Implications of Team Expertise and Domain Knowledge on Collaborative Learning:

A Cognitive Load Approach

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1. General Introduction

In today's society there seems to be a globally widespread notion that students must learn via collaboration (Graesser et al., 2018; Hesse, Care, Buder, Sassenberg, & Griffin, 2015; OECD, 2017; Partnership for 21st Century Learning, 2019). However, not all scientific evidence supports the assumption that collaborative learning is beneficial for student learning and, at best, the results of research on collaborative learning are inconsistent (Kester & Paas, 2005; F. Kirschner, Paas, & Kirschner, 2009a; P. A. Kirschner, Sweller, Kirschner, & Zambrano R., 2018; Kreijns, Kirschner, & Jochems, 2003; Retnowati, Ayres, & Sweller, 2016; Slavin, 2014). These inconsistent results have led to the conclusion that grouping students together to learn does not mean that they will work properly as a group and that they will take advantage of their interactions to learn effectively or efficiently. Inconclusive results have motivated researchers to investigate what factors should be taken into account to design and promote productive collaborative learning environments from different perspectives (Hmelo-Silver & Chinn, 2015). A crucial aspect that may contribute to understanding why and when collaboration is favorable or detrimental for learning is taking into account the features of human cognitive architecture (Sweller, 2012; Sweller, Van Merriënboer, & Paas, 1998). It involves taking into account the multiple factors that affect the cognitive load associated with group information processing (i.e., transactional activities) and schema acquisition (F. Kirschner et al., 2009a; F. Kirschner, Paas, & Kirschner, 2011; P. A. Kirschner et al., 2018).

Research Questions

The goal of the research contained in this thesis was to explore the consequences of decreasing the cognitive load associated with group interactions in order to improve collaborative learning in carrying out highly complex learning tasks. In this research, collaborative learning groups are considered as information processing systems (Hinsz, Tindale, & Vollrath, 1997; Tindale & Sheffey, 2002) that can simultaneously process more information elements due to the combination of the working memories of its members (i.e., collective working memory; F. Kirschner, et al, 2011) and its transactional activities (i.e., communication and coordination processes). Inter-individual information processing can be affected by the interaction of several variables related to individual learners (e.g., prior knowledge with respect to the task), groups as a whole (e.g., group-member experience in similar tasks or distribution of information among members), or learning tasks (e.g., level of element interactivity). Investigating these variables in controlled learning situations may help to understand how to enhance group information processing and its cognitive load. By optimizing inter-individual processing during collaborative learning, group members may invest more resources from their working memories to acquire better task schemas in long-term memory.

The primary research question of this thesis was:

> How do experienced groups differ from non-experienced groups in terms of performance, mental effort, and efficiency in the learning process and outcomes?

Based on this question, the goal was to determine if group experience allows peers to appropriately use their transactional activities to learn better, invest lower cognitive load, and be more efficient than members of groups without this collaborative experience (i.e., non-experienced groups). It was assumed that a way to optimize transactional activities and their related cognitive load is to provide groups with collaborative experience based on relatively similar tasks (i.e., task-based experienced groups) before learning new problems. Prior collaborative experience in relevant tasks (i.e., similar, analog or transferable) may be a type of generalizable structure of shared knowledge that guides inter-individual processing activities (i.e., learning process) of domain-specific problems, optimizes intra-group working memory load, and promotes the construction of better long-term memory schemes.

Underlying the primary research question were four specific goals/questions. One specific goal/question was to examine the types of transactional activities that experienced and non-experienced groups carry out during learning and that may be associated with performance and cognitive load. Because the cognitive load of transactional activities may depend on how group members work with the interactive information elements of the learning task, a second specific goal/question was to examine how the distribution of information among group members (i.e., high-density information vs. low-density information) affect group and individual learning of experienced and non-experienced groups. A third specific goal/question was to determine how prior knowledge of the task (i.e., novice versus advanced learners) impacts the group learning process and learning outcomes at the individual level. The final specific research goal/question was to determine how prior knowledge of the task (i.e., novice versus advanced learners) impacts the experienced and non-experienced group learning process and learning outcomes at an individual level.

Overview of the Dissertation

Chapter 2 explore the state of the art of cognitive load theory regarding collaborative learning. Specifically, the principles of human cognitive architecture, knowledge acquired through this cognitive architecture, and the types of cognitive load involved in acquiring new knowledge are discussed. It is suggested that the essential theoretical assumptions of cognitive load theory, although they have been built mostly through individual learning research and for domain-specific problems, may apply to understand when and why collaborative learning may be an effective and efficient instructional method. One way to improve this understanding is to examine the cognitive load factors related to intra-group processing of complex tasks. It is suggested that mutual cognitive interdependence may be a principle that explains the evolution of human cognitive architecture (P. A. Kirschner et al., 2018; Zambrano R., Kirschner, & Kirschner, 2020). However, it does not follow, from an instructional perspective, that collaborating to acquire domain-specific knowledge will always be appropriate because carrying out learning tasks in groups may impose an unnecessary cognitive load associated with the transactional activities in addition to the 'normal' load of the task (Paas & Sweller, 2012). For this reason, it is proposed to consider the role of generalized domain knowledge (Kalyuga, 2013; Kalyuga & Hanham, 2011) with respect to group work and prior task knowledge to optimize the working memory cognitive load associated with intra-group processing to acquire better schemas in long-term memory. The chapter concludes by suggesting research hypotheses derived from this discussion concerning information distribution, team size, group familiarity, group experience, task-group experience, and task expertise.

Chapter 3 examines whether prior collaborative experience based on having carried out similar tasks increases performance, decreases cognitive load and, therefore, increases efficiency in the learning, short-term retention, and delayed retention phases (Zambrano R., Kirschner, & Kirschner, 2018). It was found that having task-based group experience improves the learning outcomes. That is, members of the groups that had taken part in a preparation session designed to provide them with experience in collaborating to carrying out relatively similar tasks performed better, experienced less mental effort, and were more efficient than non-experienced groups on the retention and delayed tests. In addition, this study examined the differences between experienced and non-experienced groups concerning socio-cognitive, socio-regulatory, and socio-emotional and task unrelated transactional activities. Based on similar investigations (e.g., Näykki, Isohätälä, Järvelä, Pöysä-Tarhonen, & Häkkinen, 2017), analyses of verbal interactions were conducted with five experienced and five non-experienced groups. The results showed that experienced groups spent more time solving the learning task problems, had more socio-cognitive interactions and fewer socio-regulatory as well as fewer task unrelated interactions. The number of socio-emotional interactions did not differ between the conditions. These results suggest that collaborative work schemas acquired in the preparation phase may guide collaborative learning and optimize the working memory cognitive load devoted by group members to inter-individual information processing of learning tasks.

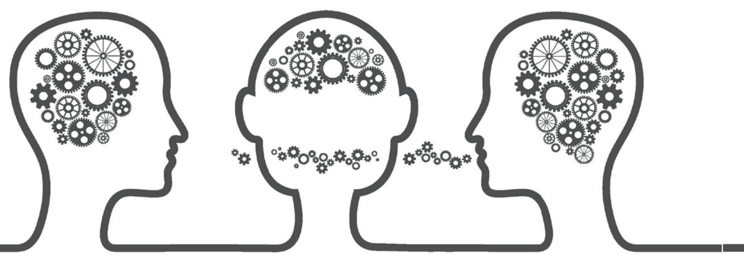
Chapter 4 examines whether the distribution of information across learners affects the effectiveness and efficiency of groups with and without collaborative experience. Previous research has shown that the way information is distributed among individuals affects performance (Brodbeck, Kerschreiter, Mojzisch, & Schulz-Hardt, 2007; Deiglmayr & Spada, 2010), but it has not been investigated whether this occurs when groups learn when carrying out complex learning tasks. Based on the essential concept of element interactivity (Paas, Renkl, & Sweller, 2004; Sweller, 2010), it was assumed transactional activities are a type of group-based information element that imposes cognitive load, and that this may result in different levels of information density. Results suggest that experienced groups optimized their working memory resources and were more efficient in executing complex learning tasks (i.e., learning tasks with a high level of element interactivity) with a high level of information density (i.e., group-based element interactivity) than complex tasks with a low level of information density. Also, as expected, no significant differences were found between experienced and non-experienced groups in performance, mental effort, and efficiency in all phases on tasks with lower information density. It seems that groups that previously worked on similar tasks acquired relevant schemas of group work and transferred them to learn highly complex tasks. Results suggest that experienced groups can optimize their collective working memory resources (F. Kirschner, Paas, & Kirschner, 2011) to deal with the high cognitive demand of inter-individual processing and task information elements.

Chapter 5 examines the effect of task-specific prior knowledge level (i.e., novices vs. advanced learners) on experienced groups and individual learners (Zhang, Kalyuga, Lee, & Lei, 2016; Zhang, Kalyuga, Lee, Lei, & Jiao, 2015). For this study, the same design was used as the one reported in the previous chapter with the distribution of information that produced a high level of interactivity among students (i.e., a high level of information density). Advanced learners received an additional session that had the purpose of providing specific undeveloped schemas of the new learning tasks. Regarding the learning condition, it was found that when students learn individually, advanced learners outperform novice learners in retention and delayed tests. This was expected. However, experienced groups invested more mental effort in the retention test and an equivalent amount of mental effort in the delayed test. As was expected, when students learn in experienced groups, more knowledgeable learners outperform novices and invest an equivalent amount of mental effort in the retention and delayed tests. Concerning prior knowledge, when learners are novices, groups outperform individuals in retention and delayed tests as expected. However, experienced groups invested more mental effort in the retention test and an equivalent mental effort in the delayed test. As expected, no difference between experienced groups and individuals when students had prior knowledge was found in all tests, except that in the retention test knowledgeable groups outperformed the individual learning condition. These results revealed that knowledge structures considerably define the advantage and disadvantage of collaborative learning. It appears that task-based prior collaborative experience (i.e., team expertise) and task-specific schemas (i.e., task expertise) make up structures in long-term memory that optimize group information processing to learn highly complex learning problems.

The dissertation ends (Chapter 6) with a systematic discussion of the results found. It addresses theoretical implications for collaborative learning and cognitive load theory, as well as instructional recommendations for those who design or implement collaborative learning environments. Moreover, future investigations are proposed.

2. Collaborative Cognitive Load Theory[1]

It has been said that “[W]ithout an understanding of human cognitive architecture, instruction is blind” (Sweller, 2017). In this respect, collaborative learning as an instructional approach is at best sight-impaired and at worst stone-blind. While collaborative learning is increasingly used in school and lifelong learning for acquiring work-life skills, there is little evidence-informed theory based on human cognitive architecture to guide its implementation. Cognitive load theory, an instructional design theory based on human cognitive architecture, has traditionally been associated with individual learning. Based on evolutionary educational psychology and our knowledge of human cognition, in this chapter we indicate that the theory can be used directly to explain and optimize collaborative learning. Additions to the theory are needed to account for the particulars of collaboration, but those additions also require the basic concepts used by the theory. The major additions are the concept of a collective working memory and generalized domain group knowledge. We suggest that cognitive load theory, with these additions, can clarify collaborative learning, generate novel hypotheses, and help design collaborative learning both face-to-face and computer-supported.



[1] This chapter is based on:

Zambrano R., J., Kirschner, P. A., & Kirschner, F. (2020). How cognitive load theory can be applied to collaborative learning: Collaborative cognitive load theory. In J. Sweller, S. Tindall-Ford, & S. Agostinho (Eds.), *Advances in cognitive load theory: Rethinking teaching* (pp. 30-40). London, UK: Routledge.

Kirschner, P. A., Sweller, J., Kirschner, F., & Zambrano R., J. (2018). From cognitive load theory to collaborative cognitive load theory. *International Journal of Computer-Supported Collaborative Learning*, 13, 213-233. doi:10.1007/s11412-018-9277-y

Modern learning is increasingly moving from individual learning to learning in teams (i.e., collaborative learning) for acquiring lifelong learning and working skills (Care, Scoular, & Griffin, 2016; Graesser et al., 2018; Hmelo-Silver & Chinn, 2015). The problem is that, in contrast to individual learning, there is limited well-researched, evidence-informed theory to guide designing, developing, and implementing collaborative learning. One consequence of this void is poor implementation and, thus, ineffective, inefficient, and unsatisfying use of collaborative learning both for the teacher and for the learner. Another consequence is that, due to this poor implementation, teachers, and learners waste precious resources (i.e., time, effort, money) on ineffective and inefficient learning and teaching inside and outside of the classroom (i.e., computer-supported collaborative learning; CSCL). This represents a severely missed chance for learners to acquire necessary work-life skills.

Cognitive load theory lies at the base of the design and implementation of effective and efficient individual instruction (Sweller, Ayres, & Kalyuga, 2011). In essence, cognitive load theory holds that our cognitive architecture and how we acquire information is limited by the capacity and duration of our working memory processes, directly affecting learning and performance. Learning tasks cause learners to expend working memory resources (i.e., cognitive load associated with cognitive processes) due to a learning task's inherent complexity (i.e., interacting information elements related to the task and the additional elements related to the instructional approach), and long-term memory schemas. In order to contribute to the design and implementation of beneficial collaborative settings, which consist of individual learners effortfully working together to attain a common learning goal, a review of cognitive load theory is presented. This theoretical review aspires to expand the cognitive load theory assumptions and propose some lines of research to understand the advantages and limitations of collaborative learning from a cognitive load perspective.

State of the Art: Cognitive Load Theory

Knowledge can be categorized in many different ways (e.g., a priori, posteriori, explicit, implicit/tacit, declarative, procedural, propositional, etc.). In the context of this chapter, a choice has been made to use a categorization that has a more or less direct effect on learning and instruction: Geary's (2012) distinction between biologically primary and secondary knowledge. Cognitive load theory sees this distinction as a useful categorization schema for educational purposes that can lead to different instructional procedures. We have, as a species, evolved to acquire *biologically primary* knowledge almost effortlessly and without explicit instruction due to group support of the members of a community. Generally, because it is more or less effortlessly acquired, biologically primary knowledge does not need to be formally taught. Examples of such primary skills are hearing, listening, and joint attention (Callaghan et al., 2011; Tomasello & Rakoczy, 2003), and their respective derived primary knowledge is planning, generalizing, speaking in one's native language (Sweller, 2015; Tricot & Sweller, 2014). Collaboration is also a biologically primary skill that we have evolved to acquire (Paas & Sweller, 2012). We have, however, not evolved to acquire specific examples of *biologically secondary* knowledge. To acquire such knowledge we require intentionally designed, effective learning environments (e.g., schools, colleges and universities, professional and company trainings, etc.). Substantial effort and therefore proper support and guidance is required (i.e., instruction) (P. A. Kirschner, Sweller, & Clark, 2006; Sweller, Kirschner, & Clark, 2007). Without explicit instruction and appropriate biologically primary skills, carrying out the domain-specific tasks that characteristically constitute biologically secondary information is severely compromised. Some examples of secondary skills and domains are: reading and writing our native language as well as one or more non-native languages, computer programming, solving engineering and science problems, analyzing philosophical theories, or other learning tasks for which guided instruction is required and we, therefore, learn in an instructional context.

All our knowledge and learning is shaped and limited by our cognitive system and how it functions. The way in which biologically secondary knowledge is constructed by the human cognitive system is analogous to the way in which evolution by natural selection processes information (Sweller & Sweller, 2006). This architecture is described in five principles which are summarized in Table 1.

