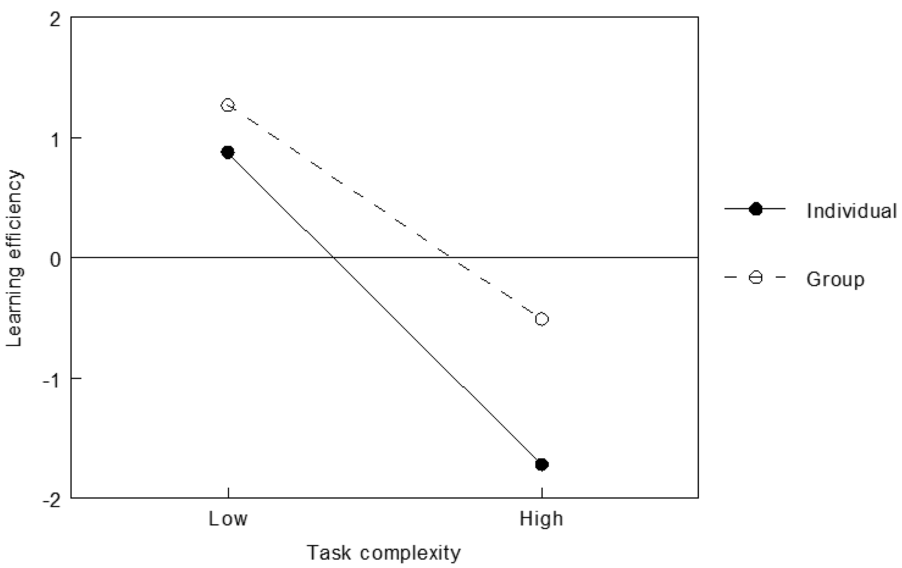


Figure 5.2. Learning phase: learning condition × task complexity interaction.

Test phase

The omnibus MANOVA comparing learning condition (individual vs. group) and task complexity (low vs. high) did not yield a significant main effect of learning condition, multivariate Wilks' Lambda = .97, $F(2, 78) = 16.02$, *ns.* It did, however, reveal a significant main effect for task complexity, multivariate Wilks' Lambda = .78, $F(2, 78) = 129.42$, $p < .001$, and a significant interaction between learning condition and task complexity, multivariate Wilks' Lambda = .90, $F(2, 78) = 3.99$, $p < .05$. Again, univariate ANOVAs were conducted on the dependent variables to further examine these significant effects.

The ANOVA for test performance did not yield a significant main effect for learning condition, $F(1, 77) = 1.24$, $MSE = 0.04$, *ns.* The main effect for task complexity was significant, $F(1, 77) = 14.84$, $MSE = 0.04$, $p < .001$, $f = 0.14$, indicating that participants who had learned from the low-complexity tasks performed better than participants who had learned from high-complexity tasks. The analysis did not reveal an interaction between learning condition and task complexity, $F(1, 77) = 1.43$, $MSE = 0.04$, *ns.*

For the perceived amount of mental effort invested in solving test problems, the ANOVA did not reveal a main effect for learning condition, $F(1, 77) < 1$, $MSE = 2.21$, *ns*, but did reveal a main effect for task complexity, $F(1, 77) = 7.107$, $MSE = 2.21$, $p < .01$, $f = 0.29$. The main effect was qualified by the crossover interaction effect of learning condition and task complexity, $F(1, 77) = 6.27$, $MSE = 2.21$, $p < .02$, $f = 0.27$, reflecting that the participants who had learned individually from low-complexity tasks perceived investing less mental effort when carrying out the test tasks than participants that had learned from those tasks in a group. The reverse effect was found for participants who had learned from high-complexity problems; participants that had learned in a group perceived investing less mental effort than participants who had learned individually.

The ANOVA performed on the test efficiency scores did not reveal a main effect for learning condition, $F(1, 77) < 1$, $MSE = 1.25$, *ns*, but did reveal one for task complexity, $F(1, 77) = 14.40$, $MSE = 1.25$, $p < .001$, $f = 0.42$. As expected, the main effect was qualified by the crossover interaction effect between learning condition and task complexity, $F(1, 77) = 4.93$, $MSE = 1.25$, $p < .05$, $f = 0.23$, indicating that when participants had learned from low-complexity tasks individually, performed the test tasks more efficiently – as indicated by a more favorable relationship between test effort and test performance – than did those who learned within groups. The reverse effect emerged for high-complexity tasks; those participants who had learned within groups performed the test tasks more efficiently than participants who learned individually (see Figure 5.3).

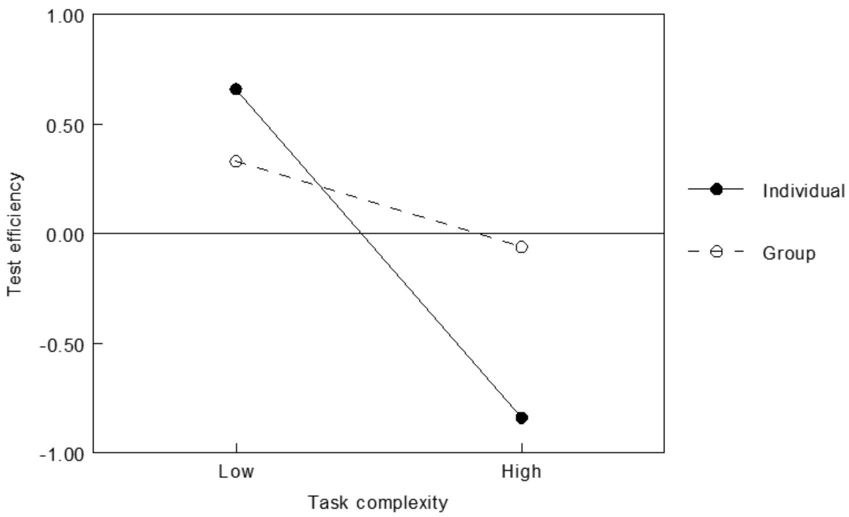


Figure 5.3. Test phase: learning condition × task complexity interaction.

The ANOVA performed on time-on-test-task did not yield a significant main effect for learning condition, $F(1, 77) = 1.15$, $MSE = 45.08$, *ns*, but did yielded one for task complexity, $F(1, 77) = 4.60$, $MSE = 45.08$, $p < .05$, $f = 0.24$. The main effect was qualified by a crossover interaction between learning condition and task complexity, $F(1, 77) = 4.46$, $MSE = 45.08$, $p < .05$, $f = 0.23$, indicating that participants who had learned individually from low-complexity tasks spent less time working on the test tasks than participants who had learned from those tasks within groups. A reverse effect was found for high-complexity tasks where participants who had learned within a group spent less time working on the test tasks than participants who had learned individually.

Discussion

Educators and researchers have expressed high expectations for the value and power of collaborative learning as educational approach, but the results of research on its use have often been disappointing, not unequivocal with respect to student learning and performance, or both. One of the primary causes for this could be that the tasks presented to students in collaborative learning settings are not *complex enough* to necessitate working in teams and that this low complexity impedes both learning and performance. In trying to better understand the impact of task complexity on the effectiveness of collaborative learning environments, CLT was used as an indicator of the efficiency with which both groups and individuals learn. This efficiency was expected to be affected by the trade-off between the possibility to divide information processing amongst group members and the associated costs of information communication and action coordination.

This study was designed to investigate the effects of task complexity on the efficiency of collaborative versus individual learning, both in terms of learning process and learning outcome. It was expected that when learning from high-complexity tasks, the advantage of being able to use each others' WM through sharing cognitive load would be relatively larger than the disadvantage of having to invest mental effort in the communication of information and the coordination of actions (i.e., transaction costs). As a result, group members would process information elements more deeply and consequently construct higher quality schemas in their LTM than learners working individually. In contrast, when learning from low-complexity tasks, it was expected that the limited WM of an individual would be sufficient to process all information elements and therefore sharing the cognitive load within a group would not be advantageous for the quality of schema constructed. Working in collaboration on low-complexity tasks was even expected to have a detrimental effect on group member learning, for the 'advantage' of being able to make use of each others' WM, would be outweighed by the relatively high mental effort associated with the transaction costs needed to do this. In conclusion, it was hypothesized that for high-complexity tasks, group members would learn in a more efficient way – both in terms of the learning process and outcomes – than individual learners, while for low-complexity tasks, individual learning would be more efficient.

The data presented largely confirm this interaction hypothesis with respect to the efficiency of the learning process. Although groups achieved higher performance, invested less mental effort and were, thus, more efficient than individuals while learning from the high complexity learning tasks, individuals performed equally well, invested the same amount of mental effort, and were equally efficient on the low complexity learning tasks. In other words, as expected, learners profited from being able to expand their limited WM capacity in the group when working on high complexity tasks. Furthermore, the limited WM capacity of individuals was apparently sufficient for working on the low-complexity tasks since both group members and individuals performed equally well on those learning tasks. However, unexpectedly, learners within a group did not experience a disadvantageous effect of having to invest the mental effort associated with the transaction costs when working on low-complexity tasks. This effect could be explained in two ways. The first explanation relates to the way that the learning tasks were designed. All problems had a single correct answer, all elements required for their solution were known, and the solution required using logical processes. Solving these well-structured problems (Kitchner, 1983) could have resulted in learners having to invest minimal transaction costs to arrive at and agreeing upon a common solution by combining and integrating individual ideas into a shared and collective one was not that difficult. The second explanation is related to the experimental design. The research was set up so as to restrain and, thus, minimize off-task communication. In a more natural setting, there might be significantly more discussion and, thus, significantly higher transaction costs. Future research should investigate the contribution of ill-structured tasks on the effects of task complexity on the efficiency of learning in a group as well as the effects of unrestrained communication between group members.

With respect to the efficiency of learning outcomes, the data largely confirmed our expectations. Participants who had learned individually from low complexity tasks performed equally well but invested less mental effort, and were therefore more efficient when carrying out the transfer-test tasks than participants who had learned from those tasks in a group. Although participants who had learned individually from high complexity tasks indicated equal performance, they invested more mental effort and were, thus, less efficient when performing the transfer-test tasks, than participants who had learned from those tasks in a group. In other words, with respect to the efficiency with which cognitive schemas were constructed during the learning process, learners profited from having learned from high-complexity tasks in collaboration, while learners profited from having learned from low-complexity tasks individually. This interaction effect increases when time-on-test is taken into account. Time-on-test has been identified as an important factor that, together with transfer-performance and mental effort, should be taken into account when determining the quality of the cognitive schemas constructed in the learning phase (Tuovinen & Paas, 2004; Van Gog & Paas, 2008). With respect to time-on-test, participants who had learned individually from low complexity tasks carried out the test tasks more quickly than participants who had learned in a group. Participants who had learned individually from high complexity tasks carried out the test tasks less quickly than participants who had learned in a group.

The results presented in this chapter are both a replication and an extension of two previous studies focusing on the efficiency of individual versus group learning as a function of task complexity. With regard to replicating previous findings, these results confirmed the hypothesis formulated and confirmed in F. Kirschner et al. (2009a [Chapter 3]) that when learning from *high-complexity tasks*, participants who learned in groups would demonstrate more efficient transfer performance (i.e., *efficiency of the learning outcomes*) than participants who learned individually. The result that the efficiency of learning (i.e., *efficiency of the learning process*) in a group was higher than the efficiency of learning individually when learning from *high-complexity tasks*, but not when learning from *low-complexity tasks* was also found in F. Kirschner et al. (2009c [Chapter 4]), although they used a different domain (i.e., mathematics) and the participants were younger. With regard to extending the results of previous studies, this study included both *low-complexity* and *high-complexity tasks*, focusing on the efficiency of both the *learning process* and the *learning outcomes*. This resulted in a more complete picture of the effects of task complexity on the efficiency of collaborative learning.

Within the context of CLT, the results presented here have strong implications for the design of certain types of collaborative learning environments, such as those making use of problem-based learning (Hmelo-Silver, Duncan, & Chinn, 2007; Schmidt, Loyens, Van Gog, & Paas, 2007) or project-based learning (Van Bruggen, Kirschner, & Jochems, 2002). Human cognitive architecture, and in particular the limitations of WM capacity at the individual level (Cowan, 2001), has been argued to be an important reason for assigning complex learning tasks to groups rather than to individuals. The rationale behind this is that the more complex the task (i.e., the higher the intrinsic cognitive load), the more efficient it will be for individuals to collaborate by distributing and sharing this load (F. Kirschner et al., 2009b [Chapter 2]). Indeed, the results of this study reveal that the more complex the tasks, the more efficient it is to learn in a collaborative learning setting.