Table 1.
Natural Information Processing System Principles

Principle	*Function*
Information store	Primary and secondary knowledge and skills are stored in long-term memory.
Borrowing and reorganizing	Knowledge is mostly borrowed from other's knowledge and is reorganized depending on previous knowledge.
Randomness as genesis	In the absence of relevant knowledge, required new/novel knowledge is created by random generate-and-test processes.
Narrow limits of change	Limited capacity and duration of working memory processing prevent rapid random changes of the store.
Environmental organizing and linking	Interacting with the environment or problems requires environmental signals that allow organized information to be transferred from long-term to working memory to perform actions appropriate to that environment.

Cognitive load theory is based on the assumption that when presented with novel information, there are two additive sources of cognitive load imposed on working memory (Sweller, 2010) which combined should not exceed its limits: Intrinsic and extraneous cognitive load. *Intrinsic load* deals with the inherent complexity of the information in a learning task. It is defined in terms of the amount of novel interacting information elements in a task; the higher the number of novel interacting elements, the more complex the task, especially when time is an issue. Time is almost always an issue, since learning to successfully solve a problem demands the rapid processing of many interconnected elements (Ricker & Cowan, 2018). For example, learning to remove the brackets in the expression $5(3-4x)$ seems to be similar to removing the brackets in $-7(-4+2x)$. However, the second problem is more complex (thus causing more cognitive load) because it requires considering the negative sign before 7 which generates more connections between elements and potentially more errors of multiplication (Ayres, 2006).

In addition, there may be interacting elements unrelated to the intrinsic complexity of the task that impose an *extraneous load* on working memory. This load is therefore unproductive and hampers learning. It can be controlled by instructors and be varied by using different instructional procedures. Some procedures (e.g., discovery or inquiry learning) impose more extraneous or unproductive load on working memory than others (e.g., worked examples, process worksheets) (Atkinson, Derry, Renkl, & Wortham, 2000) and demand more time on the task.

Germane load, which is sometimes treated as a third type of load, "is purely a function of the working memory resources devoted to the interacting elements that determine intrinsic cognitive load" (Sweller, 2010, p. 126). Furthermore, according to Kalyuga (2011, p. 1), "germane load is essentially indistinguishable from intrinsic load, and therefore this concept may be redundant … the dual intrinsic/extraneous framework is sufficient and non-redundant and makes boundaries of the theory transparent". As such, germane load is not treated as an additive source of load here.

Both types of cognitive load interact with each other as well as with the learner's level of expertise (O. Chen, Kalyuga, & Sweller, 2016). If the task has a high level of intrinsic interacting elements, a learner who has relevant knowledge in long-term memory (i.e., an advanced learner) will experience a lower cognitive load and achieve better learning results than a novice with little relevant knowledge in long-term memory. If extraneous interacting elements are added (e.g., if the learner must apply a discovery strategy), the task may overwhelm the learner and impede her/his learning. Learning will also be hindered when an advanced learner (i.e., a learner with considerable prior knowledge or experience in the learning task) receives instruction that combines new with redundant information (e.g., diagrams with integrated text) (Kalyuga, Chandler, & Sweller, 1998). The embedded texts interfere with the information already available in long-term memory, increase the cognitive load, and, thus, reduce the performance (i.e., expertise reversal effect; O. Chen et al., 2016). Research and application of cognitive load theory has led to the development of a broad range of instructional procedures to reduce extraneous load and increase working memory resources devoted to intrinsic load to facilitate learning (see Sweller et al., 2011).

Beyond the State of the Art: Collaborative Cognitive Load Theory

Cognitive load theory allows for the design of effective and efficient individual learning and informs good instructional design for individuals (e.g., Paas, Renkl, & Sweller, 2003; Van Merriënboer & Kirschner, 2018) as well as for the design of multimedia learning (Mayer, 2014). What has not yet been attempted, and what the field sorely needs, is a cognitive theory for collaborative learning: Collaborative Cognitive Load Theory. Learning collaboratively involves two or more learners who actively contribute to attaining a mutual learning goal and who share the effort needed to reach this goal (Teasley & Roschelle, 1993). As an instructional method, collaborative learning uniquely affects cognitive load as learners must interact with their teammates to communicate with each other and coordinate their actions on a task. The collaborative cognitive load represents an extra and inevitable cost. However, working together also provides the possibility to share some of the load imposed by a task because collaboration can make use of other people's processing capacity which can lower the experienced cognitive load. Approaching collaboration from a cognitive load perspective, specifically from the principles of cognitive architecture and the evolutionary knowledge categories, may imply the expansion of some assumptions in order to consider the interactional dimension of the cognitive load.

Cognitive Architecture and Evolutionary Categories of Knowledge

Considering the advances of developmental comparative psychology, namely evolutionary dynamics (Rand & Nowak, 2013; Tomasello & Gonzalez-Cabrera, 2017), a crucial, new principle for human cognition specific to the *processes* of collaborative learning, namely the *mutual cognitive interdependence principle* (P. A. Kirschner et al., 2018) is proposed. It is suggested that collaboration is the decisive organizing principle for the development and functioning of human cognitive architecture. When determining cognitive principles under collaborative conditions, it is decisively important to include the effects of interaction between natural information processing systems. Environmental variations are a crucial factor for genetic evolution, and mutations must be stored in a reservoir of information in order to be transmitted through reproduction. Something similar happens in human cognition with respect to cultural knowledge (Sweller & Sweller, 2006). Changes in the information store are produced and reproduced through learning and instruction processes. However, for natural and cultural selection to work, mutual collaboration between individuals and groups is required (Geary & Huffman, 2002; Sterelny, 2012; Tomasello & Rakoczy, 2003). Genetic and cognitive evolution depends on the mutual interdependence of group members, where expert and more advance individuals (i.e., fittest) collaborate by modelling and transmitting relevant information (e.g., skills, knowledge, artifacts and so forth) to the group (Rummel & Spada, 2005; Rummel, Spada, & Hauser, 2006; Sterelny, 2012).

The *borrowing and reorganizing principle* answers the question of how we learn and the *environmental organizing and linking principle* indicates why we learn (Sweller et al., 2011). However, these and other principles must be considered not only at the level of individual learning but at the interactional level (Alexander, Schallert, & Reynolds, 2009) in a broader evolutionary framework: "create culture - a system of shared ideologies and rules for social behavior that enable the formation of large cooperative groups" (Geary, 2012, p. 615). Geary has suggested that schools were created (i.e., cultural adaptation) to formalize the cross-generational transfer of secondary knowledge needed in modern societies. However, this does not mean that in the past human groups have not had other cultural ways (formally or informally) to transfer knowledge, for example, from parents to children, from experts to novices or from groups to individuals (Dukas, 2017; Sterelny, 2012). Nor does it mean that in modern societies schools are the only means of transferring secondary knowledge. There is evidence that school success is also related to the learning opportunities provided by parents, the influence of the home environment, the socioeconomic level of the family, the electronic media and the community (Schunk, 2016). The principle of mutual cognitive interdependence aims to consider the relations involved in cultural reproduction (i.e., learning materials, scientific research, technological innovations), which affect the evolution of human cognitive architecture (Tomasello, 1999) and even give a functional idea of purpose (i.e., the "why" of learning). Concerning the latter, Geary (2009) has suggested that "In modern societies, the why of learning is more strongly related to historically recent cultural changes and technological and scientific innovations than to our evolutionary history" (p. 200). From this perspective, the inter-individual activities that characterize collaborative learning should not only be considered as part of an instructional technique but also as a dynamic factor that may significantly affect human learning in school and non-school contexts.

In school settings, when the focus lies on learning secondary knowledge, the benefit of collaborating depends for a large part on the cognitive costs associated with transactional activities (Geary, 2012; Geary & Huffman, 2002; Hinsz et al., 1997; P. A. Kirschner et al., 2018). These activities refer to inter-individual communication and coordination cognitive operations whose purpose is to allow group members to learn to solve highly complex problems (F. Kirschner et al., 2009a; Van Merriënboer, 2016). In cultural reproduction, experts (e.g., instructors) invest cognitive resources in novice learners by collaborating with them to provide tailored instructional environments as is the case, for example, in the cognitive apprenticeship approach (Collins, Brown, & Newman, 1987). Similarly, in groups of learners with heterogeneous knowledge, advanced learners invest transactional resources that benefit novices, and novices in turn pay the cognitive cost of learning from/with experts, other learners, or designed (i.e., by instructors) learning materials. Advanced learners may also take advantage of collaborative instructional contexts with highly complex tasks for consolidating undeveloped schemas and transferring their knowledge to relatively novel problems (Zambrano R., Kirschner, Sweller, & Kirschner, 2019b). Domain-specific experts and advanced learners borrow/collaborate providing their knowledge and skills to others, and novices reorganize their previous schemas. Thus, the interaction between collaboration, learning environments, and expertise may appropriately explain the principles and evolution of human cognitive architecture (Coolidge, Wynn, & Overmann, 2013). This suggests that the key to genetic and cultural evolution is not only individual cognitive fitness but mutual cognitive interdependence (Allen & Nowak, 2016).

The mutual cognitive interdependence principle also gives sense to the claim that humans have evolved to work together in mutualistic contexts (Rand & Nowak, 2013). People learn and develop in multigroup contexts, constantly sharing, receiving, and retrieving information from their cognitive schemas (i.e., long-term memory structures) and environments (i.e., learning, socialization, and working contexts) by means of their common biologically primary ability to process information (i.e., working memory operation) (Camos & Barrouillet, 2018; Cowan, 2014). In fact, it has been suggested that interacting and collaborating in complex and competitive environments may have been crucial factors for the evolutionary development of communication and survival of the species (Knofe, Engelmann, Tomasello, & Herrmann, 2019; Nowak, 2006, 2012; Tomasello, 2008). If we have evolved to acquire joint knowledge, then collaboration may be biologically primary or a *general skill* and may place little strain on working memory (Paas & Sweller, 2012). This low cognitive load could be due to the fact that humans have natural mechanisms to acquire culturally general knowledge such as language. Emitting and receiving information (i.e., primary skills) using the native language (i.e., secondary cultural knowledge) are relatively easy to perform cognitive skills in typical humans due to biologically inherited and culturally enhanced natural mechanisms. Therefore, general collaborative skills and their derived artifacts (e.g., learning modules, multimedia, schools) could be the essential means of cultural reproduction.

Accordingly, the mutual cognitive interdependence principle considers collaborative learning both as an interactive learning context that includes individual learning settings as well as a specific instructional technique (i.e., learning groups) whose advantage depends on the environment in which it is carried out (i.e., the subject area/domain context) (Könings, van Zundert, & van Merriënboer, 2019). One piece of evidence supporting the mutual cognitive interdependence principle may be what is known as biologically primary general skills. Most school learning tasks are more complex cultural processes than simple intuitive/counterintuitive or general knowledge (Anders, 2004; Geary & Berch, 2016; Kapon, 2017; Sherin, 2006; Tricot & Sweller, 2014). General skills are the foundation of any form of knowledge construction. People seem to have certain intuitive physics knowledge (e.g., intuitive physics knowledge; Sherin, 2006) which they acquire without the need for conscious reasoning and which is the basis for the acquisition of more complex knowledge through systematic instruction (Fischbein, 1987). Intuitive or primary knowledge (and counterintuitive because it violates intuitive assumptions; Barrett & Gregory, 2009) is easy to remember and spread because it represents cross-culturally prevalent classes of concepts (e.g., space, time, speed) that people expect to find and have evolved to find. However, complex, domain-specific knowledge cannot be learned only through primary skills such as random and trial-and-error search (Simon & Newell, 1972) or applying primary intuitive schemas (e.g., horizontal and vertical motion dimensions; Hast & Howe, 2013). Learners need explicit guidance to acquire secondary knowledge (P. A. Kirschner et al., 2006).

Similarly, people also have intuitive skills about how to work together (folk-psychology; Geary, 2012). Michael Tomasello and his colleagues present important results about these primary collaborative abilities. For example, Melis and Tomasello (2019) suggest that chimpanzees have the indispensable socio-cognitive skills to naturally develop a simple communicative strategy to ensure coordination in a collaborative task. When compared chimpanzees with children, they found that dyads of 5-year-old children overwhelmingly selected a mutually profitable approach that allowed both children to solve turn-taking problems. The authors concluded that while chimpanzees mostly collaborate in the context of long-term cooperative relationships, it seems that humans have developed unique socio-cognitive cooperative skills for dealing with complex coordination activities (Knofe et al., 2019). Nevertheless, primary collaborative skills performed in an instructional context may have higher cognitive costs and result in inefficient learning (if any) than individual learning (F. Kirschner, Paas, & Kirschner, 2011; Sweller et al., 2011). Primary collaborative cognitive activities (i.e., transactional activities) may produce better domain-specific schemas when students receives guided instruction on how to collaborate (i.e., through observation, imitation, explicit integration with knowledge)

(P. A. Kirschner et al., 2006; Rummel & Spada, 2005; Rummel et al., 2006; Zambrano R. et al., 2018; Zambrano R. et al., 2019b).

Consequently, it is essential to take into account that collaborative learning, used as an instructional technique (i.e., forming learning groups in schools), does not always result in a better and more efficient learning (F. Kirschner, Paas, & Kirschner, 2009b, 2011; Retnowati, Ayres, & Sweller, 2010; Retnowati et al., 2016). Learning complex domain-specific knowledge implies that students know how to collaborate (i.e., have minimal collaboration schemas; Rummel & Spada, 2005; Rummel et al., 2006) according to the demands of the learning task (P. A. Kirschner et al., 2018; Rummel & Spada, 2005; Zambrano R. et al., 2018; Zambrano R. et al., 2019b). For this reason, acquiring task-specific knowledge requires learners to obtain appropriate support and guidance to work together for particular domains (e.g., solving a math problem vs. writing a prose text) (Zambrano R. et al., 2018). Effective and efficient collaboration depends on the quality of the communication and coordination (i.e., transactional activities) *related* to the specific characteristics of the learning task (P. A. Kirschner et al., 2018). Since learning in school-domains requires primary knowledge (e.g., communicating with each other, sharing attention), it can be argued that humans have evolved also to acquire biologically secondary knowledge through collaboration (Zambrano R. et al., 2018; Zhang et al., 2016; Zhang et al., 2015). Consequently, learning teammates can and should develop *task-based generalized domain skills* (Kalyuga, 2015) at the group level.

Collaborative Learning and Categories of Cognitive Load

Cognitive load theory has been developed mainly through investigations of individual learning conditions. However, the incorporation of evolutionary educational psychology, specifically the distinction between primary and secondary knowledge (Sweller, 2004, 2008, 2011, 2016) allows us to propose new hypotheses and explanations that could improve our understanding of learning and the cognitive load related to the processing of individual and collective information.

By definition, intrinsic cognitive load is imposed by "the intrinsic nature of the information… that the learner needs to acquire for achieving learning goals irrespective of the instructional procedures used"(Sweller et al., 2011, p. 57). Whereas extraneous cognitive load is imposed by "the manner in which the information is presented or the activities in which learners must engage…This load is imposed solely because of the instructional procedures being used" (Sweller et al., 2011, p. 57).

Collaborative learning as an instructional technique is based on active communication among learners to learn within a specific domain. These communication activities are possible thanks to an accumulation of biologically primary skills such as observation, shared attention, imitation, or listening, and therefore impose a low cognitive load (Paas & Sweller, 2012). However, according to the definitions of cognitive load types, the activities related to collaborative learning would be a type of extraneous cognitive load because it's used as an instructional technique and therefore not part of the intrinsic nature of the task information. For this reason, although communication depends on primary skills which require little effort investment, by definition collaborative learning can impose an extraneous cognitive load.

Transactional Activities and Prior Knowledge

Cognitive load associated with collaborative learning is productive when the inter-individual activities facilitate better and more efficient knowledge than individual learning. There are theoretical grounds to hypothesize that group learning may reduce element interactivity while fostering better task schemas at the individual level. Good collaborative learning induces *collective working memory* (F. Kirschner, et al., 2011) that otherwise does not exist. In collaborative tasks, the various interconnected elements of the task can be distributed among multiple working memories (i.e., the group members) reducing the cognitive load on a single working memory. Under individual learning, a single working memory must process all task information elements. Multiple working memories constitute a collective memory larger than a single one. Collaboration as an instructional procedure thereby may change the total cognitive load at the individual level when the elements of the task are distributed among the multiple working memories of the learners (F. Kirschner, et al., 2011). During collaborative learning information can come from collaborators based on the borrowing and reorganizing principle and, thereby, is likely to become available exactly when needed resulting in decreased load and increased learning (Gupta & Hollingshead, 2010).

Communication and coordination during collaborative learning bring transaction costs (F. Kirschner et al., 2009b; Yamane, 1996) in terms of cognitive load. These 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…to allow a work team to produce more than the sum of its parts" (Ciborra & Olson, 1988, p. 95). In collaborative learning, the communication and coordination costs are the cognitive load that have to be taken into account caused by the acts learners must carry out when studying, communicating with each other and coordinating both their own learning and that of others (Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010; F. Kirschner et al., 2009b).

As transactive activities impose additional costs in terms of cognitive load, these activities can either impede or improve learning. Collective working memory is effective when a group takes advantage of its larger collective capacity (e.g., when the task is extremely complex) and also exchanges productive transactive activities (F. Kirschner, Paas, & Kirschner, 2011; Wegner, 1995; Zambrano R. et al., 2019b). To obtain maximum benefit from the collective working memory effect, the effects of the distribution of the task elements among multiple working memories must be examined. Assuming stable motivation and prior knowledge, the way information items and the processes to carry out a learning task are distributed can generate different transactional activities. For example, the collaboration between three students to solve quadratic equations may vary depending on how the constants and variables have been distributed, what the position of the values is in relation to the equal sign (e.g., to perform calculations the values $-2x^2 + 5x =$ must be moved to the right side of the equation), and which mathematical operations must be carried out (e.g., does it include fractions, or is it necessary to use a formula or factoring). Depending on the distribution of the elements, a member would have to perform some operations individually (i.e., homogeneous distribution), with another member, or between all (i.e., heterogeneous distribution) to solve each step of the problem. Additionally, transactional activities can vary substantially, affecting learning when the same task elements are distributed among four or five group members. It can be expected that the collaborative cognitive load will be lower if the distribution is homogeneous and if groups have an appropriate number of members. Distribution and size of the team are determined based on the types and number of transactional activities required solve a complex problem.

Transactive activities also can be enhanced by providing different group schemas. These schemas can be understood as including familiarity between the members of a group (e.g., classroom norms; Janssen, Erkens, Kirschner, & Kanselaar, 2009) and sharing knowledge about how to collaborate for specific tasks (Fransen, Weinberger, & Kirschner, 2013). From this spectrum of alternatives (see Table 2), knowledge specialization may reduce the extraneous cognitive load among group members by avoiding the overlap in individual knowledge and providing the group with access to a larger reservoir of information across domains (Gupta & Hollingshead, 2010;

Tindale & Sheffey, 2002). Currently, we know that learners with low levels of previous knowledge benefit from collaborative learning when they form heterogeneous groups instead of homogeneous groups (Zhang et al., 2016; Zhang et al., 2015). In line with this, we can expect that when one or more group members have relevant knowledge needed to carry out the task, collaborative learning becomes more effective and efficient especially under high cognitive load (i.e., via a temporal restriction) conditions (Prichard & Ashleigh, 2007).

Generalized domain knowledge (Kalyuga, 2013) at the group level may also reduce the unproductive cognitive load when group members have acquired appropriate schemas of collaborative work. We assume that all learners have general knowledge (i.e., generalized schemas) about how to collaborate with others. For example, they should know whom to work with, the general rules of collaboration, the general rules of courtesy, interpersonal expectations, and so on. However, these previously acquired schemas can interfere with the specific demands of the collaborative learning task at hand (e.g., when a task requires shared calculation or involves argumentative writing). When members of a group do not have appropriate prior knowledge to collaborate with each other, they may expend working memory resources on communication unrelated to the learning tasks or interactions related to the task such as organizing and coordinating work-processes among each other (i.e., socially shared regulatory activities; Järvelä & Hadwin, 2013; Zambrano R., Kirschner, Sweller, & Kirschner, 2019a) that could be reduced if group members have experience working together in analog or transferable tasks (Kalyuga, 2013; D. J. Peterson & Wissman, 2018). Group learners must receive instructional guidance and support (e.g., task-based scripts or training) until they appropriate a socially shared domain schema. These group schemas allow learners to reduce their cognitive load and focus their working memory resources on transactional activities that enable the acquisition of better/more appropriate specific knowledge schemas (Zambrano R. et al., 2019a).

The advantage of having a greater working memory capacity and either generalized or specific shared domain knowledge has important implications for collaborative learning. Bringing together learners in a group is no guarantee that they will work and learn properly both as a group and as individuals within the group. They must develop a shared mental model or collective schema of cognitive interdependence on how to effectively communicate and coordinate their transactional activities. Groups must form adequate processes of and procedures for working together (Fransen et al., 2013; Prichard & Ashleigh, 2007) that allow them to experience and further develop the expertise that they have, share group knowledge, appropriately distribute available task information amongst themselves, and exploit the quality of participation of each group member in carrying out the task at hand. Consequently, one could state that for complex tasks/problems, collaboration becomes a scaffold (just like worked examples) for the individuals' knowledge acquisition processes. Collaboration will be effective if it becomes a scaffold in this sense. If it does not, or if it, in itself adds too much extraneous load, it will be harmful (P. A. Kirschner et al., 2018).

Table 2.

Collaborative Cognitive Load Effects and their Hypotheses

Effects	*Description*
Information distribution	The more heterogeneously the information is distributed among team members working on a learning task, the higher the extraneous load caused by transactive activities (communication and coordination).
Team size	The more members that a team working on a learning task, the higher the extraneous load caused by transactive activities (communication and coordination).
Familiarity	The better team members know each other well (i.e., are familiar with each other), but have not had experience working with each other on a learning task, the lower extraneous load caused by communication.
Experience	The more experience team members have working with each other on unrelated learning tasks, the lower the extraneous load caused by transactive activities (communication and coordination).
Task-group experience	The more experience team members have coordinating their actions on specific tasks relatively related to the learning task at hand (i.e., they know what to expect from each other in terms of task execution), the lower extraneous load caused by coordination.
Task expertise	The greater the expertise of team members in the task domain, the lower the extraneous load caused by transactive activities (communication and coordination).

Conclusion: Educational Implications

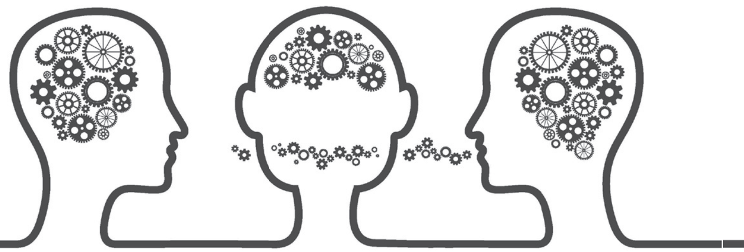
The execution of a collaborative learning task is an interaction between the characteristics of the task, the individual learners, and the team. Thus, the general framework used by cognitive load theory is directly applicable to collaborative learning but needs specific additions to account for collaboration. The major additions required when dealing with collaborative learning are the a) *mutual cognitive interdependence principle* for human cognitive architecture, and b) concepts of the collective working memory and generalized domain group knowledge along with the effects, due to the transactional activities, associated with the multiple individual working memories that constitute the collective working memory. These additions provide novel hypotheses associated with the effects of differential domain-specific knowledge on collaborative effectiveness. This leads to a number of hypotheses (i.e., implications) as to the effects mentioned for future research, summarized in Table 2.

Using collaborative cognitive load theory to conduct research on collaborative learning means that we can go beyond determining whether the effects found in individual learning conditions and measurement methods work in collaborative conditions, and test new hypotheses and measurements that explain the specific complex interactions between students and multiple information resources. Furthermore, the specialized focus on collaborative learning provides teachers with clear and to-the-point instructional guidelines (i.e., the collaborative cognitive load theory effect) for designing effective collaborative learning environments. The instructional guidelines support teachers to think about the cognitive properties of their students and the effect that a specific task and a specific group composition will have on the cognitive process that will take place. Using collaborative cognitive load theory, the choice for collaborative learning as an instructional tool, will always be an informed one.

3. Benefits of Task-Based Prior Group Experience on Collaborative Learning[2]

Preparing group-members with relevant experience on how to solve complex, analogous problems may improve collaborative learning at both group and individual levels. We tested this hypothesis with a 2-phase explanatory sequential design. In Phase 1 of this report, 15 triads that received guidance on how to work collaboratively and 45 other individual learners worked on high-complexity mathematics tasks for four sessions. Subsequently, the 15 experienced triads and the 45 students who then formed 15 non-experienced triads received new, analogous, high-complexity economics tasks. The experienced groups outperformed, invested less mental effort, and were more efficient than non-experienced groups in both a retention test and a delayed test. In Phase 2, an analysis of the transactional activities performed during group learning was conducted. Audio recordings of five experienced and five non-experienced groups were coded, categorized, and quantified to examine the types of group interaction exhibited. The results showed that experienced groups exhibited more socio-cognitive interactions, fewer socio-regulatory interactions, an equal number of socio-emotional interactions, and fewer task unrelated interactions than the non-experienced groups. Groups with collaborative experience appear to transfer their group work-schemas to relatively new, analogous tasks, and their transactional activities focus more on task information leading to more effective and efficient learning.

Keywords: collaborative learning, cognitive load theory, prior collaborative experience, transactional activities



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Zambrano R., J., Kirschner, F., Sweller, J., & Kirschner, P. A. (2019). The benefits of task-based prior group experience on collaborative learning: An exploration of the effects of transactional activities.

Collaborative learning (including cooperative learning) is an instructional practice in which students learn while they solve academic problems or carry out academic tasks in small groups (Slavin, 2014). As an approach to learning, it has been broadly used across many different subject areas at all educational levels and has been studied from multiple theoretical perspectives (Hmelo-Silver, Chinn, Chan, & O'Donnell, 2013; Slavin, 2014) using both quantitative and qualitative methods. Many meta-analyses offer convincing evidence of its profound benefits (see Gillies, 2016), though the effects are sometimes mixed (Kuhn, 2015). A problem with collaborative learning is that the situations under which collaborative learning is effective and efficient (i.e., the factors that affect its success) are insufficiently understood (Kester & Paas, 2005; F. Kirschner et al., 2009a; Kreijns et al., 2003). Studying collaborative learning from a cognitive load perspective can provide more understanding, insight, and guidelines for designing effective and efficient collaborative settings (P. A. Kirschner et al., 2018), most importantly the positive and negative effects of transactive activities within the collaborative learning environment.

Processes for Successful Collaboration

Placing learners together to learn from each other does not necessarily produce better learning, even if all of them have advanced knowledge (Lou et al., 1996). Literature on this subject is replete with strategies for designing learning environments based on collaboration (D. W. Johnson & Johnson, 2009; Slavin, 2012) such as structured academic controversy (D. W. Johnson & Johnson, 1988), jigsaw (Aronson & Patnoe, 2011), reciprocal teaching (Palincsar & Brown, 1985) and division of student teams based on achievement (Slavin, 1978). Although, many factors affect group performance and/or individual learning in a group, one crucial factor is the availability of task-based group schemas (i.e., internal cognitive representations of how a group should work to solve a task) (Delise, Allen Gorman, Brooks, Rentsch, & Steele-Johnson, 2010; Fransen et al., 2013; D. W. Johnson & Johnson, 2009; Jordan & Métais, 1997; Lou et al., 1996; Yamarik, 2007).

Most collaborative learning environments strategies mentioned presuppose that groups receive proper guidance for their collaboration and acquire knowledge schemas on how to collaborate (Gillies, in press; Gillies & Ashman, 1996). Research has shown that presenting group members with a few sessions to acquire and practice proper collaboration can have long-lasting benefits. Prichard, Stratford, and Bizo (2006), for example, trained groups of learners with two 45-min sessions delivered one week apart. Groups that received training and remained intact performed better than groups composed of reassigned members and untrained groups. As to long-term benefits, Prichard, Bizo, and Stratford (2006) examined the benefits of collaboration experience for two semesters comparing three cohorts of learners. In cohort 1, learners worked in groups during semester 1 without guidance, and in semester 2 were reassigned to new groups. In cohort 2, groups received instruction on how to collaborate in semester 1 and in semester 2 group members were reassigned to new groups. Cohort 3 received guidance and their groups remained intact during both semesters. The researchers found that groups that were instructed on how to collaborate (cohort 2) outperformed untrained groups. However, the guidance advantage of cohort 2 decreased significantly in semester 2 while cohort 3 maintained its performance in both semesters. They concluded that the benefits of collaboration guidance might be lost if group members are separated. There are also situations in which collaboration training may not work (e.g., Salas, DiazGranados, Weaver, & King, 2008). The proposed rationale for these benefits was that the trained groups had acquired shared, internal representations of working together (i.e., a shared mental model of collaboration). That is, once groups have developed an appropriate task-based collective schema, they can transfer it to relatively novel learning tasks as long as the group remains intact.

A Shared Mental Model for Collaboration

A *shared mental mode*l for collaboration is a construct which holds that team performance improves if team members have "a shared understanding of the task that is to be performed and of the involved teamwork" (Jonker, van Riemsdijk, & Vermeulen, 2011, p. 132). When group members have built collective schemas, the group will function as an integrated whole (Tindale, Meisenhelder, & Dykema-Engblade, 2001). Cannon-Bowers and Bowers (2010) describe four types of mental models that can improve a group’s performance, namely a *task model* that includes the overall goals and demands of the task, a *team interaction model* comprising individual and group’s understanding of interaction demands, a *team model* that involves group members' understanding of one another's knowledge, skills, abilities, strengths, and weaknesses, and an *equipment model* that refers to the use of available tools. In the context of collaborative learning, the primary goal is to construct task-mental models (Fransen et al., 2013) with the other models being subsidiary depending on nature of the task and the instructional environment (e.g., devices used during computer-supported collaborative learning). In this context, task-based group schemas refer to knowledge and experiences shared among group members on how to work with each other within a domain-specific task (e.g., math, sciences, economics). Group members with these skills may exhibit positively interdependent behaviors, share relevant group-internal representations that allow them to make better decisions, distribute resources and information load amongst themselves, provide support and feedback to each other, and provide elaborated explanations (Gupta & Hollingshead, 2010; Tindale & Kameda, 2000).