For teachers and instructional designers, it is extremely important that future research be carried out to identify the level of task complexity at which it becomes more efficient to assign tasks to groups than to individuals. All too often, students are given collaborative learning tasks that they can better and more efficiently carry out themselves, often leading to either minimal collaboration and/or stop-gap measures such as requiring students to post a minimal number of comments on a discussion board or send each other a minimal number of emails (P. A. Kirschner et al., 2008). Having said this, we note that such a recommendation cannot be made in absolute terms since task complexity, which is defined as the number of interacting elements in a task and the degree of interaction between them, is relative to and dependent on the quality and quantity of the schemas in the learner's long term memory (i.e., their expertise: Paas et al., 2003). What is complex for the novice may be moderately complex for the more experienced learner and simple or even trivial for the expert. Therefore, comparable to the expertise-reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003), it can be expected that the task-complexity threshold at which group learning becomes more efficient than individual learning will vary as a function of learner expertise. An interesting hypothesis for future research would be that for group learning to become efficient, task complexity needs to be higher for more advanced learners and experts than for novices.

Another learner characteristic determining the level of task complexity at which it becomes more efficient to assign tasks to groups than to individuals, is the learners age. One of the central findings of cognitive aging research is that the WM capacity declines with age in adults, impairing their ability to engage in complex cognitive tasks for which the successful completion is highly dependent on the availability of sufficient cognitive resources. Although learner expertise, in terms of more developed or better quality schemas in LTM, can compensate for the age-related decline in WM, this is not relevant when the information that has to be learned is new. Paas, Camp, and Rikers (2001) have shown that instructional techniques that compensate for the reduced capacity can disproportionately enhance elderly people's performance. As such, collaboration or sharing cognitive load can be considered as a potential compensatory technique. Another interesting hypothesis for future research would therefore be that the threshold for collaboration to become more effective than individual work is lower for older adults than for younger adults.

Finally, it should be noted that the learning conditions in this study can be considered artificial, for example, learners were not allowed to use pen and paper while solving the learning problems. In this sense, it is not clear the extent to which these results can be generalized to real classroom settings. It can be assumed that the complex pattern of interactions between cognitive, motivational, and social factors that characterize a real life context would add 'noise' to the data and cause the effects to be less pronounced than in our study. We acknowledge that, ultimately, research on group-based learning requires an interrelated perspective integrating cognitive, motivational, and social aspects. However, to be able to disentangle the contributions of each of these factors to the learning processes and outcomes of group-based learning, they need to be studied within tightly constrained experimental environments, one at a time, keeping all other aspects constant.

Although we have shown that learning-task complexity is an important factor that helps determine the effectiveness of group learning, it should be clear that it is not merely complexity of the tasks that determines whether group learning is favored above individual learning in a certain context. Recent research has identified a number of other task characteristics that are relevant when considering whether group learning is a good educational option. This would, for example, be the case when positive cognitive conflict is necessary or desirable when solving a problem or creating a product (Munneke et al., 2007), when diversity in expertise or a multidisciplinary approach is necessary for carrying out a task or solving a problem (Kirschner et al., 2008), or when specific cognitive or metacognitive skills (e.g., reflection: King, 2007) or socio-cognitive skills (e.g., negotiation: Beers et al., 2007 or debating: Leitão, 2000; Veerman, Andriessen, & Kanselaar, 2000) are the required products of learning.

The present study showed that task complexity is a key factor in determining learning efficiency in individual and collaborative learning environments with strong implications for the design of such environments. However, the results need further experimental confirmation with tasks that are ill-structured, using learners with varying levels of expertise and age, and in more ecologically valid collaborative learning settings to provide more specific guidelines for designing group learning environments.

6

Effects of instructional format on individual and collaborative learning efficiency: Solving conventional problems versus studying worked examples

Four conditions for learning to solve problems on the heredity of traits were studied with respect to their effects on learning efficiency. An individual and a collaborative learning condition, in which complex worked examples had to be studied, were compared with an individual and a collaborative learning condition in which the equivalent conventional problems had to be solved. Using a cognitive load theoretical framework, conventional problem solving was considered a more complex task imposing a higher cognitive load than studying worked examples. The crossover interaction hypothesis that learning by solving conventional problems would be more efficient for groups than for individuals, whereas learning by studying worked examples would be more efficient for individuals than for groups, was confirmed. Consequences of the findings for the instructional design of individual and collaborative learning environments are discussed.

This Chapter is submitted for publication as:
Kirschner, F., Paas. F., & Kirschner, P. A. (2009e). *Effects of instructional format on individual and collaborative learning efficiency: Solving conventional problems versus studying worked examples.*

Cognitive load theory (CLT: P. A. Kirschner, 2002; Paas, Renkl, & Sweller, 2003; Sweller, 1988; Sweller, Van Merriënboer, & Paas, 1998) focuses on the engineering of instructional control of cognitive load in the learning of complex cognitive tasks. To realize this control, CLT uses current knowledge about the human cognitive architecture to generate instructional techniques that facilitate changes in long-term memory associated with schema construction and automation (i.e., learning; Sweller, 1988, 2004). According to CLT the complexity of a learning task is determined by its number of interacting information elements; the more interacting elements, the higher the task complexity. Although the information elements of high-element interactivity material can be processed in isolation, they cannot be understood until all of them and their interactions are processed simultaneously. Given that working memory (WM) capacity is considered limited to 4 ± 1 interactive information elements or chunks of information (Miller, 1956), tasks that contain a high number of interacting elements that have to be processed in WM simultaneously, place high cognitive demands on WM. Within CLT, the load imposed on WM because of the element interactivity or task complexity is referred to as intrinsic cognitive load.

Overcoming learners' individual WM limitations by creating instructional manipulations compatible with human cognitive architecture that facilitate schema construction and automation has been the central focus of CLT. Research has, therefore, primarily been concerned with developing techniques for managing individual WM load imposed by the intrinsic nature of complex learning tasks. F. Kirschner, Paas, and Kirschner (2009c [Chapter 4]) have recently shown that an alternative way of overcoming individual WM-limitations lies in making use of the multiple WMs of learners collaboratively learning in groups. They investigated the effects of low-complexity (i.e., low intrinsic load) and high-complexity (i.e., high intrinsic load) tasks on individual and group learning efficiency, as indicated by the relationship between performance and effort. For high-complexity tasks that imposed a cognitive load exceeding the limited processing capacity of an individual learner, their hypothesis that collaborative learning would be more efficient than individual learning was confirmed. With those tasks, the benefits of distributing cognitive load across individuals proved to be higher than the costs of inter-individual integration and coordination of information (i.e., transaction costs: F. Kirschner, Paas, & Kirschner, 2009a [Chapter 3]). It was argued that this enabled collaborative learners to construct higher quality schemas during learning which materialized in a more favorable relationship between performance and mental effort on an individual transfer test. For low-complexity tasks, which did not impose a cognitive load exceeding an individual learner's limited processing capacity, their hypothesis that individual learning would be more efficient than collaborative learning was confirmed. With those tasks, the transaction costs proved to be higher than the benefits of distributing cognitive load across individuals. It was argued that this enabled individual learners to construct higher quality schemas during learning than collaborative learners, which materialized in a more favorable relationship between performance and mental effort on an individual transfer test for those who had learned individually.

In addition to the intrinsic load imposed by the learning task, the cognitive load that learners experience is affected by the instructional format of the task. This can take two forms. When the instructional format causes cognitive load ineffective for learning, it is called extraneous cognitive load; when it is effective for learning, it is referred to as germane cognitive load (Paas, Renkl, & Sweller, 2004; Sweller et al., 1998). Although extraneous load does not hamper learning when tasks are low in intrinsic load (i.e., low complexity), it does hamper learning when tasks are high in intrinsic load (i.e., high complexity); hence, reducing extraneous load is imperative for such tasks (Van Merriënboer & Sweller, 2005). A consistent finding of CLT research is that for tasks high in intrinsic load, problem solving imposes extraneous load on novice learners (Sweller et al., 1998). In addition to the recent studies of F. Kirschner et al. (2009a [Chapter 3], 2009c [Chapter 4]) into the effects of different levels of intrinsic load on the efficiency of individual and collaborative learning, the present study kept the intrinsic load constant and investigated the differential effects of extraneous load as induced by instructional format. More specifically, individual and collaborative learning of novices either from solving conventional problems or studying worked examples in the domain of biology was compared regarding their effects on learning efficiency.

Sweller (1988) has shown that problem solving search, when carrying out complex conventional tasks, not only places heavy intrinsic demands, but also heavy extraneous demands on WM. The strategy most commonly used by learners faced with novel problems for which they do not have previously constructed schemas – a means-ends analysis – requires them to consider the current problem state, consider the desired goal state, extract differences between the two states, and find or choose a problem-solving operator that can be used to reduce or eliminate differences between the current problem state and the desired goal state. In addition, any sub-goals that have been established need to, simultaneously, be kept in mind. This particular problem-solving search strategy, although an efficient means of solving the problem, does not leave sufficient processing capacity for learners to induce the generalized solutions or schemas that are prerequisite to learning. In an educational context, learning is the primary goal of carrying out learning tasks. Attaining a problem goal (i.e., solving a problem) is not directly relevant to the learning process itself, but is only relevant in a testing situation. Furthermore, not only is a means-ends problem-solving search strategy distant from learning, this strategy imposes very high extraneous cognitive load on the learner which interferes with schema construction goals and therefore with learning.

An effective alternative to conventional problem-solving practice that has been supported by multiple, overlapping experiments using a variety of instructional materials and a variety of populations, is studying worked examples (e.g., Carroll, 1994; Paas, 1992; Paas & Van Gog, 2006; Paas & Van Merriënboer, 1994a; Sweller, 1987; Sweller & Cooper, 1985; Trafton & Reiser, 1993; for an overview see Atkinson, Derry, Renkl, &Wortham, 2000). Studying worked examples as a substitute for solving problems is argued to be beneficial because it decreases extraneous load by eliminating means-ends search. In contrast to conventional problems, worked examples focus attention on problem states and associated operators (i.e., solution steps), enabling learners to induce generalized solutions or schemas. The surplus cognitive capacity that becomes available by the reduction of extraneous load can be devoted to activities that contribute to learning (i.e., germane load). This reasoning has led to the counterintuitive instructional guideline that for novices learning to solve problems, studying worked examples is a better strategy than solving the equivalent problems.

In the context of the theoretical framework of cognitive load, for novices studying worked examples can be considered a less complex task than solving the equivalent conventional problems in the sense that it imposes a lower extraneous cognitive load. Combining this view on instructional formats with the results of the studies of F. Kirschner et al. (2009c [Chapter 4]) on the effects of low and high complexity learning tasks on individual and collaborative learning efficiency, the main crossover interaction hypothesis of this study was that for solving conventional problems, learning collaboratively would be more efficient than learning individually, while for studying worked examples learning individually would be more efficient than learning collaboratively.

With regard to learning from solving conventional problems, it was expected that the load on the limited cognitive capacity of an individual learner would be too high for effective learning to commence. For learners in a group the benefits of distributing the cognitive load among each other would be higher than the costs of inter-individual integration and coordination of information. Group members would consequently be able to devote the freed-up cognitive capacity to activities that foster schema construction and automation (i.e., germane load), materializing in a more favorable relationship between performance and mental effort on an individual transfer test (i.e., higher learning efficiency) for learners who carried out the learning tasks in groups than for learners who carried out the learning tasks individually.

With regard to learning from studying worked examples, it was expected that learners working individually or as a member of a group would have sufficient cognitive capacity to process all information by themselves. Hence, inter-individual communication and coordination of information would result in higher transaction costs than benefits of distributing the cognitive load across group members to the collaborative learning process. Consequently, qualitative differences in constructed schemas were expected between learners learning in a group and learners learning individually, materializing in a more favorable relationship between performance and mental effort on an individual transfer test for those who learned individually than for those who learned as a member of a group.