A missing or implicit element in these shared mental models and one that is crucial for collaborative learning is a socially shared regulation schema or script (Fischer, Kollar, Stegmann, & Wecker, 2013; King, 2007; Winne, 2001). This element refers to behaviors intentionally directed to a learning goal, metacognitive processes (i.e., planning, monitoring, and control), and the regulation of behavior, cognition, and/or motivation/emotions when learning collaboratively (Järvelä & Hadwin, 2013; Tindale & Kameda, 2000). Emerging empirical evidence indicates that groups whose members display appropriate metacognitive interactions achieve higher performance levels (Kolloffel, Eysink, & de Jong, 2011; Manlove, Lazonder, & de Jong, 2009; Näykki, Järvenoja, Järvelä, & Kirschner, 2015). Self-regulation during learning implies that learners have some freedom to control and decide on the process and outcome of the tasks and that they know how to employ appropriate metacognitive strategies during learning (Zimmerman & Moylan, 2009). This supposes that group members would have to have minimal schemas for adequately performing on a similar-specific domain (Cleary & Zimmerman, 2001; Raes, Schellens, De Wever, & Vanderhoven, 2012); that is, they are fairly advanced in the domain of the task. However, learning groups not always are composed of advanced learners, and not all regulatory mechanisms are transferable across domains because they depend on task characteristics (Nugteren, Jarodzka, Kester, & Van Merriënboer, 2018b; Raaijmakers, Baars, Paas, van Merriënboer, & van Gog, 2018).

Analogical transfer processing is considered a foundation of human cognition (Gentner, Holyoak, & Kokinov, 2001; Novick, 1988). Studies in which collaborative work is modelled, for example through the use of worked examples and scripted collaboration, may provide evidence of the advantages of analogical transfer in instructional conditions. Rummel and Spada (2005) developed and tested two instructional approaches to improve collaboration for computer-mediated settings: worked-out collaboration examples (modeling learning) and scripted collaborative problem-solving. Observing a worked-out collaboration example and collaborating with the aid of a script showed positive effects on both the processes and the outcomes in what they called the application phase as compared to unscripted collaborative problem-solving and a control condition in which dyads had no opportunity to gain experience in collaborating on the task during a learning phase. In a subsequent study, Rummel, Spada, and Hauser (2009) compared five learning conditions: modeling, modeling with elaboration, scripting, scripting with elaboration, and a control. They found that observing a collaboration model with elaboration produced the best results in terms of the quality of collaborative process and outcome variables. This proved even to be the case for complex social skills. From these and others studies (Vogel, Wecker, Kollar, & Fischer, 2016; Westermann & Rummel, 2012) it can be assumed that a group can acquire shared task-based schemas and transfer them to related tasks and perform better than groups without these shared mental representations.

Guiding a team's collaborative work is associated with fewer and more productive regulatory interactions, especially under high cognitive load (Raaijmakers et al., 2018; Rummel et al., 2009). Also, groups that have built and shared schemas around analog or similar collaborative tasks may perform better and experience less cognitive load (P. A. Kirschner et al., 2018), as those schemas function as socio-metacognitive internal guides that regulate inter-individual activities during the resolution of high-complexity learning problems (Fischer et al., 2013). Further, these internal representations/scripts may also help group members regulate their emotional and non-task related interactions avoiding interference to group learning. There is some evidence that suggests that group members can regulate (i.e., monitor) their cognitive and emotional interactions during collaboration (Järvenoja, Järvelä, & Malmberg, 2017; Näykki et al., 2017), and that scripts differentially affect their exchanges in the group (Näykki et al., 2017; Vuopala, Näykki, Isohätälä, & Järvelä, 2019). In addition, Rummel and her colleagues (Rummel & Spada, 2005; Rummel et al., 2009) found that collaborative modeling can help groups optimize their regulatory and emotional interactions. From these findings it is possible to assume that task-based collaborative schemas may result in fewer regulatory and emotional interactions because group members focus their activities on the task and not on regulating activities.

In sum, it can be argued that groups with collaborative experience based on relevant tasks may have better schemas that allow them to benefit from their intra-group activities for carrying out and learn from relatively new learning tasks, as the costs incurred in communicating and coordinating activities are optimized. However, most research endeavors do not consider these incurred costs during group learning and their outcomes. Cognitive load theory provides a robust framework that can inform the design of effective individual or collaborative instructional environments based on the main characteristics of the human cognitive architecture (Sweller et al., 2011). It can help to clarify which group interactions facilitate or inhibit collaborative learning, taking into account the cognitive cost or load they impose during collaborative learning and its outcomes in subsequent individual tests (P. A. Kirschner et al., 2018).

Cognitive Load Theory

Cognitive load is a phenomenon related to the temporal demands of information processing in working memory (Cowan, 2001; L. R. Peterson & Peterson, 1959) during the (re)construction of relevant schemas in the long-term memory (Kalyuga & Singh, 2016; Sweller et al., 2011). The intensity or complexity of these demands varies depending on factors such as the amount of information or operations on the learning task or environment (i.e., external inputs) and the previously acquired knowledge (i.e., internal inputs). The first factor is usually related to controlled and conscious learning processes. It is associated with high cognitive load when learning tasks have a high level of element interactivity, which demand a significant amount of working memory resources (Sweller, 2010) and especially under time constraints (Puma, Matton, Paubel, & Tricot, 2018). The second factor is related to unconscious processes with previously learned information that is retrieved from long-term memory and imposes a low cognitive load (Evans & Stanovich, 2013).

Cognitive load is classified as *intrinsic* when it is related to strictly essential information and/or operations of the learning task, or as *extraneous* load when they are not. The latter is generally related to a poorly designed instructional environment. The germane cognitive load has been recently associated with the intrinsic load (Kalyuga, 2011), as this construct implies working memory activities involved in task information processing and storing in long-term memory. Task unrelated working memory operations may hinder learning when processing them demands almost all of the available working memory resources, exceeding the working memory resources available to learn. From this classification, unless the instructional goal is explicitly to learn how to carry out tasks that are essentially collaborative in nature (e.g., certain medical procedures in an operating room, sports, or military operations), the interactions amongst groups members can be considered as extraneous load. In any case, group interactions must be reduced/optimized in order to construct better schemas of the task. Learning conditions often are characterized by: highly complex tasks; the implementation of group work / collaboration; little time available to carry out the task; and learners who have little relevant prior knowledge. Therefore, designing appropriate environments involves managing the cognitive demands of tasks and adjusting them to prior knowledge through tailored instructional procedures that focus the working memory temporal operation on productive load.

In working memory, external and internal inputs dynamically interact in a continuum between automaticity and controllability (i.e., top-down processing and botton-up processing respectively; Kriz & Hegarty, 2007). Due to the emphasis placed on the construction of domain-specific knowledge and/or task schemas and the limitations of working memory (Sweller, 1994), most cognitive load theory studies have focused on bottom-up processing, an approach that is related to cognitively demanding and conscious operations which often produce substantial cognitive load and require explicit guidance (Evans & Stanovich, 2013; P. A. Kirschner et al., 2006). This processing considers the crucial role of prior knowledge for designing tailored instruction, as more advanced learners who have prior knowledge have to reconcile externally provided redundant information with existing long-term memory knowledge. Conciliating similarities between external and internal inputs usually results in low performance and high cognitive load; the so-called expertise reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003). This effect occurs when learners are required to acquire already known domain-specific information instead of having them use this knowledge to learn or solve relatively new or more complex tasks (i.e., transfer) (Tricot & Sweller, 2014). Consequently, this effect might be evidence for the argument that prior schemas can and should be transferred to learn relatively new tasks either on the same domain or other structurally comparable tasks (e.g., applying systems of linear equations in Mathematics to break-even point tasks in Economics).

Notwithstanding, there is an emerging construct that aims to combine the specific-domain knowledge and general knowledge from cognitive load theory: *generalized domain knowledge structures* (Kalyuga, 2013; Kalyuga & Hanham, 2011). The research on using existing generalized domain knowledge for acquiring domain-specific knowledge shows positive results (i.e., combining automaticity and controllability) although it is still in progress under individual learning conditions. Nevertheless, this type of knowledge may also be relevant for the development of task-based, collective schemas previously introduced. Generalizable domain knowledge can be composed of schematic structures on how to work in groups on specific domain tasks. Accordingly, groups that receive explicit guidance to acquire these structures may perform better than groups that have not had this guidance or previous collaborative experience (Raes et al., 2012).

Group learning activities include regulatory and emotional interactions (see the section 'A Shared Mental Model for Collaboration'). However, there is still debate about the relationship between cognitive load, regulated learning (de Bruin & van Merriënboer, 2017; Sweller & Paas, 2017), and emotions (Plass & Kalyuga, 2019). It can be expected that collaborative work structures in long-term memory guide transactional activities during group work (Rummel & Spada, 2005). This guide could reduce the number of regulatory interactions due to the transfer of these schemas to the new tasks. In contrast, groups without appropriate collaborative schemas may invest more working memory resources in organizing themselves to carry out the learning task. With respect to emotions, there are different ways of understanding their relationship with cognitive load. However, because emotions during collaborative learning can be partially expressed in learner interactions (Isohätälä, Näykki, Järvelä, & Baker, 2017; Järvenoja et al., 2017), it is possible to expect experienced groups to engage in fewer emotional interactions which interfere with learning (Khawaja, Chen, & Marcus, 2012, 2013). Thus, experienced groups with these collaborative schemas may optimize their transactional activities, which although they represent informational elements not essential for the task (i.e., impose extraneous load), may work as a scaffold for constructing better domain-specific schemas (Kollar, Wecker, & Fischer, 2018). Also, these knowledge structures may explain the differences between groups with higher and lower performance concerning their transaction activities and learning outcomes in (P. A. Kirschner et al., 2018).

This Study

The goal of the present study was twofold. First, it aimed to determine the effect of prior task-based group experience on the collaborative learning process and its outcomes (i.e., retention test and delayed test). Second, it aimed to determine what type of transaction activities explain the difference between experienced groups and non-experienced groups. For this, a two-phase explanatory sequential research design was used with both a randomized, controlled, experimental phase and an interaction analysis phase (Ivankova, Creswell, & Stick, 2016). For the first phase, we expected that experienced groups (i.e., groups of learners with prior experience working together on a similar task or problem) will outperform (h1), expend less mental effort (h2) and be more efficient (h3) than non-experienced groups (i.e., groups of learners that have not previously worked together) in the learning stage, as well as in the retention and delayed tests (i.e., its outcomes). For the second phase, we expected that experienced groups would produce more socio-cognitive interactions (h4), and fewer socio-regulatory (h5), socio-emotional (h6), and non-task interactions (h7) than non-experienced groups.

Experimental Phase

Method

Participants.

The study was conducted with 90 students (average age 13.80 years, $SD = 0.70$; 48.89% female), from a private school in Sangolquí, Ecuador, and was mandatory because it was part of their mathematics class. This research received ethical approval from the School Ethical Committee. Students were randomly allocated to two learning conditions: experienced group and non-experienced group. While they had not received instruction about the learning task which involved calculating the break-even point (BEP) in economics, they all were administered a prior knowledge test. It revealed that no learner knew how to solve the economics tasks. Students were informed of the study and that they would receive academic compensation of 10 points for their participation.

Design and procedure.

The independent variable was learning condition, operationalized as being in an experienced or a non-experienced group. The dependent variables were performance, mental effort, and efficiency.

The study was conducted in four stages: preparation, learning, retention testing, and delayed testing. Each stage consisted of sessions of 45 min. Three instructors and the experimenter guided participants throughout all stages. Instructors were previously informed about the procedure and were supervised by the experimenter to guarantee intervention fidelity. All instructions were read aloud.

Preparation stage.

The preparation stage began in the second week of the new school period, after a 2-month vacation, to ensure that the learners had neither previous classroom familiarity with each other nor prior task-based collaboration experience. This stage consisted of four 45-min sessions (180 min) over one week and was intended to allow the groups to acquire collaborative experience with each other – and thus task-based schemas – based on domain-specific tasks (i.e., solving quadratic equations) which are analogous to the actual learning tasks in the next phase. Students were randomly assigned to two groups: 45 were assigned to 15 triads (i.e., groups that would gain relevant collaborative experience) and 45 worked individually (i.e., students who would later form triads without collaborative experience). The tasks consisted of solving quadratic equations and are described in the following materials section. There were no time restrictions on the first tasks; 10 min was assigned to the two final tasks of the second session onwards (a digital clock was placed up front). Instructors encouraged group members to practice the collaboration rules that they had previously received (see Materials section), share their information which was available in the task, and maintain in their working memory their calculations to find the correct answer. Writing was not permitted when carrying out the task (i.e., all relevant information and calculations had to be maintained in working memory) but was allowed for the ultimate solution. At the end of each session, learners were given the correct answers to their tasks. The triads were asked to reflect on how they could collaborate better on the subsequent tasks for 5 min after the third and fourth session.

Learning stage.

The learning stage consisted of one session, a day or two after the preparation stage, depending upon the class schedules of the students. First, all learners were given 8 min to individually solve three simplified BEP problems to assess their prior knowledge of the subject. Then, the individual learners from the previous stage were randomly assigned to 15 triads (i.e., groups without prior collaborative experience) while the groups that were formed in the previous stage remained intact. Third, all students were asked to study a booklet for 10 min, and then answer cognitive group prompt questions during a 5 min period. Fourth, each student was asked to save the booklet, attach a voice recorder to the pocket of his/her shirt, and leave it turned on until all tasks were finished. Finally, the groups solved three tasks in 21 min (i.e., 7 min for each task). If a group finished the task before the end of the allotted time, the group was required to wait before starting on the next problem. Because it was essential that learners did not cognitively offload their working memory (Van Bruggen, Kirschner, & Jochems, 2002), pencil use was only permitted when writing the final answer and to indicate the mental effort invested after each task. The instructors made sure groups would keep to this rule.

Retention and delayed test stages.

These stages aimed to evaluate individual learning outcomes of the previous two stages regarding efficiency and effectiveness. The retention test was administered one day after the learning stage and the delayed test after seven days. In each stage, learners individually solved three BEP conventional problems in one session (10 min per task). To determine the quality of their knowledge schemas, learners were asked to record each step of the solution process and the mental effort invested after each problem.

Materials.

Materials were developed for carrying out tasks in the domains of mathematics (preparation stage) and its analog domain economy (the remaining stages). The tasks involved solving quadratic equations in the former and calculating BEP tasks for the latter. All materials were paper-based.

Preparation stage.

Domain-generalized group knowledge was provided using a whole-task scaffolding approach (Van Merriënboer, Kirschner, & Kester, 2003) plus five rules on how to collaboratively solve the equations. Both the group condition (i.e., experienced group in the learning stage) and the individual condition (i.e., non-experienced group in the learning stage) were instructed to learn the rules and apply them when working in groups. Examples of the rules are: When it is possible to perform the calculations without the help of others, do it alone; Carry out the calculations sharing your information with your peers without writing them; Continually rehearse the results to avoid forgetting them. In the first session, all participants received an introduction to quadratic equations with two worked examples using the factoring method to activate the students' prior knowledge.

In the group condition, each member received two values of the equation and a table in which they could write down the intermediate calculations. The individual participants received the same values but did not work in teams (see Appendix A). In the second session, both group and individual conditions received the collaborative rules, two conventional problems with the correct answer and a conventional problem without the correct answer. In the third and fourth sessions, the rules were removed, and groups and individuals received three conventional problems without a correct answer and with an increased number of values (from six to nine). All values were relevant for but insufficient to solve each problem.

Learning stage.