Method

Participants

Participants were 140 Dutch fourth year high school students (71 boys, 69 girls) with an average age of 14.98 years (*SD* = 0.96). They participated in the study as part of their regular biology curriculum and did not receive any academic or financial compensation. No differences in prior knowledge were expected since all participants had followed the same biology courses in the previous three years and the study topic of heredity had not yet been covered. In addition, participants were randomly assigned to the different experimental conditions to exclude possible differences in prior knowledge.

Materials

All materials were in a domain of biology concerned with heredity, specifically the transmission of genotypic and phenotypic biological traits from parents to offspring through genes carrying biological information (e.g., eye color in humans, fur length in dogs, leaf shape in plants). For the experiment, a general introduction and instruction on how to solve inheritance problems, worked examples and conventional problem-solving tasks, and transfer-test tasks were designed. The materials were approved by two biology teachers as being suitable for the learners. All materials were paper based.

Introduction. Relevant terminology, rules and theory underlying heredity, as well as a worked example on solving heredity problems was discussed in the introduction. More specifically, the introduction provided insight into the definition of genes, the genotype and phenotype of an organism, homozygosity or heterozygosity of an organism's dominant or recessive genes, the pedigree chart, and the rules concerning the Punnett square (i.e., a diagram used to predict the outcome of a particular cross or breeding experiment). The worked example showed the procedure that should be used to solve a heredity problem by combining terminology, rules, and theory. Learners were required to use the definitions, rules and theory underlying heredity problems when carrying out the learning tasks.

Learning tasks. Three complex learning tasks were used, presented either as a conventional problem-solving task or as a worked example. The learning tasks consisted of nine information elements concerning a biological trait in a human family (i.e., ear shape, eye color, hair color) and a question about the proportion of possible genotypes and phenotypes of the offspring. Each information element was relevant but insufficient by itself for carrying out the task successfully. Only by combining all nine information elements with each other the problem could be successfully solved (JIGSAW; Aronson, Blaney, Stephan, Silkes, & Snapp, 1978; Slavin, 1990). A simplified example of such a task in the domain of heredity would be that: information element 1 is eye color of the mother: blue; information element 2 is eye color of the father: brown; and information element 3 is the dominance of brown eyes over blue eyes. Each element gives a certain amount of information, but to answer the question as to what the eye color of the offspring would be, the participant must combine all three information elements. The difference between the two presentation formats (i.e., conventional and worked example) lies in the information provided to the participants on the solution of the problem. Within the conventional condition, participants were only presented with the final solution to the problem (i.e., the correct answers to the questions), and asked to use the information elements to determine how the solution was reached. Within the worked example condition, participants were additionally presented with worked-out solution steps, and asked to study the way the final solution was established (see Figure 6.1 for a conventional problem (a) and a worked example (b)).

The tasks that had to be carried out in collaboration were structured such that positive task interdependence was high (Johnson, 1981; Saavedra, Early, &Van Dyne, 1993), that is, group members had to rely on each other and interact with each other to obtain resources and to perform the task effectively. Positive interdependence reflects the degree to which group members are dependent upon each other for effective group performance (i.e., enhanced intra-group interaction). It holds that team members are linked to each other in such a way that each team member cannot succeed unless the others succeed; each member's work benefits the others and vice versa (P. A. Kirschner, Strijbos, Kreijns, & Beers, 2004). This was managed by giving each group member one third of the total number of information elements necessary for solving the problem. To stimulate collaboration, cognitive load distribution (i.e., the distribution advantage; Ciborra & Olson, 1988; Hinsz, Tindale, & Vollrath, 1997; F. Kirschner, Paas, & Kirschner, 2009b [Chapter 2]; Yamane, 1996), and information exchange amongst the learners, no information elements were redundant and the number of information elements was equal for all group members. The tasks presented to participants learning individually contained all nine necessary information elements.

Test tasks. To determine how much participants had learned and to see if they were able to apply the knowledge and skills that they were assumed to have acquired in the learning phase to different kind of problems, four transfer tasks were designed. Although the same basic terminology, rules, and underlying heredity-theory had to be used to solve these transfer test-problems, they differed from the tasks in the learning phase with respect to the families and traits used, the kind of information elements given, the task structure and the questions asked (e.g., genealogical tree, X-chromosome linked inheritance, dihybrid crossings; see Figure 6.1c for an example). To solve the transfer test-problems participants had to use the terminology, rules, and underlying heredity-theory acquired in the learning phase.

TASK 1: PIET AND LUCY'S FAMILY

GIVEN

- For humans, the gene for green eye color (G) is dominant over the gene for blue eyes (g).
- Sandra has green eyes.
- Sandra's mother has green eyes.
- Sandra's mother is homozygote for eye color.
- Sandra's father has green eyes.
- Sandra's father is homozygote for eye color.
- Wim has blue eyes.
- Lucy, a child of Sandra and Wim, marries Piet who has green eyes.
- Piet's father has blue eyes.

QUESTIONS

What could be the genotypes and phenotypes of Piet and Lucy's children? And what are their proportions?

SOLUTION

Below are the answers to the questions. However, there is no description of how the answers were arrived at. Use the given information to determine how the answers were reached.

The genotypes and their proportions are:

25% GG – 25% gg – 50% Gg

The phenotypes and their proportions are:

75% green eyes – 25% blue eyes

a.

TASK 1: PIET AND LUCY'S FAMILY

GIVEN

- For humans, the gene for green eye color (G) is dominant over the gene for blue eyes (g).
- Sandra has green eyes.
- Sandra's mother has green eyes.
- Sandra's mother is homozygote for eye color.
- Sandra's father has green eyes.
- Sandra's father is homozygote for eye color.
- Wim has blue eyes.
- Lucy, a child of Sandra and Wim, marries Piet who has green eyes.
- Piet's father has blue eyes.

QUESTIONS

What could be the genotypes and phenotypes of Piet and Lucy's children? And what are their proportions?

SOLUTION STEPS

Below, the solution steps for answering the questions are given. You need the given information to study the solution steps and find out how the steps and final answers were reached.

STEP 1. Determine Piet's genotype for eye color.
Piet's genotype is **Gg.**

STEP 2. Determine Lucy's genotype for eye color.
It is not possible to know Lucy's genotype at once; first it has to be determined:

STEP 2.1. What is Wim's genotype for eye color?
Wim's genotype for eye color is **gg.**

STEP 2.2. What is Sandra's genotype for eye color?
It is not possible to know Sandra's genotype at once; first it has to be determined:

STEP 2.2.1. What is Sandra's father's genotype for eye color?
Sandra's father's genotype is **GG.**

STEP 2.2.2. What is Sandra's mother's genotype for eye color?
Sandra's mother's genotype is **GG.**

STEP 2.2.3. Make a Punnett square between the genotypes of Sandra's mother and father.

	G	G
G	**GG**	**GG**
G	**GG**	**GG**

STEP 2.2.4. Determine Sandra's genotype.
Sandra's genotype is **GG.**

STEP 2.3. Make a Punnett square between the genotypes of Sandra and Wim.

	G	G
g	**Gg**	**Gg**
g	**Gg**	**Gg**

STEP 2.4. Determine Lucy's genotype for eye color.
Lucy's genotype is **Gg.**

STEP 3. Make a Punnett square between the genotypes of Piet and Lucy.

	G	*g*
G	***GG***	***Gg***
g	***Gg***	***gg***

STEP 4*. Determine the genotypes and their proportions of Piet and Lucy's children.*
25% GG – 25% gg – 50% Gg.

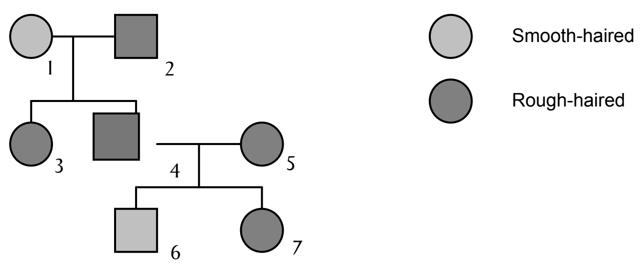
STEP 5. *Determine the phenotype and their proportions of Piet and Lucy's children.*
75% green eyes – 25% blue eyes.

b.

<u>THE FAMILY TREE</u>

A family tree displays all phenotypes of a family in one glance. In a family tree the males are depicted by a square and females by a circle. In a dog family both rough-haired and smooth-haired dogs can be found. The figure below shows a specific dog family tree with information about their hair characteristic.

<u>GIVEN</u>



<u>QUESTION</u>

1. Which of the genes, smooth-haired or rough-haired is dominant and which is recessive?
2. What are the genotypes of dog number 4, 5 and 6 concerning their hair characteristic (use capital letter 'H' for the dominant gene and the lower case 'h' for the recessive gene)?

<u>ANSWER TO</u>

Question 1:

Write down all of the steps needed to the answer this question

Question 2:

Write down all of the steps needed to the answer this question

c.

Figure 6.1. A conventional (a) and worked example (b) learning task, as well as a transfer-test task (c.).

Instruction. A non-content related instruction on the procedure, rules and regulations concerning solving problems was twice presented to the participants; once preceding the learning-tasks and once preceding the test tasks. The instruction preceding the learning tasks differed slightly for participants in the different conditions. Learners in the individual learning condition had to read all information elements before solving the problem, while learners in the group learning condition only had to read those information elements that were allotted to them (i.e., one third of the total number of elements), but were also required to share the information elements with each other. In the conventional condition, participants had to find out how the solution to the problem was established, while in the worked example condition participants had to study the given solution steps. Because the main hypothesis of this study is focused on WM load, it was important that none of the participants could offload their WM during the learning phase. Therefore they were instructed that they were not allowed to use pen or pencil and paper to write things down. The instruction preceding the test tasks was the same for all participants: First they had to read all information elements thoroughly, then read the questions, and finally try to answer the questions as correctly and quickly as possible using all information elements. In contrast with the instruction preceding the learning tasks, they used pen or pencil and paper to write down the solution steps.

Cognitive-load measurement. To measure the participants' cognitive load after each learning task and test task, the subjective 9-point mental-effort rating scale developed by Paas (1992) was used. Participants were asked to rate how much effort it took them to solve a problem, on a scale ranging from very, very low effort (1) to very, very high effort (9). This cognitive load measure has been used in numerous studies dealing with cognitive load and has proven to be non intrusive, valid and reliable (Paas, Van Merriënboer, & Adam, 1994).

Performance measurement. During the learning phase, the solutions to the problems were provided to the participants. Performance scores, therefore, could only be obtained during the test phase. Successfully carrying out the test tasks meant correctly answering two questions per task related to the heredity characteristics of a certain trait in a family. Every question could be scored on multiple elements, with 1 point for a correctly mentioned element and 0 points for an incorrectly or not mentioned element. A maximal score of 28 points could be earned for the four transfer-test tasks. The minimum score for all tasks was zero. For the statistical analysis, the performance scores were transformed into proportions. In other words, a participant's score on the four transfer-test tasks was divided by the maximum score of transfer-test tasks (i.e., 28).

Efficiency measurement. The combination of performance and cognitive load measures can provide a reliable estimate of the efficiency of instructional methods, both in terms of the learning process and learning outcomes. Paas and van Merriënboer's (1993; see Van Gog & Paas, 2008) computational approach was used to calculate efficiency as a function of instructional format. The basic idea underlying this approach is that instructional conditions that require less learning effort (i.e., for which learners report a lower level of cognitive load) and that lead to the same or higher performance are more efficient than instructional conditions that require more learning effort (i.e., for which learners report a higher level of cognitive load) and that lead to the same or lower performance. Learning efficiency was calculated by standardizing each of the participants' scores for the transfer-test task performance and cognitive load invested while working on the test tasks. For this purpose, the grand mean was subtracted from each score and the result was divided by the overall standard deviation, which yielded z-scores for effort (R) and performance (P). Finally, a performance efficiency score, E, was computed for each participant using the formula: $E = [(P - R)/2^{1/2}]$. High learning efficiency was indicated by a relatively high transfer-test task performance in combination with a relatively low mental effort rating. In contrast, low learning efficiency was indicated by a relatively low learning-task performance in combination with a relatively high mental effort rating.

Time-on-task. During the learning and test phase, time on task was fixed and managed by a proctor. The learning phase had to be finalized in 21 min, giving participants 7 min to study each task. The test phase had to be finalized in 20 min, giving participants 5 min to carry out each task.

Design and procedure

Participants were randomly assigned to conditions, in such a way that 34 participants had to learn individually from conventional learning tasks (i.e., problem-solving tasks), 34 had to learn individually from worked examples, 36 had to learn from conventional learning tasks in 3-person groups (i.e., triads), and 36 had to learn from worked examples in 3-person groups. In the beginning of the learning phase, all participants had to individually study a paper-based general introduction to heredity-related concepts and a worked example and had to return the introduction after 15 min. Participants were then assigned to one of the four experimental conditions to carry out the first series of problem-solving tasks in 7 min. After each task in the series, independent whether the participant was in a group or in an individual condition, all participants had to rate the amount of invested cognitive load on the 9-point mental effort rating scale. The second and third series of learning tasks followed the same procedure. The instruction for all participants preceding the series of learning tasks consisted of advising them to read all information elements thoroughly, read the questions carefully, and finally try to reach the solution to the problem that was provided in the case of the conventional problem condition or understand the solution steps given in the case of the worked example condition using all of the information elements. For learners in the group learning condition, it was also stressed that working together was necessary for solving the problem. Face-to-face communication was very important. However, to keep the load that is ineffective for learning to a minimum, learners were only permitted to communicate about task-related topics. To prevent participants from offloading their WM both those learning individually and those learning in groups were not allowed to use a pen or pencil to write anything down. After this learning phase, the test phase required all participants to work on four transfer tasks for 5 min each. The amount of invested mental effort was measured after each transfer task using the same rating scale used in the learning phase. Use of pen or pencil and paper was allowed and stimulated in this phase.

Results

The results for the learning phase and test phase are described separately. A significance level of .05 was used for all analyses. Due to registration problems there were incomplete data from 4 participants in the learning phase and an additional 5 in the test phase. Case-wise deletion of those participants was used to analyze the data. Table 6.1 shows the resulting number of participants as well as the means and standard deviations for mental effort as a function of learning condition and instructional format in the learning phase, and performance, mental effort, and learning efficiency as a function of learning condition and task complexity in the test phase. Cohen's f is provided as a measure of effect size, with *f*-values of .10, .25, and .40, corresponding to small, medium, and large effects respectively (Cohen, 1988).

Learning phase

The data obtained in the learning phase were analyzed using a 2 (learning condition: individual vs. group) × 2 (instructional format: conventional problem solving vs. worked example studying) between-subjects analysis of variance (ANOVA). With regard to the only dependent variable in this phase (i.e., perceived amount of mental effort invested in studying the learning tasks) ANOVA revealed a main effect for learning condition, $F(1, 132) = 10.36$, $MSE = 14.02$, $p < .01$, $f = 0.28$; group members rated the mean mental effort to be higher than individuals, independent of instructional format. There was no main effect for instructional format, $F(1, 135) < 1$, $MSE = 0.04$, *ns*, nor was there an interaction effect between learning condition and instructional format, $F(1, 135) < 1$, $MSE = 0.60$, *ns*.

Table 6.1. Means and standard deviations of the dependent variables in the learning and test phase as a function of learning condition and instructional format

		Instructional format	Learning condition: Individual		Group	
			M	*SD*	*M*	*SD*
Learning phase[a]	Mental effort (1-9)	Conventional	4.14	1.29	4.91	0.94
		Worked	4.24	1.20	4.75	1.19
Test phase[b]	Performance (0-1)[c]	Conventional	0.57	0.22	0.76	0.13
		Worked	0.69	0.19	0.66	0.23
	Mental effort (1-9)	Conventional	4.90	1.45	4.88	1.29
		Worked	4.59	1.30	4.75	1.56
	Learning efficiency[d]	Conventional	-0.37	1.24	0.26	0.80
		Worked	0.16	1.16	-0.02	1.45

[a] n = 34 for each condition.
[b] n = 32 for all individual conditions, n = 34 for the group - conventional conditions, n = 33 for the group - worked example conditions.
[c] Performance is the proportion of correct answers on the learning or test tasks.
[d] Based on *z*-scores of mental effort and performance in the test phase.

Test phase

The data obtained in the test phase were analyzed using a 2 (learning condition: individual vs. group) × 2 (instructional format: conventional problem solving vs. worked example studying) between-subjects multivariate analyses of variance (MANOVAs). Performance, mental effort and learning efficiency were the dependent variables. The omnibus MANOVA revealed a significant main effect for learning condition, multivariate Wilks' Lambda = .95, $F(2, 126) = 3.38$, $p < .05$, but no significant main effect for instructional format, multivariate Wilks' Lambda = .99, $F(2, 126) < 1$, *ns*. It did, however, yield a significant interaction between learning condition and task complexity, multivariate Wilks' Lambda = .92, $F(2, 126) = 5.36$, $p < .02$. Univariate ANOVAs were conducted on the dependent variables to further examine the significant effects.

Transfer-test performance for each participant was determined by dividing her/his score on the transfer test by the maximum score of that test (i.e., 28), turning individual scores into proportions. The ANOVA for transfer-test performance showed a significant main effect for learning condition, $F(1, 127) = 4.81$, $MSE = 0.19$, $p < .05$, $f = 0.19$, but no main effect for task complexity, $F(1, 127) < 1$, $MSE = 0.001$, *ns*. The main effect was qualified by the significant crossover interaction effect of learning condition and instructional format, $F(1, 127) = 9.47$, $MSE = 0.36$, $p < .02$, $f = 0.27$, reflecting that participants who had learned individually from studying worked examples performed better on the test tasks than participants who had learned from those tasks in a group. The reverse effect was found for participants who had learned from solving conventional problems; participants that had learned in a group performed better on the test tasks than participants who had learned individually (see Figure 6.2).

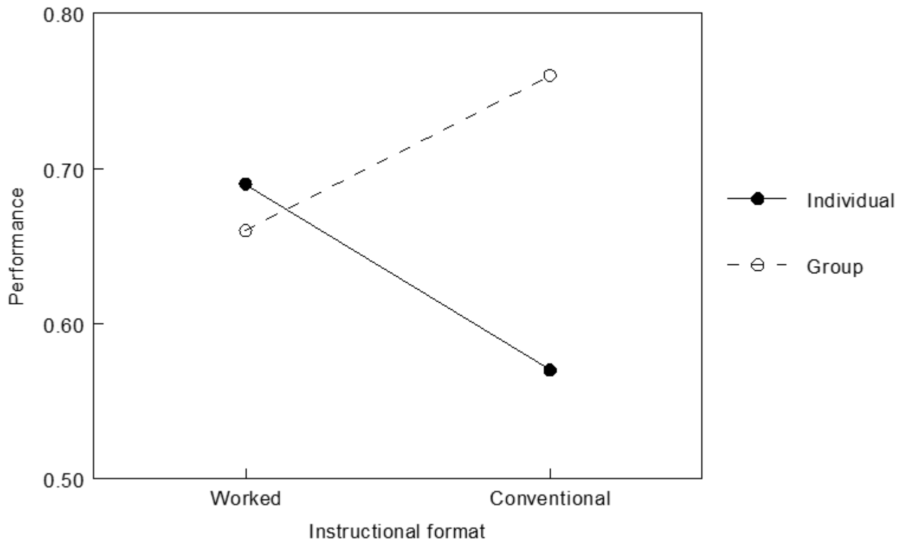


Figure 6.2. Performance scores in the test phase as a function of learning condition and instructional format.

For the perceived amount of mental effort invested in solving test-problems, the ANOVA did not reveal a significant main effect of learning condition or instructional format, $F(1, 127) < 1$, $MSE = 0.13$, *ns*, and $F(1, 127) < 1$, $MSE = 1.57$, *ns*, respectively. Moreover, it did not yield a significant interaction between learning condition and instructional format, $F(1, 127) < 1$, $MSE = 0.29$, *ns*

With regard to the learning efficiency scores, the ANOVA did not reveal a main effect for either learning condition, $F(1, 127) = 1.20$, $MSE = 1.67$, *ns*, or instructional format, $F(1, 127) < 1$, $MSE = 0.52$, *ns*. However, as expected, the main effect was qualified by the crossover interaction between learning condition and instructional format, $F(1, 127) = 3.92$, $MSE = 5.49$, $p = .05$, $f = 0.17$, indicating that when participants had learned from studying worked examples individually they performed the test tasks more efficiently – as indicated by a more favorable relationship between test effort and test performance – than did those who learned within groups. The reverse effect emerged solving conventional problems; those participants who had learned within groups performed the test tasks more efficiently than participants who learned individually (see Figure 6.3).

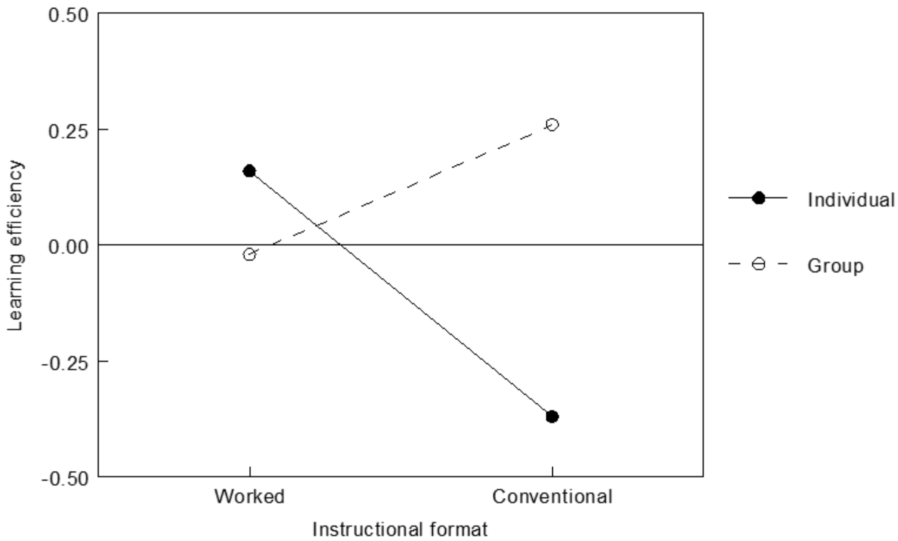


Figure 6.3. Learning efficiency scores in the testphase as a function of learning condition and instructional format.

Discussion

This study was set up to examine the effects of instructional format, learning condition, and combinations of the two on mental effort in the learning phase, and on mental effort, transfer-test performance and learning efficiency in the test phase. The learning phase results revealed that regardless of the instructional format (i.e., studying worked examples and solving conventional problems), those learning in groups invested more mental effort than those learning individually. The test phase results revealed the expected crossover interaction between instructional format and learning condition. The interaction graph (Figure 6.3) reveals that while participants who had learned from solving conventional problems in a group had a more favorable relationship between mental effort and performance (i.e., higher learning efficiency) than those who had learned from solving those problems individually, participants who had learned from studying worked examples had a reverse relationship between learning in a group and learning individually. As there were no differences in the amount of mental effort invested during the transfer test, and a similar crossover interaction was found for transfer-test performance, the interaction between learning condition and instructional format for learning efficiency seems to be primarily caused by the performance scores on the transfer-test.

Learning efficiency was determined by the crossover interaction between having to learn individually or in a group from tasks that impose a high or low total cognitive load upon learners. With regard to solving conventional problems, although the total cognitive load exceeded the limited processing capacity of the individual learner, within groups it could be distributed across group members. Consequently, individual learners had difficulties processing all the information and constructing schemas, as indicated by the lower learning efficiency scores. Group members devoted the freed-up capacity to activities that actually fostered schema construction and learning, as indicated by the higher learning efficiency score. Those results make clear that the costs of inter-individual integration and coordination of information were lower within groups than the benefits of distributing cognitive load across individuals. With regard to studying the equivalent worked examples it can be argued that the decrease in extraneous load left individual learners with enough spare processing capacity to deal with the information successfully, thereby negating the distribution advantage of groups. Although both individual and group learners were able to process the information successfully, only group learners had transaction costs. This disadvantage for group learners resulted in group learners constructing lower quality schemas, as indicated by a lower learning efficiency score.