BEP tasks have similar features to quadratic equations, such as combining multiple numerical values, using basic mathematical operations, and calculating intermediate steps. Likewise, learners had to hold partial answers in their working memory and then combine them to find a unique correct answer. In this way, the rules of collaboration also applied to the BEP tasks.

Each participant received a booklet with the relevant concepts, two worked examples, cognitive prompt questions, three conventional problems, a piece of paper with examples of fixed and variable costs and the BEP in units' formula, and a voice recorder. The worked examples had seven steps (see Table 1). Some of the prompt questions were: a) What is the BEP? b) What are the seven steps to calculate the BEP? c) What is the difference between the BEP in units and sales? d) How do you calculate the contribution? and so forth. No task-step could be performed without each member communicating his/her items to the others and coordinating their actions. The information on the piece of paper was given to avoid confusion.

An approximate high level of complexity was determined computing the number of elements and assuming that processing these elements demand other mental operations in working memory (Sweller & Chandler, 1994). Each problem had seven steps with nine items (Table 1) that had to be interconnected to obtain a correct answer. Each step varied in the number of elements and type of mental operations required (Column 2 and 3 of Table 1). If only mathematical elements are considered, there are a total of 45 interacting elements (including signs). Additionally, for each step, an intermediate temporal answer had to be calculated and held in working memory (Column 4 of Table 1) that needed to be integrated with another number. Based upon this computation and the fact that the learners lacked relevant prior knowledge and were not permitted to write down their answers, it was assumed that the tasks were of high complexity.

Table 1

Steps to Calculate the BEP

Steps to solve the problem	*Example of calculations*	*Interacting elements*	*Temporal results to maintain in working memory*
1. Recognize cost items	Nine items of the problem 155, 63, 82, 50, 41, 108, 71, 119, 52	9	
2. Total variable cost	$V_1 + V_2 + V_3 = TV$ 155 + 63 + 82 = 300	7	300
3. Variable cost per unit	TV ÷ amount produced = CU 300 ÷ 50 = 6	5	300, 6
4. Contribution	Price – CU = C 41 – 6 = 35	5	6, 35
5. Total fixed cost	$F_1 + F_2 + F_3$ + profit margin = TF 108 + 71 + 119 + 52 = 350	9	35, 350
6. BEP in units	TF ÷ C = BU 350 ÷ 35 = 10	5	35, 350, 10
7. BEP in sales	BU × price = BS 10 × 41 = 410	5	10, 410

Note. V = variable cost; F = fixed cost; TV = total variable cost; CU = variable cost per unit; C = contribution; TF = total fixed cost; BU = BEP in units; BS = BEP in sales.

Retention and delayed test stages.

Six high-complexity BEP situations with different cost values were used. Participants received worksheets with three conventional problems constituting the retention test, one day after the learning stage, and another three problems after seven days constituting the delayed test. Each problem included a table with seven numbered rows to write down the calculations for each solution step.

Measurement.

Cognitive Load.

Cognitive load was measured after each consecutive task during learning with the subjective 9-point mental effort rating scale Paas (1992). Mental effort refers to the aspect of cognitive load that refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). This scale has been found to be sensitive to changes in task complexity and is non-intrusive (Van Gog & Paas, 2008). Each participant rated how much effort it took for them to solve the problems. This measurement provided an indirect overall indication of the cognitive load experienced by the learners.

Performance.

Performance was measured in the learning, retention test, and delayed test stages. The total number of scorable points for the three learning tasks was 3 points: 1 for each if the answer was correct or 0 if it was incorrect. This rating scheme did not take into account the learning process because group members were asked to make the steps required to solve the problem verbally. However, for each of the three retention and delayed test tasks, 7 points could be awarded based on the seven steps to calculate the BEP (i.e., the learning process). Each step was scored individually considering whether correct values and correct mathematical operations were used. A correct step's calculation received 1 point and an incorrect step's calculation 0, resulting in a maximum score of 21 points and a minimum of 0. If a step was partially correct (e.g., if only two of the three variables were recognized in step 2), a proportional score was given. The scores were then transformed into proportions.

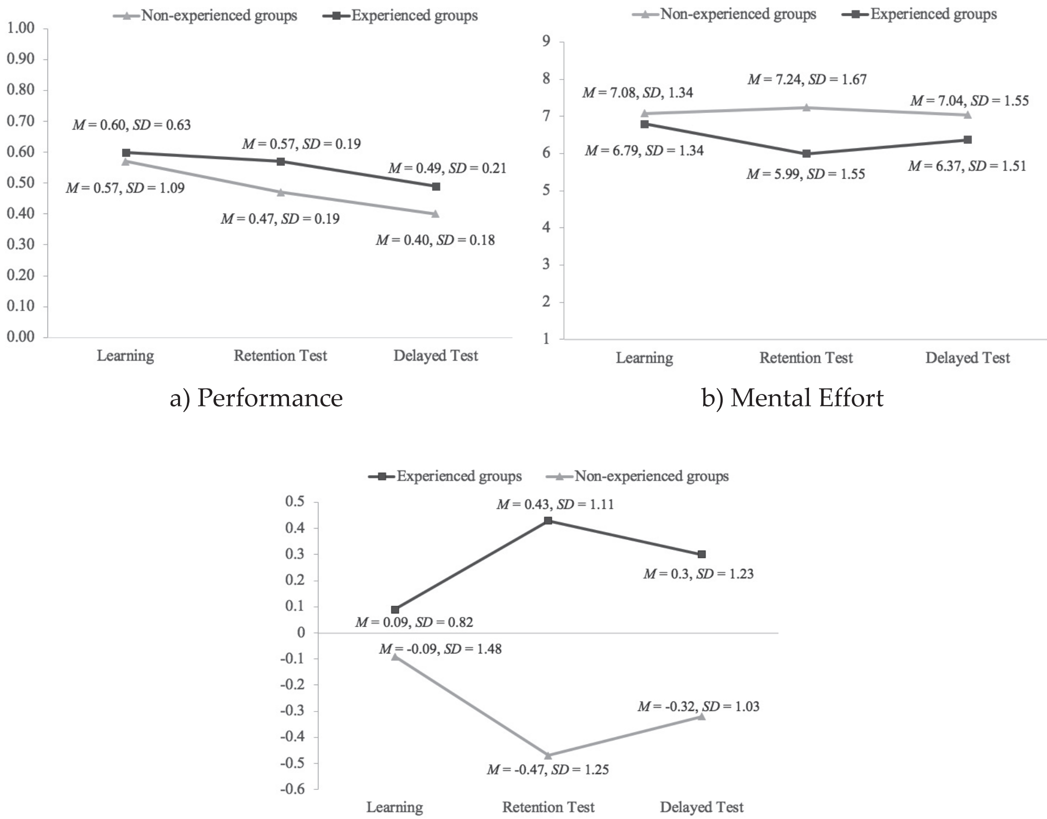
Efficiency.

It refers to the combination of performance and cognitive load measures to estimate the efficiency of the instructional method and learning outcomes. High efficiency indicates relatively high performance in combination with relatively low mental effort. Conversely, low efficiency means relatively low performance in combination with relatively high mental effort (Paas, Tuovinen, et al., 2003). Efficiency for learning retention and delayed test stages were calculated. Z-scores for performance (P) and mental effort (R) were computed with the formula $E = [(P - R)/2^{1/2}]$ (Paas & Van Merriënboer, 1993).

Results

Data were analyzed with one-way ANOVAs using a significance level of .05 and a partial eta-squared to indicate the effect size, with values of .01, .06 and .14, corresponding to small, medium, and large effects respectively (Cohen, 1988). Further, the intraclass correlation coefficient (ICC) was calculated for the retention and delayed measures to estimate the degree of non-independence (Kenny, Mannetti, Pierro, Livi,

& Kashy, 2002). No student could solve the problems on the prior knowledge test. Figure 1 shows the descriptive results of the measures of the dependent variables (i.e., performance, mental effort, and efficiency) during study stages.



a) Performance b) Mental Effort

c) Efficiency

Figure 1. Scores of the dependent variable for learning, retention test, and delayed test stages.

For performance, the difference between experienced and non-experienced groups in the learning stage was not significant, $F(1, 27) = .008$, $MSE = .779$, *ns*. However, significant differences were found in the retention, $F(1, 84) = 6.754$, $MSE = .035$, $p = .011$, $\eta_p^2 = .074$, $ICC = .23$, and delayed tests, $F(1, 83) = 4.557$, $MSE = .039$, $p = .036$, $\eta_p^2 = .052$, $ICC = .35$. For mental effort, ANOVA also did not reveal a significant difference in the learning stage, $F(1, 27) = .336$, $MSE = 1.793$, *ns*, but there were significant differences in retention, $F(1, 84) = 12.890$, $MSE = 2.587$, $p = .001$, $\eta_p^2 = .133$, $ICC = .31$, and delayed tests, $F(1, 83) = 4.095$, $MSE = 2.330$, $p = .046$, $\eta_p^2 = .047$, $ICC = .18$.

For efficiency, consequently, there was no significant difference in the learning stage, $F(1, 27) = .162$, $MSE = 1.407$, *ns*, but there was a significant difference on retention, $F(1, 84) = 12.479$, $MSE = 1.391$, $p = .001$, $\eta_p^2 = .129$, $ICC = .31$, and delayed tests, $F(1, 83) = 6.176$, $MSE = 1.297$, $p = .015$, $\eta_p^2 = .069$, $ICC = .40$. As expected, learning by experienced groups resulted in higher performance, less mental effort, and higher efficiency than learning in non-experienced groups. However, it is necessary to examine the transactional activities to explain why these differences were not observed in the learning stage (see below).

Discussion

This first phase of the study aimed to determine the effect of the prior relevant, task-based group experience in the collaborative learning process and its outcomes. The results present evidence for our hypotheses that groups provided instruction in collaborative learning outperformed, expended less mental effort, and were more efficient in retention and delayed tests but did not differ in the learning stage. It seems, these experienced groups invested substantial working memory resources in transactional activities when learning to solve the learning problems.

The results on performance, mental effort and efficiency in the retention and delayed tests suggest that learners that worked in experienced groups constructed and took advantage of better-generalized knowledge structures to learn relatively new, highly demanding tasks (P. A. Kirschner et al., 2018; Van Gog, Paas, & Van Merriënboer, 2005). The joint-work mental model (i.e., the collaboration model) acquired through explicit guidance in the preparation stage positively affected the results of the collaboration. The higher performance with less mental effort and more cognitive efficiency of learners in experienced groups suggest that the socially shared schemas of task-based collaborative learning may have functioned as internal cognitive and metacognitive scripts that guided inter-individual activities during group learning (Fischer et al., 2013; P. A. Kirschner et al., 2018). That is, when groups have group knowledge structures of a generalizable domain, this substantially improves the results of collaborative learning although this benefit is not immediately observed in the collaborative learning stage. Furthermore, the results of posttests may be a good indicator of long-term retention (Soderstrom & Bjork, 2015) because they were applied one and seven days after the learning stage. Given that the benefit of collaborative learning must be seen in individual post-tests (F. Kirschner et al., 2009a), the performance results of the retention stage were considered as representative for both conditions.

The lack of evidence of the benefit of having task-based collaborative knowledge structures in the learning stage can be explained by the type of measurement used and the task complexity. In our study, the performance of the collaboration process in this phase was only determined by the accuracy of the final answer. This criterion did not allow an in-depth understanding of the performance during the collaborative process, which in turn suggests that collaborative learning performance does not always reflect the benefits of collaboration (Kester & Paas, 2005). Regarding mental effort, the equivalent scores were probably because the mental effort rating took into account the cognitive load produced by both essential elements of the task (i.e., intrinsic load) and by the transactional activities (i.e., extraneous load). As was the case when measuring group performance, the perception of mental effort included all working memory cognitive activities imposed by the tasks without being able to discriminate their possible temporal fluctuations of cognitive load during collaboration (Van Gog, Kirschner, Kester, & Paas, 2012). It would be interesting to examine the consistency of the subjective measures of cognitive load in each step of each collaborative task using protocol analysis of verbalized thoughts (Ericsson, 2018).

Due to the fact that this study did not obtain differential results in the learning stage and that, to our knowledge, there is no research that examines transactional activities from a cognitive load perspective (Janssen, Kirschner, et al., 2010), a more in-depth analysis of the intra-group interactions was carried out to reveal the cognitive activities between individuals that were associated with collaboration in this study.

Interaction Analysis Phase

Selection of Learning Groups

This phase was carried out to examine the type and number of transactional activities of the learning process that characterized the groups with and without previous collaborative experience. The experimental phase found that the experienced groups did not perform better than the non-experienced groups in the learning stage. Given that group interactions are considered to be extraneous load because the instructional goal was learning to solve BEP tasks, it is important to examine the differences in transactional activities between experienced and non-experienced groups during the learning stage to understand the advantage of experienced groups in later stages. Accordingly, ten groups whose average performance in the retention stage was close to the average of their respective learning condition were selected. The five groups with collaborative experience selected had an average performance of .57 (SD = .07) and the five without previous collaborative experience .48 (SD = .05). The ANOVA analysis revealed no significant difference in performance between both types of groups, $F(1, 8) = 5.06$, $MSE = .004$, *ns*, and, thus, any differences in main and specific interactions can be safely attributed to prior group-experience.

Data Collection and Data Analysis Procedure

A total of 208 min and 28 sec (M = 21.19 min per group, SD = .51) of group interactions were transcribed into 10 documents, one per group. Data were encoded, conceptualized and processed using traditional quantitative methods. A substantive open coding approach was carried out to develop a category system to identify recurrent transactional activities in the selected groups. Once the conceptualization of the data related to a group activity pattern was reached, it was related to a system of more abstract, previously elaborated categories from the cognitive and emotional aspects of self-regulated learning (Järvelä, 2011). For a detailed overview of the categories see Table 2 (and Appendix B).

There are many schemas to analyze the group discussions associated with different theoretical backgrounds (De Wever, Schellens, Valcke, & Van Keer, 2006). For this research, the selection of the unit of analysis for the coding process required taking into account what is known about cognitive processes in working memory (Kalyuga & Plass, 2018). In collaborative learning, working memory cognitive activity can be partially revealed through transactional activities. These activities, although not equivalent to all internal cognitive processes, can indicate the intensity of cognitive load (i.e., the interaction between previous knowledge and learning-task characteristics) at the individual and inter-individual levels (Hinsz et al., 1997; Tindale & Sheffey, 2002). A group-member interaction can result from multiple and varied individual cognitive processes which in turn trigger other multiple mental and behavioral operations in other members that may be explicit during collaboration. The level of cognitive load associated with these activities may be different, and its intensity on a temporal scale can contribute differentially to the acquisition and consolidation of knowledge structures in long-term memory. However, the relationship between transactional activities and cognitive load under conditions of collaboration is still poorly understood (Janssen, Kirschner, et al., 2010). For example, some linguistic features associated with cognitive load in non-school environments have been identified (Khawaja et al., 2012, 2013). Khawaja and colleagues found an association between the number and type of words (e.g., emotional, cognitive, or personal pronoun type) with different perceived intensity of working memory operations (i.e., cognitive load). Given that cognitive load has been studied considering words, pauses and grammatical features (see F. Chen et al., 2013), it seems reasonable to relate cognitive load to the quantity and type of interactions during collaborative problem-solving.

Thus, for this study, the unit of analysis was an individual interaction, or part of an individual interaction that can be regarded as meaningful in itself (Strijbos, Martens, Prins, & Jochems, 2006). A learner interaction can have one or more codes. For example:

- Juan: [“Ahhh! I don’t remember”: *Task-related negative emotions*], [“what did we do first, fixed or variable?”: *Specific questions on an item/step*].
- María: [“Let’s start with variable costs” *Specific answer on an item/step*]. [“The only variable I have is: writing material 15 dollars”: *Sharing task items*].
- Paúl: [“I have refreshment”: *Sharing task items*].

Documents were processed using the MAXQDA program (Woolf & Silver, 2017), version 2018, following four steps. First, two experienced groups and two non-experienced groups were randomly selected to identify the more frequent types of interactions (i.e., codes). A researcher (first author) analyzed these four documents (i.e., one per group) and created a preliminary coding system with the goal of developing a coding schema. The unit of analysis was a member interaction, and each was coded with one or more codes (Strijbos et al., 2006) (see examples in Appendix B). Second, an independent rater who was completely unaware of the details and purpose of the study was trained to code the four already coded documents using the same code system. The number of interactions that were coded and discussed for the four documents by both raters was 4,114 (2,053 by the researcher and 2,061 by the independent rater). Third, the raters discussed and reached agreement about their discrepancies resulting in an improved coding system (see Table 2). Lastly, the researcher coded the remaining six documents, and the codes were regrouped into four main categories associated with the socially shared regulative learning schema (Järvelä, 2011; Näykki et al., 2017): socio-cognitive, socio-regulatory, socio-emotional and task-unrelated interactions. The total number of interactions coded by the researcher for the ten documents was 4,583 (see Appendix C).

Concerning the categories of interactions, the Kappa coefficient for intercoder agreement was calculated. Before discussing disagreements with the independent rater, the intercoder agreement was $k = .73$, meaning a substantial strength of agreement (Landis & Koch, 1977). After discussing the disagreements, the intercoder agreement improved to $k = .91$.

Table 2
Code System

Category	*Sub-categories*
Socio-cognitive interactions	Interpreting the problem
	Sharing task items
	Specific questions on an item or step
	Specific answers on an item/step
	Implicit answer to an item/step
	Discussion for agreement
	Self-correction
	Affirmative confirmation
	Negative refutation
	Correction to others
	Question for clarification
	Individual calculation
	Shared calculation
	Individual overload
Socio-regulatory interactions	Organization interaction
	Coordination interaction
	Explicit offloading information
	Time control
Socio-emotional interactions	Task-unrelated positive emotions
	Task-related positive emotions
	Task-related negative emotions
Task unrelated interaction	Expletives
	Task-unrelated talks

Results

Data of the main categories were explored, and all meet the assumptions of homogeneity of variances and had an acceptable normal distribution. The ANOVA analysis found that experienced groups spent significantly more time on task

($M = 21.21$ min, $SD = .24$) than non-experienced groups ($M = 20.46$, $SD = .51$), $F(1, 8) = 6.711$, $MSE = .158$, $p = .032$, $\eta_p^2 = .456$. ANOVA analyses also revealed differences between experienced groups and non-experienced groups for the main categories of interactions that may be related to the time spent on learning tasks. Experienced groups ($M = 412.0$, $SD = 37.86$) invested more socio-cognitive activities, $F(1, 8) = 5.442$, $MSE = 3210.40$, $p = .048$, $\eta_p^2 = .405$, than non-experienced groups ($M = 328.4$, $SD = 70.62$). Experienced groups ($M= 30.2$, $SD = 11.17$) invested less socio-regulatory interactions, $F(1, 8) = 5.796$, $MSE = 91.95$, $p = .043$, $\eta_p^2 = .420$, than non-experienced groups ($M = 44.8$, $SD = 7.69$). No significant difference was found between experienced ($M = 24.8$, $SD = 18.93$) and non-experienced groups ($M = 27.8$, $SD = 16.60$) concerning socio-emotional interactions, $F(1, 8) = .071$, $MSE = 316.95$, *ns.* Finally, experienced groups ($M = 7.0$, $SD = 2.24$) invested less task unrelated interactions, $F(1, 8)$, $MSE = 479.65$ $p = .037$, $\eta_p^2 = .438$, than non-experienced groups ($M = 41.6$, $SD = 30.89$).

Data of specific socio-cognitive interactions (see the number of interactions in Appendix C) did not meet the assumptions of parametric analyses. For this reason Mann-Whitney analyses were employed which revealed that interactions of self-correction, $U = 1.00$, $z =$ 2.44, $p = .02$, $r = -.24$, and shared calculation, $U = 2.00$, $z = -2.19$, $p = .03$, $r = -.22$, were significantly higher in experienced groups than in non-experienced groups. However, interactions for interpreting the problem, $U = 22.00$, $z = 2.11$, $p = .03$, $r = .21$, and individual calculation $U = 25.00$, $z = 2.62$, $p = .01$, $r = .26$, were lower for experienced groups than non-experienced groups. Regarding the specific task-unrelated interactions, experienced groups' members had less expletives $U = 25.00$, $z = 2.64$, $p = .01$, $r = .26$, and task-unrelated talk $U = 25.00$, $z = 2.63$, $p = .01$, $r = .26$, than non-experienced groups members.

Discussion

The goal of this second phase was to examine the transaction activities that may explain the differences between experienced groups and non-experienced groups. We expected that experienced groups would have more socio-cognitive interactions, and fewer socio-regulatory, socio-emotional and non-task interactions. The quantitative data analysis shows evidence for our hypotheses excepting socio-emotional interactions. Results suggest that groups with previous collaborative experience in relevant tasks acquired shared schemas to work collaboratively in an appropriate manner. Specifically, experienced groups may have taken advantage of their previously shared schemas to carry out cognitive and regulatory group activities focused on relevant aspects of the tasks, optimizing cognitive load related to interactions.

Both experienced and non-experienced groups invested substantial working memory resources compared to the other type of interactions. However, it seems that experienced groups invested more cognitive load in productive interactions. Assuming that the number and type of interactions are related to the cognitive load, it can be suggested that experienced groups spent fewer cognitive resources on interpreting the problem. Although the learning tasks were of a relatively different domain, experienced groups probably associated the characteristics of the new tasks with those already learned in groups (e.g., distribution of numerical values between group members or shared calculation) by means of cognitive cues or analogical transfer (de Bruin & van Merriënboer, 2017; Gick & Holyoak, 1980). This allowed them to concentrate their cognitive resources on acquiring schemas of the learning tasks. In contrast, non-experienced groups invested more cognitive resources in interactions to understand the problem due to their lack of generalizable group schemas related to the specific task. The higher number of self-corrections during learning performed by the experienced groups suggests that the previous collaborative experience in mathematics tasks probably provided them with cognitive monitoring mechanisms to evaluate their on-task self-efficacy judgments (Ramdass & Zimmerman, 2008). In contrast, non-experienced groups may not be able to adequately evaluate the accuracy of their cognitive activities, which may have negatively affected their performance.

The learning tasks required a large number of mathematical calculations incorporating intermediate results in the working memory. Our analyses showed that the experienced groups expended more cognitive resources on shared calculations and less on individual calculations than non-experienced groups. Perhaps performing shared mathematical calculations reduced the intrinsic cognitive load of the task by off-loading some of the essential task steps to other members of the group but increased the extraneous load related to the collaboration. Learning to solve BEP tasks required the acquisition of many concepts and a complex procedure. The large number of numerical calculations with their high level of interactive elements imposed a high intrinsic cognitive load that might be expected to impair the construction of schemas in long-term memory in non-experienced groups. However, although group interactions induce an extraneous load because they are not an essential part of the task, it seems experienced groups were better able to take advantage of sharing working memory resources. Sharing calculations may have reduced the intrinsic load associated with the numerical calculations and promoted better schemas of the task in long-term memory. As an example, it is possible to assume that experienced group members coordinated their cognitive activities better by elaborating mental calculations based on the other members' calculations (Webb, Troper, & Fall, 1995) which probably allowed them to construct better long-term memory structures of the new tasks (F. Kirschner, et al., 2011). Experienced groups, unlike non-experienced ones, also invested less working memory resources on interactions unrelated to the task (i.e., expletives and irrelevant talk). Although both experienced and non-experienced groups used the same amount of time in the learning stage, the time analysis indicated that experienced groups took more time to learn to solve the task. Considering that non-experienced groups invested more working memory resources on non-task related interactions, it might be the case that the transactional activities were optimized due to the previous experience in similar tasks.

The results on regulatory interactions showed, as expected, that experienced groups showed fewer regulatory transaction activities, which in turn suggested their acquisition of prior schematic structures of how to work appropriately in groups. Self-directed learning requires some freedom to decide on appropriate schemas to avoid additional working memory resources that harm learning. Recent literature suggests that learners have difficulty regulating themselves when domain knowledge is very different (Raaijmakers et al., 2018). However, our data support the hypothesis that regulation works best when learners already have task-based representations in their long-term memory that are similar to the specific task to be learned (Kalyuga, 2013; Raes et al., 2012). We suggest that all these advantages may explain why experienced groups had better learning outcomes in the posttests.

Interestingly, both conditions had equivalent levels of emotional interaction, which supports the general idea that emotions and feelings are an integral part of learning and problem solving (Isohätälä et al., 2017; Polo, Lund, Plantin, & Niccolai, 2016) and are not affected by prior experience. However, it is necessary to examine in more detail the type of emotions related to tasks since there is suggestive evidence that emotions can indicate different levels of cognitive load that differentially affect performance (F. Chen et al., 2013). For example, Khawaja, et. al (2013) who studied linguistic features with groups of emergency fire management personnel found a significant interaction between the use of emotion word types (positive and negative emotion words) and cognitive load levels (low load and high load). Participants expressed more positive emotion words than negative emotion words under low-load conditions and more negative emotion words than positive emotion words under high-load conditions (see a recent discussion in Plass & Kalyuga, 2019). Overall, our results suggest that the resources of collective work memory (F. Kirschner, et al., 2011) can be optimized by providing groups with task-based collaborative work schemas whose aspects can be transferred to relatively new learning tasks (P. A. Kirschner et al., 2018).

General Discussion

The purpose of this study was to determine the effect of prior task-based group experience on the collaborative learning process and its outcomes and examine what type of transaction activities may explain the difference between experienced groups and non-experienced groups. The results of the experimental phase showed support for our premise that experienced groups may transfer their group work schemas based on relevant tasks to analogous, relatively new learning tasks. It seems, a shared mental model of collaboration (i.e., generalizable, domain-specific, collaborative task) appropriately guided transactional activities of the experienced groups and optimized the working memory resources of group members (P. A. Kirschner et al., 2018). All groups experienced a high cognitive load during learning, which indicates that collaboration is an effortful task (Webb & Mastergeorge, 2003). However, it seems that explicitly guided, task-based, intergroup activities allowed better, and longer-lasting learning compared to the absence of such guidance.

The analysis of transactional activities allowed a better understanding of the collaborative learning processes. Experienced groups showed more cognitively productive intergroup activities such as shared calculations, and self-correction. We suggest that these group activities may be considered as collective mechanisms of information processing associated with the construction of shared mental representations in long-term memory. The evidence suggests that socio-regulatory activities require more group interactions which in turn may increase cognitive load during learning (Janssen, Erkens, Kirschner, & Kanselaar, 2010; Khawaja et al., 2013). However, the use of guidance materials based on similar tasks allowed experienced groups to reduce the number of regulatory interactions because they already had shared knowledge on how to solve this type of problem. In other words, the assimilation of collective group work structures reduced the need to perform coregulatory activities such as organization, coordination and cognitive control during collaborative learning. These internal scripts may also have decreased the number of redundant or non-task related interactions leaving more working memory resources for learning (Fischer et al., 2013).

The results of this study can be interpreted from theoretical frameworks other than cognitive load theory. However, the design was conceived from this theory, and mental effort measures were used. Accordingly, this research may contribute to expanding the implications of cognitive load theory. Being an instructional theory, its implications should guide the design of individual and collaborative learning environments. However, most of the effects of cognitive load theory have been developed for and are almost exclusively applied to individual learning conditions. Empirical studies of the variables that explain the advantages and disadvantages of collaborative learning from a cognitive load perspective are scarce. This study may lead to more specific investigations that examine the interactions associated with group learning processes (Janssen, Kirschner, et al., 2010; Kalyuga & Singh, 2016; P. A. Kirschner et al., 2018). Inter-group activities are a fruitful field of study that may allow a better understanding of the multiple factors that interact at the group level and its effects at the individual learning level. We suggest carrying out more research about the types of transactional activities in tasks of high and low complexity, with experienced and non-experienced groups, and with different levels of domain-specific knowledge.

A limitation of this research is that there was not a large enough number of groups to perform multilevel analyses (Janssen, Erkens, Kirschner, & Kanselaar, 2013). The results of this study should, therefore, be treated with some caution. We suggest replicating the research with more groups before analyzing the data with multilevel analyses. This study was designed to stimulate and capture group interactions verbally. Because of this, learners were not allowed to write the steps to solve the problem during the learning stage. Future research should improve ecological validity using other technologies (e.g., Martinez-Maldonado et al., 2017).

Instructional Implications

This research of the collaborative experience based on task analogs has clear implications for instruction. From a cognitive load perspective, learning complex collaborative problems demands substantial resources from working memory due to the interacting information elements of the tasks and individual as well as intergroup cognitive activities. To avoid overload working memory and maximizing learning, we suggested designing a sequence of analogous collaborative tasks (i.e., from the same domain or with similar structural characteristics to the learning problems) that provide appropriate group work schemas. Experienced groups can transfer their collaboration schemas to new domain-specific analogous tasks. The schemas will function as internal regulatory scripts that guide group work focusing learners' working memory collective resources on more productive cognitive activities such as task information, which in turn, should promote the construction of better task knowledge at group and individual level. This research may bring teachers and instructors one step closer to the effective use of collaborative learning in education.