These results regarding the investment of mental effort in the learning phase indicated that participants in the group condition overall invested higher amounts of mental effort than participants in the individual condition, independent of instructional format. With regard to learning by studying worked examples this was according to our expectation because of the extra effort needed in groups for inter-individual integration and coordination of information. This effect was strengthened because the design of the learning tasks – regardless of instructional format – strived to maximize positive interdependence (Johnson, 1981; P. A. Kirschner et al, 2004; Saavedra, Early, &Van Dyne, 1993) where group members had to rely on each other and interact with each other to obtain resources and to perform the task effectively. This explanation of group members having to invest an additional cognitive effort that is not directly effective for learning was supported by the learning efficiency scores; whereas group members invested higher amounts of mental effort than individual learners, this did not accumulate in the construction of cognitive schemas causing them to learn less efficient than individual learners.

With regard to learning from solving conventional problems we did not have a specific hypotheses regarding the differential effect of learning condition on invested mental effort. However, the results suggest that the freed-up WM capacity of group members, achieved by the distribution advantage, was devoted to activities that foster learning. The results on learning efficiency give some support for this explanation as the higher amount of invested mental effort in the learning phase for group members resulted in a more favorable relationship between mental effort and performance on the individual transfer test. This explanation should be further investigated by, for instance, observing and analyzing the group communication and coordination processes so as to determine what the precise nature of the invested mental effort is.

The crossover interaction that was found in this study for learning individually or collaboratively by solving conventional problems or studying worked examples is identical to the interaction found by F. Kirschner, Paas, and Kirschner (2009c [Chapter 4]) for learning individually or collaboratively by working with low-complexity and high-complexity problems. Although task complexity (low vs. high complexity) is related to intrinsic cognitive load and instructional format (conventional problems vs. worked examples) to extraneous load, the overall or total cognitive load imposed on the learner by the learning tasks, that is, the sum of intrinsic, extraneous and germane cognitive load (Paas et al., 2003), can be identified as the common denominator in these studies. Therefore, it can be argued that the efficiency of individual and group learning is determined by the fact that low-complexity tasks and worked examples impose a lower total cognitive load than high-complexity tasks and conventional problems. The general conclusion that can be drawn from this and the previous studies is that learning from tasks that impose a high cognitive load on the learner are more efficient for groups than for individuals, while the opposite effect is expected for learning from tasks that impose a low cognitive load. An interesting topic for future research would be to investigate at which level of cognitive load it becomes more effective and efficient to learn as a member of a group or individually.

Regarding individual learners, the results of this study replicated the so called worked example effect, indicating that for novices worked examples are a more effective instructional format than conventional problems because they reduce the high extraneous load imposed by solving conventional problems. Interestingly, we found the opposite effect for groups. This crossover interaction between learning condition and instructional format, is similar to the expertise reversal effect identified by Kalyuga, Ayres, Chandler, & Sweller (2003). This effect holds that instructional techniques, such as studying worked examples, that are highly effective with inexperienced learners can lose their effectiveness when used with more experienced learners, or vice versa when it concerns instructional techniques, such as solving conventional problems, which are more effective with experienced learners than with inexperienced learners (e.g., Kalyuga, Chandler, Tuovinen, & Sweller, 2001; Kalyuga et al, 2003). The expertise reversal effect is explained by the fact that experienced learners have higher quality cognitive schemas than inexperienced learners, which are useful when solving, for example, conventional problems, but redundant when, for example, studying worked examples. The current result that collaborating novices learned more from solving conventional problems than from studying worked examples challenges this schema-based explanation and seems more in line with a cognitive capacity explanation. The essential difference between collaborating novice learners and individual novice learners is namely not the quality of schemas, but the available cognitive capacity. It suggests that the advantage of conventional problem solving of more experienced learners found in previous research and of groups of novices in this study was caused by an expanded cognitive capacity. Evidence for this capacity-based explanation was also found by Paas, Camp, and Rikers (2001). They compared young adults to old adults with regard to their learning from solving goal-specific and nongoal-specific problems. Older adults having less available working memory capacity profited disproportionately more from nongoal-specific problem solving than younger individuals who had more working memory capacity. It would be interesting for future research to oppose the schema-based and capacity-based explanation, for instance by comparing low WM capacity to high WM capacity novices. According to the capacity-based explanation it would be expected that high WM novices would learn more from solving conventional problems than from studying worked examples.

The present results and the results of the previous studies of F. Kirschner et al. (2009a [Chapter 3], 2009c [Chapter 4]) indicate that collaborative learning is more effective than individual learning with tasks that impose a relatively high cognitive load upon the learners. As the cognitive load imposed by a learning task is the result of the interaction between learner and task characteristics (see Paas & Van Merriënboer, 1994b), more research is needed into (combinations of) those characteristics, not only from a cognitive perspective, but also from motivational and social perspectives. As an instructional guideline it can be argued that if an institution chooses collaborative learning as an educational model, then the educational designers (most often the teachers) need to guarantee that the learning tasks given to the groups (e.g., problems, projects, et cetera) are cognitively demanding in nature and thus cannot be easily carried out by an individual. This also suggests that practitioners should not make an exclusive choice for individual or collaborative learning, but rather that they vary the approach depending on the complexity of the tasks to be learned.

7
General discussion

Collaborative learning, while touted as an important approach to learning and instruction, often does not meet the expectations of its proponents. Although different educational, social, and economic arguments have been advanced to explain the potential of collaborative learning and justify its use, this dissertation argued that the basic rationale for choosing collaborative learning as an approach to education and learning should be based upon its relative effectiveness and efficiency for achieving learning results in comparison to individual learning. However, the results of studies comparing individual to collaborative learning have not been unequivocal, often only showing positive results of collaboration if extra measures were implemented to either ensure that group members worked together (e.g., requiring a certain number of emails or postings to discussion boards) or ensure that students effectively engaged in the learning process (e.g., defining learner roles, scripting interaction, and so forth). One of the primary causes for the equivocal results could be that the tasks presented to students in collaborative learning settings are *not demanding enough* to necessitate working together. Under such circumstances, working together can be expected to either impede student learning or cause students to choose to not work together. This dissertation identified the challenges a learning task poses to the cognitive capacity of the learner as a possible factor determining whether collaborative learning is more effective and efficient than individual learning. Learning efficiency can be derived from the relationship between task performance and the amount of mental effort learners have to invest to attain the performance; the higher the performance and the lower the effort, the higher the efficiency. Additionally, to be able to make a good comparison between individual and group learning, the studies in this dissertation focused on the learning of each individual group member instead of on the learning of the group as a whole.

The results of the review study (F. Kirschner, Paas, & Kirschner, 2009b [Chapter 2]) suggested that the challenges a learning task poses to the cognitive capacity of the learner, in terms of imposed cognitive load, is an important factor for determining learning efficiency of groups. Studies that compared the performance of collaborating individuals (i.e., group performance) to the performance of a nominal group (i.e., fictitious groups formed by pooling the non-redundant performances of individuals working alone), revealed that collaboration only became more effective when more complex problem-solving tasks (i.e., high cognitive load) were used instead of relatively simple recall tasks (i.e., low cognitive load). When learners were required to work with the information elements relevant for carrying out the task, relate them to each other, and by doing so come up with a solution to a problem, groups performed better than the nominal groups (Andersson & Rönnberg, 1995; Laughlin, Bonner, & Andrew, 2002; Laughlin, Hatch, Silver, Boh, 2006; Laughlin, Zander, Knievel, & Tan, 2003; Ohtsubo, 2005). Under such conditions, participating in a group facilitated the performance of individual group members.

In trying to better understand the impact of how demanding a task is, or the load imposed by a learning task, on the efficiency of collaborative learning environments, cognitive load theory (CLT: P. A. Kirschner, 2002; Paas, Renkl, & Sweller, 2003, 2004: Sweller, Van Merrienboer, & Paas, 1998; Van Merriënboer & Sweller, 2005) was used. This theory is concerned with learning of and from complex cognitive tasks and states that any instructional procedure that ignores the structures that constitute human cognitive architecture is not likely to be effective. Human cognitive architecture consists of an effectively unlimited long-term memory (LTM), which interacts with a working memory (WM) that is very limited in both capacity (Baddeley, 1986; Miller, 1956) and duration (Peterson & Peterson, 1959). The cognitive load that a task imposes on the limited WM of the learner, working in a group or individually, is determined by the intrinsic nature of the task and by the manner in which the information within the task is presented (Sweller et al., 1998). 'Intrinsic' load is imposed by the number of information elements in a task and the degree to which those elements can, or cannot, be understood in isolation (i.e., element interactivity). The manner in which the information is presented to learners can impose either 'extraneous' or 'germane' load. Extraneous load is the load that is imposed on the learner's WM by information and activities that do not directly contribute to learning while germane load is the load imposed on the learner's WM by information and activities that foster learning processes. Intrinsic load, extraneous load, and germane load are additive, and for learning to occur it is important to take into account that the total cognitive load associated with an instructional design – the sum of the three separate loads – should stay within WM limits (P. A. Kirschner, 2002; Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Only then will stable changes of the content and structure of the hierarchically organized schemas in LTM occur; here defined as 'learning'.

With complex or demanding tasks which impose a high or too high cognitive load upon the learner, the limited processing capacity at the individual level is considered a bottleneck for successful learning. Therefore, overcoming individual learners' WM limitations by employing instructional manipulations compatible with human cognitive architecture has been the central focus of CLT. Research has, therefore, mainly been concerned with developing techniques for managing WM load imposed by a learning task in order to facilitate the changes in LTM associated with schema construction and schema automation (i.e., learning). To accomplish this, extraneous load first must be eliminated or at least minimized. Although, freeing up WM capacity by eliminating or minimizing extraneous load has been identified as an effective instructional means to foster learning, its effectiveness can be further improved by managing the intrinsic load in such a way that the simultaneous processing of all interactive information elements leaves the learner with spare cognitive capacity and that learners are encouraged to invest these now available extra processing resources in schema construction and schema automation, evoking germane load.

This dissertation argued that another way of overcoming individual WM-limitations is by making use of the multiple WMs in groups of collaborating learners. When groups of collaborating learners are considered as information-processing systems (see e.g., Hinsz, Tindale, & Vollrath, 1997), the information necessary for carrying out a learning task and its associated cognitive load can, through inter-individual communication and coordination of information, be divided across multiple collaborating WMs. On the one hand, this can result in lowering the risk of overloading each group member's WM because individual WM capacity is freed up, while on the other hand, the group's reservoir of cognitive capacity is expanded. In terms of CLT, this has two consequences. First, this *distribution advantage* causes collaborating individuals to invest less cognitive effort when carrying out the learning task as compared to individuals learning alone. Second, the inter-individual communication and coordination of information require group members to invest additional cognitive effort, an effort that individuals learning alone do not have to exert. These so called *transaction costs* (Ciborra & Olson, 1988; Yamane, 1996) can be effective (i.e., by imposing germane cognitive load), or ineffective (i.e., by imposing extraneous cognitive load) on the learner depending on the situation. For example, if a collaborative task can successfully be solved by an individual alone, the communication and coordination processes will not be necessary for learning or may even interfere with it, imposing extraneous cognitive load. In contrast, when a collaborative task requires more individuals working together for it to be solved successfully, the communication and coordination processes are necessary for learning and facilitate it, imposing germane cognitive load.

The efficiency of group versus individual learning from tasks imposing a high or low cognitive load was expected to be affected by the trade-off between the possibility to divide information processing amongst group members and the associated costs of inter-individual communication and coordination of information. In general, the results of the experiments reported in this dissertation confirmed the main interaction hypothesis. When learning from tasks imposing high cognitive load, group members (i.e., learners learning in a group) learned more efficiently than individual learners (i.e., learners learning alone). In contrast, when learning from tasks imposing low cognitive load, individual learners learned more efficiently than group members. For learning tasks imposing high load, individuals did not have sufficient processing capacity to successfully process the information. For group members, the benefits of distributing the cognitive load among each other proved to be higher than the costs of inter-individual integration and coordination of information. Consequently, they were able to devote the freed up cognitive capacity to activities that fostered schema construction and schema automation (i.e., learning), visible in the higher learning efficiency (i.e., a more favorable relationship between performance and mental effort on an individual transfer test) for group members than for individual learners. For learning tasks imposing low cognitive load, both learners working individually or as a member of a group had sufficient cognitive capacity to process all information by themselves. Hence inter-individual communication and coordination of information were unnecessary and resulted in transaction costs that were higher than the benefits of distributing the cognitive load across group members during the collaborative learning process. Consequently, qualitative differences in constructed schemas materialized in higher learning efficiency for those who learned individually than for those who learned as a member of a group.

The remainder of this general discussion will consist of an overview of the main results of the different studies and a discussion of their theoretical, research, and instructional implications.

Overview of the dissertation

This dissertation consists of a review study and four empirical studies investigating the effectiveness and efficiency of group versus individual learning from learning tasks imposing high and low cognitive loads upon the learners.

Chapter 2 presented a review of research comparing the effectiveness of individual learning environments with collaborative learning environments. It was determined that there is no clear picture of how, when and why the effectiveness of these two approaches to learning differ. The differing complexities of the learning tasks used in the research and the concomitant loads imposed on the learner's cognitive system, and were identified as an important factor contributing to the described inconclusiveness. This was subsequently discussed in the context of neuroscientific research on interhemispheric integration. It was argued that learning by an individual becomes less effective and efficient than learning by a group of individuals as task complexity increases. The hypothesis following from this argument was further investigated in the empirical studies described in the Chapters 3 through 6 of this dissertation.

The study presented in Chapter 3 focused on the learning process and outcome of high-complexity learning tasks. In line with the hypothesis presented, the results revealed that group members had more processing capacity available during learning for relating the information elements needed for carrying out the learning task to each other and by doing so for constructing higher quality cognitive schemata than individuals. In contrast, individuals who learned by carrying out the same complex tasks alone needed all available processing capacity for remembering the interrelated information elements, and, consequently, were not able to allocate the resources needed to relate them to each other. This resulted in a more favorable relationship between retention test performance and mental effort for the individual learners as opposed to a more favorable relationship between transfer test performance and mental effort for the students who learned in groups.

The study reported on in Chapter 4 focused solely on the learning process of learners studying low and high-complexity learning tasks. In line with the stated hypothesis, the results showed a more favorable relationship between mental effort and performance in the learning phase for students who worked in a group than for students who worked individually with high-complexity tasks, but not with low-complexity tasks. In addition, on a transfer test, participants performed better and invested less mental effort and time on topics that were learned in a group than on topics that were learned individually.

The study reported on in Chapter 5 provided a more complete picture by investigating the effects of low-complexity and high-complexity learning tasks on the efficiency of both the individual and group learning process and learning outcome. As expected, with high-complexity tasks, group members learned more efficiently and attained higher learning outcomes than individual learners, while the learning processes and outcomes of learning from low-complexity tasks were more efficient for individual learners than for group members.

In Chapter 6 the cognitive load imposed by the task was varied by manipulating the instructional format. Conventional problem solving was considered to be a more complex task imposing a higher cognitive load than studying worked examples. As expected the crossover interaction found in Chapter 5 was replicated in this study; Learning by solving conventional problems was more efficient for groups than for individuals, whereas learning by studying worked examples was more efficient for individuals than for groups.

Although the results of Chapters 3, 4, 5 and 6 have been explained on the basis of CLT, there may be other ways of explaining the crossover interaction between group and individual learning from tasks imposing a low or high cognitive load upon the learner. The appendix of Chapter 4 showed that, in addition to the cognitive explanation, the results could also be explained by an alternative affective explanation based on perceptions of efficacy.

Theoretical implications

Throughout this dissertation CLT was used as theoretical framework to better understand the circumstances under which the learning of group members would be more effective and efficient than learning of individual learners. Other than the original focus of CLT on individual learning environments, the CLT was extended to collaborative learning environments. This extended focus has some implications for the level of cognitive load a learner experiences when performing a task. Different from learning individually, when learning collaboratively it is not only the task characteristics, learner characteristics and the interaction between both that are important for determining the level of cognitive load, but also the activities related to collectively acquiring, storing, manipulating, and exchanging information.

CLT assumes that individual learning from complex tasks is constrained by the limited processing capacity of the learner's cognitive architecture. Instructional control of the high or too high cognitive load typically imposed on the limited WM capacity of learners has been the central goal of CLT. In the past two decades, cognitive load research has generated a substantial knowledge base on the design of instruction for individual learners. Because efficient instructional design for group-based learning environments can be expected to differ from those of individual learning environments, it was considered important to reconsider the cognitive load perspective to determine the conditions under which group-based learning environments may or may not be efficient and/or effective. The cognitive load imposed by a task is a key factor determining learning efficiency in both individual and collaborative learning environments. However, what may be efficient and/or effective for the individual learner need not necessarily be efficient and/or effective for the group member, and vice versa. Based upon the results presented in this dissertation, it can be concluded that individual learning is best achieved when performing low complexity tasks, while collaborative learning is best when performing high complexity tasks.

In trying to manage individual WM load, instructional techniques should try to find a balance between the different types of cognitive load that can be imposed on the learner by a learning environment; extraneous load must be minimized and intrinsic load must be managed in such a way that spare cognitive capacity is created that can be used for relevant learning processes, evoking germane load. This facilitates the changes in LTM associated with schema construction and schema automation and enables individuals with limited WM capacity to master highly complex cognitive skills. An important theoretical implication of the studies described in this dissertation is the idea that the limited processing capacity of an individual learner can be expanded by learning in collaboration with other learners. From this perspective, collaborative learning can be considered an instructional technique for managing individual WM load. When groups of collaborating learners are considered as information-processing systems (see e.g., Hinsz, Tindale, & Vollrath, 1997), the information necessary for carrying out a learning task and its associated cognitive load can be distributed across multiple collaborating working memories. The freed up cognitive capacity of group members can consequently be devoted to activities that foster schema construction and schema automation (i.e., evoking germane load). This view on groups of collaborating learners has some implications for CLT. Most importantly, it seems that the functional properties of an individual learner's cognitive architecture change by collaborating with other learners. The expanded limited processing capacity can only be used effectively by inter-individual information communication and coordination processes. It is clear that these processes not only lead to cognitive costs, but also to affective costs. Until now, CLT has focused on the alignment of instruction with cognitive processes, without recognizing the role of affective processes. This research on group learning might stimulate cognitive load theorists to address affective issues in their research.

Research implications

The research presented in this dissertation has implications along a number of lines. First, the research has revealed an interesting corollary to the expertise reversal effect which may have very important effects in today's ever increasing population of older, lifelong learners. The expertise reversal effect holds that instructional techniques that are highly effective with inexperienced learners can lose their effectiveness or even be counterproductive when used with more experienced learners, or vice versa (e.g., Kalyuga, Chandler, Tuovinen, & Sweller, 2001; Kalyuga, Ayres, Chandler, & Sweller, 2003). The results of the studies in this dissertation yielded a similar pattern for the relationship between the load imposed by the learning task and collaborative versus individual learning. For learning tasks imposing high cognitive load, collaborative learning is more efficient than learning individually and vice versa when it concerns learning tasks imposing low cognitive load. This corollary to the expertise reversal effect is explained by the fact that experienced learners have higher quality cognitive schemas than do inexperienced learners which are, for example, useful when solving conventional problems but redundant when studying worked examples. The result that collaborating novices learned more from solving conventional problems than from studying worked examples (Chapter 6) challenges this schema-based explanation and seems more in line with a cognitive capacity explanation. The essential difference between collaborating novice learners and individual novice learners is clearly not the quality of schemas, but the available cognitive capacity. The advantage of conventional problem-solving for more experienced learners found in previous research and of groups of novices in the study presented in Chapter 6 is suggestive of a capacity-based explanation. Evidence for this explanation was also found by Paas, Camp, and Rikers (2001) who compared young adults to older adults with regard to learning from solving goal-specific and non goal-specific problems. Older adults having less available WM capacity profited disproportionately more from non goal-specific problem solving than younger individuals who had more WM capacity. It would be interesting for future research to compare the schema-based and capacity-based explanations, for instance by comparing low WM-capacity to high WM-capacity novices. A capacity-based explanation would expect that high-WM novices would learn more from solving conventional problems than from studying worked examples.

Building upon this capacity-based explanation, it can be argued that learning as a member of a group could compensate age-related cognitive declines. One of the central findings of cognitive aging research is that WM capacity in adults declines with age, impairing their ability to engage in complex cognitive tasks for which successful completion is highly dependent on the availability of sufficient cognitive resources. Although learner expertise in terms of more developed or better quality schemas in LTM can compensate for the age-related decline in WM, this is not relevant when the information to be learned is new. Paas et al. (2001) showed that instructional techniques that compensate for reduced capacity can disproportionately enhance older learner's performance. Learning as a member of a group – with the ability to distribute cognitive load and expand available cognitive capacity – can be expected to be an alternative compensatory technique, which would be interesting to investigate in future research.

A second research implication or question deals with the often highly regarded social dimension of collaborative learning. Although specific hypotheses in the research presented in this dissertation were formulated regarding the possible beneficial and/or deleterious effects of inter-individual communication and coordination of information (i.e., transaction costs), those activities were not monitored or analyzed. Consequently, it is not clear: what topics were discussed; whether the discussions were content related or social in nature; whether social talk was part of those discussions and, if so, to what extent; whether learners actually engaged in discussions at all; whether all group members participated in the communication and coordination equally, or whether there were roles or patterns of communication; and so forth. This needs further study. In addition, relating the aforementioned information on the amount and/or type of communication and coordination between group members to their subsequent performance could inform the type of load imposed by these inter-individual activities. Future research should therefore record and analyze the quality and quantity of group processes.

Related to the previous implication, the learning setting used in the studies reported on in this dissertation can be considered to be optimal for collaboration, and as such different from settings encountered in 'regular' education in a number of ways. First, all participants in the research presented here received unique information elements and, consequently, were required to exchange information to solve the problems or carry out the learning tasks in the group learning conditions. Second, the participants were not allowed to offload their WM by using pencil and/or pen and paper while learning, which also stimulated them to collaborate. Finally, the learning setting was highly structured and scripted, which resulted in minimal transaction costs, making collaboration more attractive as compared to situations where the transaction costs are high (e.g., with ill-structured tasks). These specific conditions were created so that the research could focus solely on task complexity and instructional format as factors influencing the efficiency and effectiveness of collaborative learning. It could, therefore, be expected that under conditions of shared information (i.e., where each individual has access to all information elements), where there is a possibility to offload WM by writing things down, and where there are high transaction costs, different results might have been obtained. Future research should investigate the contribution of those aspects to the effects of the load imposed by learning tasks on the effectiveness of learning in a group.

As a result of all of this, it would be interesting for future research to determine whether there is a level of task complexity at which it becomes more efficient to assign tasks to groups rather than to individuals. However, it should be clear that such recommendations cannot be given in absolute terms since task complexity (i.e., intrinsic cognitive load) is relative to the quality and quantity of the schemas in the learner's long term memory (i.e., expertise; Paas et al., 2003). Therefore, comparable to the expertise-reversal effect (Kalyuga et al., 2003), it can be expected that the task-complexity threshold at which group learning becomes more efficient than individual learning will vary as a function of learner expertise. An interesting hypothesis for future research would be that for group learning to become efficient, task complexity needs to be higher for more advanced learners and/or experts than for novices.

As became apparent in the appendix to Chapter 4, the research presented in this dissertation has shown that though the cognitive load imposed by a learning task on a learner or group of learners is an important factor in determining the relative efficiency of individual and group learning, the efficiency of the approach chosen depends on a complex pattern of interactions between cognitive, motivational, and social factors. Ultimately, an integrative perspective is needed to study the complex interactions between these factors, but only after the contributions of each of these factors to the learning processes and outcomes of group-based learning have been disentangled. This can only be realized by studying the different factors within tightly constrained experimental environments, one at a time, keeping all other aspects constant.

A final, very important issue for future research is related to the measurement of cognitive load at the group level. The results obtained in the research presented in this dissertation showed that the load experienced by group members may differ from the load experienced by individual learners for the same task. Whereas the measurement of individual cognitive load is quite common in CLT-based research, it is not clear whether the same methodology used for determining cognitive load in individuals can be reliably used for determining group cognitive load. More research is needed to determine how cognitive load could be measured at the group and group member levels.