Appendix A

Table A1

Example of Material used by Individuals in Preparation Stage

STEPS TO THE GROUP WORK	MEMBER 1	MEMBER 2	MEMBER 3
You should identify whether the values of the equation are on the **left side** or **right side** of the equal = sign.	$-10x^2 + 13 =$	$20x - 14x^2 =$	$= -7 + 3x$
You should **communicate** with the other members in order to identify other similar values. Then, **pass the values** to the left side, changing the sign, and keep the **result in mind**.			
Perform quickly and without error, **all of the operations** that are possible and maintain the **result in your mind**.			
Everyone must share their values with the others and **sort** them. **Keep in mind** the results.			
Factor the trinomial with your other partners. Remember to carry out these calculations **mentally**. To avoid forgetting a partial result, each member must have part of the information in his/her mind.			
When **Equal to Zero**, resolve the equations mentally.			
Write down the results on the worksheet:	$x_1 = -\frac{5}{8}$ $x_2 = \frac{4}{3}$		

Appendix B

Table B1

Code System with Examples

Category	*Sub-categories and examples*
Socio-cognitive interactions	**Interpreting the problem**: *Juan: Okay, let's read task 1. In a tutoring program for children of working mothers, calculate the break-even point in units with profit.*
	Sharing task items: *María: Mine says tutor's salary $56, snack for students $25, tuition fee for each student $48.* *Paúl: I have student writing material $15, students enrolled $10, electricity and telephone services $12.*
	Specific questions on an item or step: *María: Which is the variable?* *Juan: The tutor's salary is a fixed cost?* *Paúl: What was the result of the division?*
	Specific answers on an item/step refers to answers for the codes 'Specific questions on an item/step' and 'Question for clarification'.
	Implicit answer to an item/step: *Juan: I have the salary of the painter* [sharing task items]. *María: That is variable* [Implicit answer to an item/step].
	Discussion for agreement: *Juan: Writing material is variable* [Specific answer on an item/step]. *Paúl: No, it's fixed.* *María: No, because…Paúl: You're right, it is variable because it depends on how many students are enrolled.*
	Self-correction: *Juan: The contribution is subtracted from... No, no, the total fixed cost is divided by contribution.*
	Affirmative confirmation: *Paúl: The material is a variable cost, isn't it?* [Specific questions on an item/step]. *María: Yes, because it depends on...* [Specific answers on an item/step] *Juan: That's true* [Affirmative confirmation].
	Negative refutation: *Juan: Refreshments is variable* [Specific answer on an item/step]. *Paúl: No.*

	Correction to others: *Juan: Price 50 dollars is fixed* [Specific answer on an item/step]. *María: No, that isn't a cost.*
	Question for clarification: *Juan: Total fixed cost would be 247* [Individual calculation]. *María: Why so much?* [Question for clarification]. *Juan: Because the painter's salary is 120 plus renting 127* [Specific answers on an item/step].
	Individual calculation: *Juan: 15... 15 for 9, 45 carrying 4... It's 135.* *María: You have 62 and you have 12 and 56… is 68.*
	Shared calculation: *María: It is 12 and how much more?* *Juan: 62 and profit.* *María: 74 plus 30.* *Paúl: 104.*
	Individual overload: *Paúl: No, wait, wait. Wow much was it? 156, … no 186.* *Juan: 18 plus 47 plus 155 is two thousand…, two thousand… my brain doesn't work.*
Socio-regulatory interactions	**Organization interaction**: *Juan: First let's add the variables.* *Paúl: First the contribution, and it's obtained by calculating the fixed costs.* *María: First, let's see which the variable are and then the fixed costs.*
	Coordination interaction: *Juan: Let's add the variables.* *Paúl: Let's calculate the contribution.*
	Explicit offloading information: *María: Okay, let's remember, the contribution is 40.* *Juan: Paúl, keep in mind 132.* *Paúl: It's 350* [Individual calculation], *I remember it* [Explicit offloading information].
	Time control: *Juan: We're running out of time.* *María: Let's see how long we take?* *Paúl: We've 3 minutes left!*

Chapter 3

Socio-emotional interactions	**Task-unrelated positive emotions**: *Juan: with the Melanie* [Task-unrelated interactions], *hahaha ((laughing softly)).* *Paúl: Uhh there is when you are gonna get a hit on your ass* [Task-unrelated interactions] *hahaha.*
	Task-related positive emotions: *Juan: 80 by 10, it's 10* [individual calculation]. *María: Hahaha ((laughter)).* *Juan: Yes, yes, I know. It's 8* [individual calculation].
	Task-related negative emotions: *Juan: Ahhh! ((complaining)), enrollment of each student is variable, or not?* [Specific questions on an item/step] *María: No ahhh ((frustration)), what did we do first, fixed or variable?* [Specific questions on an item/step] *Paúl: Ahhh! I don't know ((Complaining)). Didn't you memorize it?* [Specific questions on an item/step]
Task unrelated interaction	**Expletives**: Expressions such whore or shit.
	Task-unrelated talks: *Juan: 56? Poor he doesn't even reach the basic salary.* *Paúl: Yes, because on Monday you can go with Sandra Michelena.* *Juan: Aha, you loved her.* *María: Only because there is Erik.*

Appendix C

Table C1

Frequencies of Codes per Group

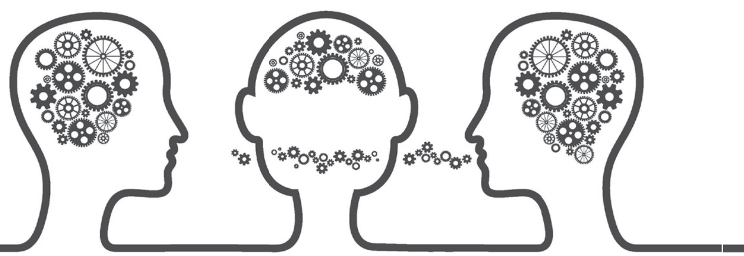
Transactional activities	*Experienced Groups*					*Non-Experienced Groups*					*Total*
	1	2	3	4	5	1	2	3	4	5	10
Socio-cognitive interactions											
Interpreting the problem	5	4	5	3	2	10	12	10	6	4	61
Sharing task items	27	29	36	12	19	15	34	19	17	13	221
Specific questions on an item/step	77	72	82	91	83	44	70	106	59	63	747
Specific answers on an item/step	56	58	89	83	63	31	52	104	56	50	642
Implicit answer to an item/step	17	20	10	13	21	2	22	4	31	6	146
Discussion for agreement	16	18	5	9	3	10	0	5	15	0	81
Self-correction	3	4	3	8	10	0	3	1	2	2	36
Affirmative confirmation	58	68	95	58	54	25	35	61	58	12	524
Negative refutation	5	1	7	6	7	5	5	8	11	10	65
Correction to others	24	20	20	19	13	27	27	21	17	8	196
Question for clarification	7	9	9	2	9	7	9	4	7	3	66
Individual calculation	8	12	13	8	16	42	44	26	24	33	226
Shared calculation	126	70	64	79	41	61	29	14	56	18	558
Individual overload	14	11	18	12	21	3	7	24	13	10	133
Socio-regulatory interactions											
Organization interaction	11	1	14	2	7	23	12	4	1	14	89
Coordination interaction	12	12	25	21	30	18	33	32	28	19	230
Explicit offloading information	0	2	0	0	0	5	3	0	0	0	10
Time control	3	2	6	2	1	5	5	9	12	1	46

Transactional activities	*Experienced Groups*					*Non-Experienced Groups*					*Total*
	1	2	3	4	5	1	2	3	4	5	10
Socio-emotional interactions											
Task-related positive emotions	16	3	12	3	34	20	19	17	3	13	140
Task-related negative emotions	11	8	9	3	13	3	12	5	4	6	74
Task-unrelated positive emotions	1	0	2	1	8	2	25	4	6	0	49
Task unrelated interactions											
Expletives	2	1	3	1	1	5	13	7	21	4	58
Task-unrelated talks	5	5	7	3	7	18	47	17	66	10	185
Sum	504	430	534	439	463	381	518	502	513	299	4583

4. Effects of Group Experience and Information Distribution on Collaborative Learning[3]

While teachers are increasingly using collaborative learning, they often do not pay attention to either prior group experience and task collaborative intensity caused by the distribution of information amongst group members. This study examined the interaction effects of prior collaborative experience (i.e., experienced versus inexperienced groups), and distribution of information amongst collaborators (i.e., high-intensity distribution versus low-intensity distribution), on the efficiency of solving highly complex tasks. The results obtained with 240 secondary school students showed that experienced groups outperformed and were more efficient than inexperienced groups, and low-intensity distribution increased performance during the learning process. Also, when tasks required high-intensity group processing, experienced groups were more efficient than inexperienced groups. For tasks with low intensity of group processing, no difference was found. These results provide instructional implications for designing efficient collaborative learning environments.

Keywords: collaborative learning, cognitive load theory, group experience, information distribution.



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Collaborative learning is a promising instructional technique for learning to solve complex problems (Hesse et al., 2015). However, research shows that its benefits are not always consistent (Kester & Paas, 2005; Slavin, 2014). Discrepancies may be due to a lack of knowledge about the many different interacting variables involved in inter-individual activities (Hogg & Gaffney, 2018). To reduce this gap, this paper first discusses the advantage of preparing groups to collaborate effectively and shows some existing knowledge gaps in the research. Second, cognitive load theory is used to suggest the advantages of preparing groups to collaborate because this would optimize the collaborative cognitive load, taking into account the effect of the distribution of task information among group members. Third, these theoretical considerations are followed by a report on an experiment that investigated the effect of prior collaborative experience and information distribution on collaborative learning and its outcomes (i.e., in short-term retention and delayed retention tests) (P. A. Kirschner et al., 2018; Sweller et al., 2011).

Collaborative Learning

Collaborative learning has increasingly become important in schools and organizations. It is the process by which learners interact in small groups to learn (Slavin, 2014). This instructional technique has been broadly studied from different disciplines and theoretical perspectives (Hmelo-Silver et al., 2013). Consequently, there are many strategies for designing learning environments based on group work such as structured academic controversy (D. W. Johnson & Johnson, 1988), jigsaw (Aronson & Patnoe, 2011), reciprocal teaching (Palincsar & Brown, 1985), and division of student teams based on achievement (Slavin, 1978). These techniques have been categorized as cooperative when group interactions are highly structured to achieve specific learning goals, and each learner is responsible for a part of the task. Cooperative learning strategies are mostly conceived from psychological or sociological accounts. This approach is often strictly governed by rules to aid group members in their interaction and, as such, is more directive than collaborative learning and is usually strictly controlled by the teacher (Panitz, 1999). In contrast, collaborative strategies derive mostly from philosophical and political accounts that suppose that knowledge is a social construction. Here, group members are expected to share authority and responsibility amongst group members for group actions (Panitz, 1999). These perspectives advocate that learners work in small groups and knowledge communities to share, dialogue, and create meaning around their knowledge and experiences (Oxford, 1997). In this research, although collaborative learning is used, we have not distinguished between cooperative and collaborative learning because there are more commonalities than differences between them in terms of fostering deep learning. For example, learning happens in an active mode, the teacher plays the role of facilitator, teachers and learners share knowledge, students work in small-group activities, students must take responsibility for learning, and learners should develop team skills (P. A. Kirschner, 2001).

There is considerable evidence that shows the benefits and limitations of collaborative learning. For example, the meta-analysis conducted by D. W. Johnson, Maruyama, Johnson, Nelson, and Skon (1981) indicated that collaboration resulted in significantly higher test performance than interpersonal competition and individualistic efforts. It also shows that collaboration with intergroup competition is better than interpersonal competition and individualistic efforts. Furthermore, it was found that task productivity (i.e., group product) and task interdependence were associated with better results, whereas for rote decoding and correcting tasks, collaboration was less effective. In another meta-analysis, Qin, Johnson, and Johnson (1995) concluded that group members outperformed individuals competing on different problem-solving tasks. Pai, Sears, and Maeda's (2015) meta-analysis found that small-group learning can promote transfer; however, they admit that additional research is needed to clarify how the structure and complexity of the task affect transfer.

In contrast, Thanh, Gillies, and Renshaw (2008) found that groups sometimes did not work as expected if their learners have a strong culture of competition and dedicate much time engaged in individualistic learning. They concluded that a collaborative group would be difficult to implement in these social contexts. Another meta-analysis (Kyndt et al., 2013) concurs with this conclusion as it found that individualistic cultures often were less likely to obtain high effects under collaborative conditions. Other authors have found negative factors at individual and group level that hinder collaborative learning such as social loafing, social pressure, group conformity, the free-rider effect, and the sucker effect (see Kreijns et al., 2003; Rajaram & Pereira-Pasarin, 2010). To untangle the inconclusive results about the advantages of collaborative learning, some researchers have suggested preparing groups for learning collaboratively (Cortez, Nussbaum, Woywood, & Aravena, 2009; Jurkowski & Hänzea, 2016; Van den Bossche, Gijselaers, Segers, Woltjer, & Kirschner, 2011).

Preparing Groups for Collaboration

Grouping learners to learn from each other does not mean that they will work appropriately or that they will learn better (Lou et al., 1996). There are data that support the assumption that preparing learners to work together may be a way to improve collaborative learning results (Baines, Blatchford, & Chowne, 2007; Bischoff, Springer, Reisbig, Lyons, & Likcani, 2012; Buchs, Gilles, Antonietti, & Butera, 2015; Gillies & Ashman, 1996; Jurkowski & Hänze, 2015). For example, Prichard, Bizo, et al. (2006) examined the benefits of preparing learners on how to work in groups with different cohorts. They found that a cohort that received instructions on how to collaborate outperformed a cohort that was not prepared, and that the benefits of preparing for collaboration were lost when the group members split up into new groups. Buchs et al. (2015) also prepared learners by providing them with instruction on why and how to collaborate. They found that learning in dyads after 10 minutes of instruction on working together resulted in better learning results compared to learning individually or collaboratively without such instruction. Similarly, Jurkowski and Hänze (2015) used a 100-min session for training students about transactive communication to enhance group communication and knowledge acquisition during collaborative learning. Their results showed that trained groups outperformed and displayed more transactive communication than untrained groups.

Others investigations show that learners with prior group preparation can allocate effective communication patterns to efficiently complete a task (Jurkowski & Hänzea, 2016), exchange elaborated explanations and constructive activities (Webb et al., 1995), and effectively distribute high task demands amongst themselves and monitor their contributions (Fransen, Kirschner, & Erkens, 2011). Once groups have acquired task and team schemas (i.e., a shared mental model; Van den Bossche et al., 2011), they may better focus their interactions on learning tasks and obtain better learning. Conversely, a group without such prior experience may perform interactions that may be irrelevant to the task. These data suggest that groups may obtain higher test scores and be more efficient when receiving guidance on how to collaborate on relevant tasks (Jurkowski & Hänze, 2015; P. A. Kirschner & Erkens, 2013; Stevens, Slavin, & Farnish, 1991).

Among the limitations of the perspective that advocates preparing groups for collaboration is the lack of attention to the factors that may affect the quality of the interactions and whether effects are long-lasting (e.g., on delayed retention tests after one week) (Soderstrom & Bjork, 2015). Inter-individual processes may result in different outcomes depending on the test timing, characteristics of the group members (e.g., learners with prior collaborative experience) and the demands of the task.

Cognitive load theory may help to understand how task complexity affects the performance and mental effort of collaborative learning.

Cognitive Load Theory and Collaborative Learning

Cognitive load theory is an instructional theory based on the human cognitive architecture that underlies inter-individual activities (Sweller et al., 2011). According to the theory, acquiring new domain-specific knowledge depends on working memory limitations that may not allow processing of more than about two elements at once (i.e., processing around two elements at once; Cowan, 2010). If the tasks require processing many highly interacting elements in a limited amount of time, learners will need to execute many cognitive operations which increases cognitive load. Cognitive load refers to the working memory load intensity when performing cognitive activities to achieve a specific learning goal (Kalyuga & Singh, 2016). This load is intrinsic if it refers to processing essential information of learning tasks or extraneous if it is caused by instructional procedures. Germane cognitive load refers to working memory resources available to deal with intrinsic cognitive load (Sweller, 2010). Optimal instruction for novices should reduce extraneous load and maintain intrinsic load without exceeding working memory capacity. If intrinsic cognitive load is low, extraneous cognitive load differences may have less effect because working memory limits may not have been exceeded. Once a learner has stored task information elements in long-term memory, they can be recovered as an encapsulated element, freeing up working memory resources for processing new information (Sweller, 2010).

Cognitive load theory findings mostly apply to individual learning conditions. However, collaborative learning is gaining attention from cognitive load researchers (Kester & Paas, 2005). In group learning settings, one factor that may influence cognitive load, in addition to the interacting information elements of the task, is transactional activities consisting of communication and coordination activities among group members that are specific to collaborative learning. Working together is necessary when performing a group task and, as such, transactional activities play a critical role in determining the advantages and the limitations of collaborative learning (P. A. Kirschner et al., 2018).