Instructional implications

With regard to possible implications of this research for educational practice this dissertation makes clear that wholesale adoption of collaborative learning would not be sensible. The results of the different studies suggest that the challenges a learning task poses to the cognitive capacity of the learner or the amount of cognitive load a task imposes, should be a determining factor when deciding whether to employ a learning model or environment which is based upon an individual or a collaborative learning paradigm. The higher the load imposed by the learning tasks, the more likely it is that collaborative learning will lead to better learning outcomes than individual learning, either in terms of effectiveness, efficiency, or both. This means that if an institution chooses collaborative learning as educational approach, then educational designers – which are most often the teachers themselves – need to be sure that the learning tasks that are given to the groups (e.g., problems, projects, et cetera) are complex enough in nature that they cannot be easily carried out by an individual. This also suggests that it would be better for practitioners not to make an exclusive choice for individual or collaborative learning, but rather that they vary the approach depending on the complexity of the learning tasks to be carried out.

A second instructional implication based upon the results presented in this dissertation is that because task complexity and the concomitant memory and processing demands decrease as learners develop expertise with respect to a task or because these demands are higher for older adults than for younger adults or adolescents, practitioners should also consider these learner characteristics when deciding on whether to adopt an individual or a collaborative learning approach. As a possible first step, it is imperative to determine whether a learning task can be carried out successfully by an individual. If this is the case, then group learning should not be used unless the educational goals are oriented at developing social and/or collaboration skills. If an individual learner is not able to deal with the learning task because of the limitations in WM capacity, group learning would be an appropriate learning approach to use. In an educational context for training complex cognitive tasks, such an approach could be operationalized, among others, by using a fixed level of complexity of learning tasks and gradually moving from group learning towards individual learning in the learning program or only using group learning and adding increasing germane cognitive load to the learning environment.

Conclusion

This dissertation has shown that learning in a group can be more efficient and/or effective than learning individually if the learning tasks are too cognitively demanding for individual learners. In this case, group members profit from the expanded processing capacity of the group. If the learning tasks are not too demanding for individual learners to carry out alone, then learning in a group is less efficient and/or effective because distributing the cognitive load among group members is not necessary, which makes the associated costs of inter-individual coordination and communication of information ineffective for learning. From this CLT perspective, group learning can be used to control the high cognitive load typically associated with the learning by carrying out complex cognitive tasks.

Although the cognitive-load perspective used in this dissertation appears to provide an interesting and a fruitful supplement to the prevailing social and motivational perspectives that lie at the basis of collaborative learning, it should be noted that ultimately, the complex interactions between cognitive, social and affective factors need to be investigated in relation to each other. For now, the cognitive-load perspective presented in this dissertation can broaden the horizon of researchers investigating collaborative learning and can contribute both to the identification of those cognitive, non-surface level variables affecting collaborative learning and to the instructional design of effective and efficient collaborative learning environments.

The studies in this dissertation have shown that the degree to which learning tasks make demands on the cognitive capacities of learners is a key factor in determining learning efficiency and effectiveness in individual and collaborative learning environments and that this, in turn, has strong implications for the design of such environments. However, the results need further experimental confirmation with different tasks (e.g., ill-structured tasks), different learners (e.g., varying levels of expertise or age), and different environments (e.g., more ecologically valid collaborative learning environments) to be able to provide more specific guidelines for designing collaborative learning environments.

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Summary

Collaborative learning environments are seen by many as a very promising learning approach in education. Although different educational, social, and economic arguments have been advanced to both explain the potential of collaborative learning and justify its use, the basic rationale for choosing collaborative learning as an approach to education and learning should be its relative effectiveness and efficiency for learning in comparison with individual learning. In this dissertation, a theoretical framework based upon cognitive load theory (CLT) was used to, on the one hand, re-interpret empirical results of past research on collaborative learning and, on the other hand, to re-study group learning so as to identify the load imposed by a task as an important factor determining the effectiveness and efficiency of collaborative learning as compared to individual learning. From a CLT perspective, groups of collaborative learners were considered to be information-processing systems in which the information necessary for carrying out the learning task and the cognitive load associated with both the learning task and the learning processes involved in carrying out the task can be divided across the multiple collaborating working memories (WM) of the group members through inter-individual communication and coordination. Although multiple collaborating WMs can be argued to provide more processing capacity than the limited WM of the individual, whether this capacity can be used to the advantage of the group members depends upon the amount of cognitive load that the task imposes on the individual learner. Only when the cognitive load imposed by the learning task exceeds the limited WM capacity of the individual learners, will collaborative learning be more effective and efficient than individual learning. Learning efficiency was derived from the relationship between task performance and the amount of mental effort learners have to invest to attain the performance; the higher the performance and the lower the effort, the higher the efficiency. Additionally, to be able to make an honest comparison between individual and group learning, the studies in this dissertation focused on the learning of each individual group member instead of on the learning of the group as a whole.

A review of research comparing the effectiveness of individual learning environments with collaborative learning environments (Chapter 2) concluded that there is no clear and unequivocal picture of how, when and why the effectiveness of these two educational approaches differ. This inconclusiveness and the associated problem of identifying the factors that determine the effectiveness and efficiency of collaborative learning was attributed to four characteristics of the way research in this field has typically been designed and conducted. It was argued that by applying CLT, collaborative learning research could provide a better understanding of effective instructional procedures for individual and group learning. Subsequently, the different complexities of learning tasks and the concomitant different cognitive loads imposed on the learner's cognitive system, were discussed in the context of neuroscientific research on interhemispheric integration. Based upon this research and CLT, it was hypothesized that learning in a group would become more effective and efficient than learning alone as the task complexity increases. Dividing the processing of information amongst individuals is useful when the cognitive

load is high (i.e., when carrying out high complexity learning tasks) because it allows information to be divided across a larger reservoir of cognitive capacity. Although such division requires that information be recombined and that processing be coordinated, under high-load conditions these cognitive costs are minimal compared to the gain that is achieved by this division of labor. In contrast, under low-load conditions (i.e., when carrying out low complexity learning tasks), an individual can adequately carry out the required processing activities alone, and the costs of recombination and coordination are relatively more substantial. The implications of this interaction hypothesis for the effectiveness and efficiency of collaborative learning as compared to individual learning, were also discussed in Chapter 2 and tested in the four empirical studies described in Chapters 3, 4, 5, and 6.

Applying CLT, the limited working memory capacity at the individual level was considered an important reason to assign complex learning tasks to groups rather than to individuals. Chapter 3 presents a study in which the effects of individual versus group learning on the efficiency of retention-test and transfer-test performance were investigated among Dutch high-school students. It was hypothesized that if the high cognitive load imposed by complex learning tasks could be shared among group members, the learners would have more processing capacity available for constructing high quality cognitive schemas than would individuals. In contrast, it was expected that individuals who learn from carrying out the same complex tasks alone would need all of their available processing capacity for remembering the interrelated information elements, and, consequently, would not be able to allocate resources necessary for working with them. Students, individually or as a member of a 3-person group, had to work on complex problem solving tasks in a domain of biology that is concerned with heredity. After carrying out these learning tasks, the groups were dissolved and all students had to work on retention-test and transfer-test tasks individually. The interaction hypothesis was confirmed by the efficiency data on a retention and transfer test; there was a more favorable relationship between mental effort and performance on the retention test for the students who learned individually as compared to those who learned in a group, as opposed to a more favorable relationship between performance and mental effort on the transfer test for the students who learned in groups as compared to those who learned individually.

The study reported in Chapter 4 investigated the efficiency of individual versus group learning from low and high complexity tasks among Dutch high school students. Based upon CLT, it was hypothesized that learning processes and outcomes of individuals working in groups would become more efficient than those of individuals working alone as the task complexity increases. Although, both individuals and groups would have no problem coping with the load imposed by low-complexity tasks, only groups would be able to deal with the high cognitive load imposed by high-complexity tasks by dividing it across their larger reservoir of cognitive capacity. In a within-subjects design, students had to work both individually and as a member of a 3-person group on low-complexity and high-complexity problem solving tasks in a domain of mathematics concerned with surface area calculation. After carrying out these learning tasks, the groups were dissolved and all students had to carry out a transfer test individually. The results obtained in this study confirmed the hypothesis, indicating a more favorable relationship between effort and performance (i.e., higher learning efficiency) for groups in the learning phase on high-complexity tasks, but not on low-complexity tasks. In addition, on the transfer test participants performed better and invested less mental effort (i.e., higher test efficiency) and time on the topics that were learned in a group than on topics that were learned individually. In an appendix to Chapter 4, an alternative affective explanation for the results was investigated by analyzing the learners' expectations about the amount mental effort they would have to invest. According to this affective explanation which was inspired by research on group-efficacy, it was hypothesized that participants learning together in a group would have more confidence in their ability to solve a problem together and that there would, thus, be a greater willingness (i.e., motivation) by them to carry out the task than in individuals working alone. By measuring the amount of mental effort participants expected to invest to perform a task successfully before the task had to be carried out, the hypothesis was confirmed; Group members who had to solve a complex problem expected to invest less mental effort than individual learners. When confronted with low complexity tasks, the expectation did not differ between group members and individual learners.

Chapter 5 presents an investigation into the differential effects of the complexity of learning tasks on both learning process and outcome efficiency of Dutch high-school students working individually or in a group. Whereas the studies reported on in the previous chapters either focused solely on the learning process and outcome of high-complexity learning tasks (Chapter 3) or solely on the learning process while studying low-complexity and high-complexity learning tasks (Chapter 4), the study discussed in this chapter was designed to provide a more complete picture by investigating the effects of low-complexity and high-complexity learning tasks on the efficiency of both the individual and group learning process and the learning outcome. It was expected that for high-complexity tasks, group members would learn in a more efficient way than individual learners, while for low-complexity tasks, individual learning would be more efficient. Students, individually or as a member of a 3-person group, had to work on low-complexity or high-complexity problem solving tasks in a domain of biology concerned with heredity. After carrying out these learning tasks, the groups were dissolved and all students had to carry out a transfer test individually. The hypothesis was confirmed by the crossover interaction that was found, supporting the premise that the learning efficiency of group members and individuals is determined by a trade-off between the possibility to distribute information processing among team members and the associated costs of information communication and action coordination.

In the study presented in Chapter 6, the cognitive load imposed by the task was varied by manipulating the instructional format. The study investigated the efficiency of individual versus group learning from either studying worked examples or by solving conventional problems by Dutch high school students. Based upon a large body of research, conventional problem solving was considered to be a more complex task imposing a higher cognitive load than studying worked examples. Students, either individually or as a member of a 3-person group, had to study worked examples or solve conventional problems in a domain of biology concerned with heredity. After carrying out these learning tasks, the groups were dissolved and all students had to perform on a transfer test individually. As expected, the crossover interaction found in Chapter 5 was replicated in this study; Learning by solving conventional problems was more efficient for groups than for individuals, whereas, learning by studying worked examples was more efficient for individuals than for groups.

Chapter 7 presents a general discussion of the theoretical, the research and the instructional implications of the results obtained in the studies presented in this dissertation.

Samenvatting

Samenwerkend leren wordt tegenwoordig gezien als een veelbelovende onderwijsmethode. In de literatuur worden verschillende educatieve, sociale en economische argumenten gegeven om de kracht van samenwerkend leren te verklaren alsmede het gebruik ervan te rechtvaardigen. In dit proefschrift wordt gesteld dat de keuze voor samenwerkend leren als onderwijsmethode gebaseerd zou moeten zijn op een verhoging van de relatieve effectiviteit en efficiëntie van leren in een groep in vergelijking met onderwijsmethoden waarbij men individueel leert. Het theoretische raamwerk van *cognitieve belasting theorie* (CBT) wordt gebruikt om enerzijds de empirische resultaten van eerder uitgevoerd onderzoek naar samenwerkend leren te herinterpreteren, en anderzijds de effecten van samenwerkend leren opnieuw te bestuderen. De door een leertaak veroorzaakte cognitieve belasting wordt hierbij geïdentificeerd als bepalende factor voor de effectiviteit en efficiëntie van samenwerkend leren in vergelijking met individueel leren. Vanuit het perspectief van CBT, kunnen groepen waarin men gezamenlijk werkt aan een leertaak beschouwd worden als informatieverwerkingssystemen. In deze systemen kan het informatieverwerkingsproces dat nodig is om de leertaak succesvol uit te voeren, en de daarmee geassocieerde cognitieve belasting, gedistribueerd worden over de werkgeheugens (WGs) van de verschillende groepsleden. Dit *distributievoordeel* gaat echter gepaard met additionele cognitieve belasting veroorzaakt door de communicatie en coördinatie van zowel de informatie-uitwisseling als de werkuitvoering binnen de groep; de zogenoemde *transactiekosten*. Hoewel gesteld kan worden dat de informatieverwerkingscapaciteit van meerdere samenwerkende WGs groter is dan het gelimiteerde WG van een individuele lerende, hangt het van de hoeveelheid cognitieve belasting die een leertaak oplegt af of deze toegenomen capaciteit in het voordeel van de groepsleden zal werken. Slechts als de cognitieve belasting die de leertaak oplegt de gelimiteerde cognitieve capaciteit van het individuele WG overschrijdt, zal samenwerkend leren effectiever en efficiënter zijn dan alleen leren. Efficiëntie van leren wordt bepaald door de relatie tussen de behaalde (test)prestatie en de hoeveelheid geïnvesteerde mentale inspanning die nodig was om deze prestatie te bereiken; hoe hoger de prestaties en hoe lager de inspanning, hoe hoger de leerefficiëntie. Om een eerlijke vergelijking te kunnen maken tussen individueel en samenwerkend leren waren de studies in dit proefschrift gericht op de leerresultaten van elk afzonderlijk groepslid in plaats van op de leerresultaten van de groep als geheel.

Een nadere beschouwing van wetenschappelijk onderzoek waarin de effectiviteit van individuele en samenwerkende leeromgevingen vergeleken werd (Hoofdstuk 2) liet zien dat er geen duidelijk beeld bestaat van hoe, wanneer, en waarom de effectiviteit van deze twee onderwijsbenaderingen van elkaar verschilt. Hoofdstuk 2 beschrijft een aantal kenmerken van van eerder onderzoek die een mogelijke verklaring vormen voor de niet eenduidige resultaten. Het toepassen van CBT bij het onderzoek naar de effectiviteit en efficientie van de twee benaderingen wordt als mogelijke oplossing gezien, waarmee beter inzicht verkregen zou kunnen worden in de factoren die de efficiëntie en effectiviteit van leren bepalen. Vervolgens wordt het verschil in complexiteitsniveau van leertaken en het daarmee samenhangende verschil in cognitieve belasting besproken in de context van neurowetenschappelijk onderzoek naar interhemispherische integratie. Op basis hiervan, wordt verondersteld dat leren in een groep effectiever en efficiënter wordt dan individueel leren naarmate de complexiteit van de leertaak hoger is (i.e., een leertaak met veel informatie elementen met veel interactie tussen die elementen). Wanneer de cognitieve belasting van een leertaak zo hoog is (i.e., bij het uitvoeren van leertaken met een hoge complexiteit) dat een individu niet voldoende cognitieve capaciteit heeft om deze succesvol uit te voeren, zou het verdelen van de belasting over een groter reservoir van cognitieve capaciteit voordelig zijn. Hoewel een dergelijke verdeling vereist dat informatie met elkaar wordt gedeeld en dat het verwerken van die informatie wordt gecoördineerd, zijn de cognitieve kosten die hieraan verbonden zijn minimaal vergeleken met de winst die wordt bereikt door de verdeling van arbeid. Daarentegen, wanneer de cognitieve belasting van een taak zo laag is (i.e., bij het uitvoeren van lage complexiteit leertaken) dat een individu, of elk groepslid afzonderlijk, de vereiste cognitieve capaciteit heeft om deze succesvol uit te voeren, dan zou samenwerken geen voordeel opleveren. Samenwerken zou zelfs nadelig kunnen werken omdat de cognitieve kosten voor het delen en coördineren van de informatie relatief hoger zouden zijn. De implicaties van deze interactiehypothese voor de effectiviteit en efficiëntie van samenwerkend leren in vergelijking met individueel leren worden besproken in Hoofdstuk 2 en onderzocht in de vier empirische studies beschreven in Hoofdstukken 3, 4, 5 en 6.

Vanuit een CBT perspectief wordt het beperkte WG op individueel niveau beschouwd als belangrijke reden om leertaken van hoge complexiteit aan groepen te geven in plaats van aan individuen. In Hoofdstuk 3 wordt een studie beschreven waarin de effecten van individueel versus samenwerkend leren op (de efficiëntie van) de bereikte prestaties van middelbare scholieren op een retentie en transfer test werden onderzocht. Verondersteld werd dat indien de hoge cognitieve belasting die gepaard gaat met het uitvoeren van een complexe leertaak verdeeld kan worden over leden van een groep, er meer verwerkingscapaciteit beschikbaar is om cognitieve schema's van hoge kwaliteit te construeren. Daarentegen werd verwacht dat lerenden die een dergelijke complexe leertaak individueel zouden moeten uitvoeren, al hun beschikbare cognitieve verwerkingscapaciteit zouden moeten inzetten om de informatie elementen te *onthouden*, en daardoor onvoldoende capaciteit zouden overhouden om de informatie elementen aan elkaar te relateren. Het aan elkaar *relateren* van informatie elementen is noodzakelijk om de cognitieve schema's die nodig zijn om transfer problemen op te lossen, te construeren. De scholieren moesten, individueel of als lid van een groep (i.e., van drie personen), werken aan complexe biologieproblemen op het gebied van de erfelijkheidsleer. Vervolgens werden de groepen ontbonden en moesten alle scholieren retentie- en transferproblemen individueel oplossen. De interactiehypothese werd bevestigd voor zowel retentie als transfer. Op de retentie test was er sprake van een gunstigere verhouding tussen mentale inspanning en prestatie voor scholieren die alleen hadden geleerd dan voor scholieren die in een groep hadden geleerd. Daarentegen was er voor de transfer test sprake van een gunstigere verhouding tussen prestatie en mentale inspanning voor scholieren die in een groep hadden geleerd dan voor scholieren die alleen hadden geleerd.

De studie beschreven in Hoofdstuk 4 onderzocht de efficiëntie van individueel versus samenwerkend leren van lage en hoge complexiteit taken onder scholieren op een middelbare school. Op basis van CBT werd verondersteld dat de leerprocessen en -resultaten van scholieren die samen moesten werken efficiënter zouden zijn dan die van scholieren die alleen moesten werken bij leertaken van hoge complexiteit. Zowel scholieren die individueel moesten leren als scholieren die samen moesten leren zouden geen problemen ondervinden van de cognitieve belasting veroorzaakt door taken van lage complexiteit. Echter, alleen scholieren die samen leren zouden de hoge cognitieve belasting veroorzaakt door taken met hoge complexiteit aankunnen, omdat de cognitieve belasting verdeeld zou kunnen worden over het grotere reservoir aan cognitieve capaciteit van de groep. In deze studie moesten scholieren zowel alleen als in een groep van drie (zgn. within subjects design) werken aan hoge en lage complexiteit leertaken in het domein wiskunde (meetkunde). Hierna werden de groepen ontbonden en moest iedere scholier transferproblemen individueel oplossen. De verkregen resultaten tonen aan dat in de leerfase de groepen een meer gunstige verhouding hadden tussen mentale inspanning en prestatie (i.e., hogere leerefficiëntie) bij leertaken van hoge complexiteit, maar niet bij leertaken van lage complexiteit. Met deze resultaten werd de hypothese bevestigd. Daarnaast presteerden scholieren beter en investeerden zij minder mentale inspanning (i.e., hogere testefficiëntie) en tijd in de transfertest op onderwerpen die in samenwerking werden geleerd dan op onderwerpen die individueel werden geleerd. In een bijlage op Hoofdstuk 4, werd een alternatieve affectieve verklaring voor de resultaten onderzocht door de hoeveelheid mentale inspanning die scholieren verwachtten te moeten investeren, te analyseren. Aan de hand van deze affectieve verklaring, die was geïnspireerd door onderzoek naar groep- and self efficacy (i.e., het vertrouwen van een groep of een individu in het vermogen om adequaat en efficiënt te handelen in een gegeven situatie), werd verondersteld dat scholieren die samenwerkend leren meer vertrouwen zouden hebben in hun vermogen om een leertaak uit te voeren dan scholieren die individueel leren. Door de hoeveelheid mentale inspanning die scholieren verwachtten te investeren om een leertaak succesvol uit te voeren voorafgaand aan het daadwerkelijk uitvoeren van de taak te meten, werd de hypothese bevestigd; groepsleden verwachtten dat zij minder mentale inspanning zouden moeten investeren dan individueel lerenden wanneer zij geconfronteerd werden met complexe leertaken . Echter, wanneer de scholieren geconfronteerd werden met leertaken van een lage complexiteit verschilde deze verwachting niet tussen groepsleden en individuele lerenden.

Hoofdstuk 5 presenteert een onderzoek naar de differentiële effecten van de complexiteit van een leertaak op zowel de efficiëntie van het leerproces als de leeruitkomsten onder middelbare scholieren die individueel dan wel samenwerkend leerden. Daar de studie gerapporteerd in Hoofdstuk 3 uitsluitend was gericht op *hoge complexiteit taken*, en de studie in Hoofdstuk 4 uitsluitend op het *leerproces*, werd deze studie ontworpen om een meer volledig beeld te geven van het effect van leertaken met *lage en hoge complexiteit* op de efficiëntie van zowel het individueel als samenwerkend *leerproces en leerprestaties*. Verwacht werd dat voor taken van hoge complexiteit, groepsleden efficiënter zouden leren dan individueel lerenden, terwijl voor taken van lage complexiteit individueel lerenden efficiënter zouden leren. Scholieren moesten, individueel of als lid van een groep bestaande uit drie scholieren werken aan leertaken van hoge en lage complexiteit in een domein van biologie dat zich bezig houdt met het overerven van eigenschappen; de erfelijkheidsleer. Hierna werden de groepen ontbonden en moesten alle scholieren transferproblemen alleen oplossen. De hypothese werd bevestigd en ondersteunde de premisse dat de efficiëntie van leren voor zowel groepsleden als individueel lerenden bepaald werd door de wisselwerking tussen de mogelijkheid om het cognitieve informatieverwerkingsproces onder groepsleden te verdelen (i.e., distributievoordeel) en de daaraan verbonden cognitieve kosten veroorzaakt door de communicatie en coördinatie van de informatie-uitwisseling binnen de groep (i.e., transactiekosten).

In het onderzoek dat gepresenteerd wordt in Hoofdstuk 6 werd de cognitieve belasting veroorzaakt door een leertaak gevarieerd door manipulatie van de wijze van aanbieding. Bij middelbare scholieren werd het effect van het bestuderen van uitgewerkte voorbeelden versus het oplossen van conventionele problemen op de efficiëntie van individueel leren versus samenwerkend leren onderzocht. Gebaseerd op een grote hoeveelheid studies, werd het oplossen van conventionele problemen beschouwd als een complexe leertaak die een hogere cognitieve belasting veroorzaakt dan het bestuderen van uitgewerkte voorbeelden. Scholieren moesten individueel of als lid van een groep uitgewerkte voorbeelden bestuderen of conventionele problemen oplossen in een domein van biologie dat zich bezig houdt met het overerven van eigenschappen; de erfelijkheidsleer. Hierna werden de groepen ontbonden en moesten alle scholieren transferproblemen individueel oplossen. Zoals verwacht werd de in Hoofdstuk 5 gevonden interactie gerepliceerd; leren door het oplossen van conventionele problemen (i.e., hoge complexiteit taken) was efficiënter voor groepsleden dan voor individueel lerenden, terwijl leren door het bestuderen van uitgewerkte voorbeelden (i.e., lage complexiteit taken) efficiënter was voor individueel lerenden dan voor groepsleden.

Tot slot geeft Hoofdstuk 7 een algemene bespreking van de theoretische, onderzoeksmatige en instructie-ontwerp implicaties van de verschillende studies en resultaten in dit proefschrift.

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