Collaborative learning seems to work better when learning tasks are cognitively demanding. Studies conducted by F. Kirschner and her colleagues (F. Kirschner, Paas, & Kirschner, 2011; F. Kirschner, Paas, Kirschner, & Janssen, 2011) suggest that group learning is more efficient when tasks are highly complex. F. Kirschner et al.'s studies found that the task should be complex enough to justify investing working memory resources on transactional activities. However, if tasks had a low level of complexity, transactional activities are unnecessary and even detrimental compared to individual learning. These investigations suggest that distributing information-elements of high-complexity tasks amongst learners may increase test scores and cognitive efficiency because information elements are processed by more working memories (the collective working memory effect; F. Kirschner, Paas, & Kirschner, 2011). Further, cognitive load imposed by transactional activities may be lower compared to the load associated with processing all information elements by one learner.

Other studies conducted by Retnowati et al. (2010, 2016) suggest that collaboration may not improve learning in high-complexity tasks compared with individual learning depending on the instructional procedure being followed. They investigated the effect of conventional problems and worked-out examples on individual and collaborative learning and found that in some high-complexity tasks, individuals performed better than groups. They also found that collaborative learning was more beneficial than individual learning in solving problems but not in studying worked examples.

Optimizing Transactional Activities

In tasks that should be performed individually (i.e., that do not require collaboration), transactional activities impose an extraneous cognitive load because communication and coordination activities are not essential components. If the task is collaborative in nature, transactional activities are a type of intrinsic cognitive load. In either case, collaborative load should be optimized through instructional procedures to achieve the learning goals (P. A. Kirschner et al., 2018).

Prior collaborative experience as generalized domain knowledge.

Literature about preparing learners for collaboration suggests that learning in groups may be more beneficial when the members of the group receive explicit guidance on how to work together (see section Preparing Groups for Collaboration). Providing collaborative experiences with high-complexity tasks may help learners acquire shared mental models of joint work (Van den Bossche et al., 2011) that can guide their transactional activities during collaborative learning. This does not mean that collaborative learning is a kind of general knowledge that can be applied to any domain of knowledge indiscriminately. This general knowledge perspective fails to take into account that the characteristics of the multiple types of learning tasks can result in different forms of joint work and that there are many ways to learn collaboratively. This premise suggests that it is better to prepare learners to collaborate according to particular characteristics of a task or domain. Task- or domain-based collaborative experience may help learners to generalize those skills that are unique to that learning environment (Bischoff et al., 2012).

Prior collaborative experience is a factor that has not yet been explored using cognitive load theory. However, the emerging construct of *generalized domain knowledge* may imply this experience. While domain-specific knowledge applies to a narrow range of specific tasks in the domain, "generalized domain knowledge applies to a wider class of different tasks in this domain [and] it remains a part of domain-specific knowledge" (Kalyuga, 2013, p. 1479). Thus, it is plausible to assume that when group members solve together domain-specific tasks, they also construct relevant shared schemas of collaborative processes that can be transferred to other similar tasks (Gick & Holyoak, 1983). This group experience may be a domain group schema (i.e., a generalized domain skill at group level) that is stored in long-term memory to solve similar learning problems (Zambrano R. et al., 2019b). Furthermore, as is the case for any relevant knowledge structure, group experience may work as an internalized guidance that regulates transactional activities, optimizes collaborative cognitive load, and leads to better learning outcomes (Hagemann & Kluge, 2017; Jurkowski & Hänze, 2015; Van den Bossche et al., 2011; Zambrano R. et al., 2018).

Element interactivity and information distribution.

The number of interacting elements to be temporally processed in working memory is the major source of cognitive load (Sweller, 2010). An element can be considered as a schema that needs to be learned (e.g., a number or a set of steps to solve a mathematic problem). Any change in the elements, either in the task or in the long-term memory structure, alters the cognitive activity of working memory (Sweller et al., 2011). Consequently, variations in element interactivity may explain all cognitive load theory effects.

When learning new tasks, different ways of distributing information amongst group members may affect transactional activities and in turn collaborative learning outcomes (P. A. Kirschner et al., 2018). Mostly, investigations address the effect of information distribution from the hidden profile paradigm. From this perspective, relevant items are distributed in a way that group members are led to prefer a suboptimal solution alternative, while only the combined information uncovers the best solution (Deiglmayr & Spada, 2010; Stasser & Titus, 2003). However, information distribution has not been experimentally studied with learning problems from a cognitive load theory perspective. Despite this gap of knowledge, it is possible to anticipate specific results based on element interactivity.

Groups are viewed as information processing systems with more cognitive capacity than individual learners (Hinsz et al., 1997). This increased working memory-advantage is especially crucial when tasks are highly complex (F. Kirschner, et al., 2011a). However, having a larger cognitive reservoir may have no effect when the way of distributing task information amongst members increases unnecessarily transactional activities harming learning (Deiglmayr & Spada, 2010). If the information of a learning task is distributed so that one group member can solve one step of the problem, but then s/he communicates his/her partial result with others to solve the whole task collaboratively, the intensity of the cognitive load may decrease. Reducing the number of inter-individual activities and the associated cognitive load may free working memory resources for creating a better mental representation of the task. As a result, test scores and cognitive efficiency of collaborative learning may increase. Conversely, if no step of the problem can be performed without all members sharing and discussing each of their information elements, group processing intensity may increase which may impose an additional cognitive load and impair learning.

The Present Study

Based upon the aforementioned, this study examined the effects of prior collaborative experience on relevant tasks (experienced groups vs. inexperienced groups), and information distribution (low vs. high information density) on the performance of collaborative learning and its outcomes on short-term retention and delayed retention tests. We expected that experienced groups would focus their cognitive resources on better transactional activities, thus increasing test scores (Hypothesis 1) and reducing cognitive load leading to increased efficiency (Hypothesis 2) than inexperienced groups. Lower information density should decrease cognitive load because learners require fewer transactional activities amongst themselves, leading to higher test scores (Hypothesis 3) and lower cognitive load with increased efficiency (Hypothesis 4) than higher information density. Therefore, it can be expected that for a task with higher information density, prior collaborative experience allows groups to increase test scores (Hypothesis 5) and decrease cognitive load leading to increased efficiency (Hypothesis 6) than inexperienced groups. However, in tasks with lower information density, the advantage of having prior collaborative experience is redundant leading to a reduction in the difference in similar test scores (Hypothesis 7) and a reduction in the difference in efficiency (Hypothesis 8) between experienced and inexperienced groups.

Method

Participants

The study was conducted with 240 high-school Ecuadorian students from a large public school in Quito as part of the mathematics classes. The gender distribution was 59 female and 181 male, and the average age was 15.58 years (*SD* = .84). No difference in prior knowledge was expected because the learning phase tasks are not included in the content of the very strict Ecuadorian national curriculum which explicitly prohibits the teaching of non-prescribed topics. Further, teachers confirmed that they had not previously taught the included content and that all participants came from the same school. The use of random assignment to all conditions excluded any systematic prior knowledge differences. Despite curricular restrictions, this research received approval from the School Ethical Committee (official communication 007-VCEM/15-16) as part of their program of learning improvement. Learners were notified of the study, that their participation is voluntary and that they would receive an academic compensation of 10 points for participation.

Design and Procedure

A 2 (group experience: experienced vs. inexperienced group) x 2 (information distribution: low information density vs. high information density) factorial design was used. The study was conducted in four phases with 45-minute sessions: preparation, learning, short-term retention test, and delayed retention test. Three instructors and an experimenter carried out the study. Instructors were previously informed about the procedure and were supervised by the experimenter to ensure condition fidelity. Guidelines were read aloud, and a digital clock was used to show the number of minutes allotted to each task. Time for each task of the phases was established through a pilot study showing the amount of time needed to solve a task without high time pressure. Because data from the learning, short-term retention and delayed retention phases were analyzed independently, if a learner who participated in the learning phase did not participate in the short-term retention test, they were allowed to participate in the delayed retention test.

Preparation.

This phase aimed to prepare groups to undertake high-complexity collaborative tasks using quadratic equations (i.e., $ax^2 + bx + c = 0$, where a, b, and c represent constants and $a \neq 0$). It began in the second week of the new school year after a two-month vacation. It was ensured that participants had no previous classroom familiarity with each other nor prior collaboration experience within the last two months. Participants were randomly assigned to two conditions: one half worked in 3-person groups (experienced group condition), and the other half worked individually forming the inexperienced group condition in the next phase (i.e., the learning phase). All worked in four sessions, one session per day over one week. Both conditions worked on the same tasks. The first tasks had no time constraints. The last two tasks of the second session onward had to be solved within 10 min. While performing the tasks, each team member was required to interact with other members in order to share their items and maintaining partial results in working memory. At the end of each session, participants received the correct answers and were required to spend 5 min on planning how they could work better on subsequent tasks.

Learning.

This collaborative learning phase was conducted in one session after the preparation phase. Groups that had not completed all preparation phase sessions were excluded. Random absences were caused by the school administration asking students to perform activities related to the beginning of the school year. These absences unbalanced the number of planned groups per condition. However, as participants had learned to solve quadratic equations in the previous year and all dropouts occurred before the learning phase, it was not necessary to analyze whether there was a difference between the excluded learners and those who remained. Further, an a priori analysis with a power of .8 and a medium-size effect (i.e., .06; Cohen, 1988) revealed that the study needed 31 participants (11 triadic groups) per condition indicating that the remaining participants were sufficient to reliably test the hypotheses.

Learners who had worked individually were randomly distributed into 26 groups of 3-persons (i.e., inexperienced group condition), while 39 experienced groups remained intact. All groups were randomly assigned to two conditions of information distribution (i.e., low information density and high information density). For the experienced group condition, 18 groups received low information density and 21 the high information density materials. For the inexperienced group condition, 15 groups received the low information density and 11 the high information density materials. All groups worked on three tasks for 27 min, 9 min per task. Instructors encouraged groups to focus on the task and avoiding unnecessary conversations. Writing in this phase when performing calculations was not permitted to prevent cognitive off-loading through external representations (Van Bruggen et al., 2002). Only one group member was allowed to write down the answer for each task. If a group solved the problem before the allotted time, that group had to wait to start the next problem.

Short-term and Delayed Retention Tests.

Short-term and delayed retention tests were conducted one and seven days after the learning phase respectively. Participants individually were required to solve three similar problems with 10 min for each problem. The number of participants is shown in Table 1. In both phases, participants recorded the mental effort after each problem. Unlike in the learning phase, writing down calculations was permitted.

Table 1

Participants of the Short-term Retention and the Delayed Retention Tests

Learning Conditions	*N*
Short-term Retention Test Phase	
Experienced Groups	102
Low information density	51
High information density	51
Inexperienced Groups	76
Low information density	45
High information density	31
Delayed Retention Test Phase	
Experienced Groups	105
Low information density	54
High information density	51
Inexperienced Groups	76
Low information density	45
High information density	31

Materials

Learning materials were in the domain of mathematics and the comparable domain of economics. Quadratic equations were used in the preparation phase and break-even point problems in commercial transactions (the point at which a transaction resulted in neither a profit nor a loss) in the learning phase, as well as in short-term and delayed retention test phases. All materials were paper-based.

Preparation.

Quadratic equations are compulsory in the national curriculum, and all students had already learned to solve them the previous year. In the first session, participants received a booklet whose first part introduced quadratic equations with two worked examples using the factoring method. The second part presented rules on how to solve the equations collaboratively, followed by a worked example demonstrating how each member should apply the rules and a conventional task with the correct answer (Appendix A). Examples of the rules are: When it is possible to perform the calculations without the help of others, do it alone and continually rehearse the results to avoid forgetting them and Solving an equation will require many partial answers in your mind; decide who will have which partial result in your group; it is better that everyone has a result to avoid forgetting them or making a mistake in solving the equation.

Quadratic equation values were manipulated to provide group experience on the information distribution for the learning phase tasks. Equation values were unpacked to distribute them among learners (e.g., for $-15x^2$, each member would receive $-5x^2$). It required group members to depend on others' information to solve the problem. Individual participants (who were members of inexperienced groups in the learning phase) received the same values to solve the equations individually.

In the second session, groups and individuals again received the collaborative learning rules, two conventional problems with the correct answer and a conventional problem without the correct answer. In the third and fourth session, groups and individuals received three problems without correct answers. The values provided were relevant but were insufficient to solve the problem.

Learning.

Calculating a break-even point is considered to be an analog task to solving quadratic equations because it displays similar characteristics such as combining multiple numerical values, calculating partial step answers, holding them in working memory, and finding a unique correct answer. Participants received a booklet introducing the relevant concepts with two worked examples, questions to prompt them, three learning tasks, and a piece of paper with examples of costs and the break-even point in the units' formula. One worked example showed the students how to calculate the break-even point in units and sales with a profit margin. The other worked example was similar but without a profit margin. The worked examples had a 7-step procedure (see Table 2). Examples of the prompt questions were: a) What were the break-even points? b) What were the seven steps to calculate the break-even points? c) What was the difference between the break-even points in units and sales? d) How did you calculate the contribution?

Table 2
Steps and Information Elements to Calculate the Break-Even Points

Steps to Solve the Problem	*Calculations*	*Information Elements*	*Partial Results in the working memory*
1. Identify Cost Values	155, 63, 82, 50, 41, 108, 71, 119, 52	9	
2. Total Variable Cost	$VC_1 + VC_2 + VC_3 = TVC$		
	155 + 63 + 82 = 300	7	300
3. Variable Cost per Unit	TVC ÷ Amount Produced = CU		
	300 ÷ 50 = 6	5	300, 6
4. Contribution Margin	Price – CU = CM		
	41 – 6 = 35	5	6, 35
5. Total Fixed Cost	$FC_1 + FC_2 + FC_3$ + Profit Margin = TFC		
	108 + 71 + 119 + 52 = 350	9	35, 350
6. Break-Even Point in Units	TFC ÷ CM = BPU		
	350 ÷ 35 = 10	5	35, 350, 10
7. Break-Even Point in Sales	BPU × Price = BPS		
	10 × 41 = 410	5	10, 410

Note: VC = Variable Cost; FC = Fixed Cost; TVC = Total Variable Cost; CU = Variable Cost per Unit; CM = Contribution Margin; TFC = Total Fixed Cost; BPU = Break-Even Point in Units; BPS = Break-Even Point in Sales.

Task complexity was first checked by presenting the tasks to two Economics teachers and then questioning them as to the complexity. These teachers confirmed that the tasks were complex enough for novices. Also, the Sweller and Chandler method (1994) to determine complexity was used, which consisted of counting the approximate number of interacting elements. As can be seen in Table 2, problem-solving had seven steps and nine items. The items were three fixed costs, three variable costs, price, profit margin, and produced articles. Each step varied in the number of interacting items (Column 3 of Table 2). This amounted to a total of 45 items (including mathematical signs). For each step, a partial answer had to be calculated and held in working memory (Column 4 of Table 2) to be integrated with another partial answer. Writing was not permitted. The high complexity of the tasks was confirmed by the mean for mental effort in the learning phase tasks which was 7.38 on the 9-point scale (see Measurement section).

All groups received the same tasks, but with different information distributions. For the low information density groups, steps 2 and 5 could be solved without communication or coordination between peers. A group member only needed to share the partial answer to calculate the other steps and find the final answer. The items were balanced so that all group members had all task information during the learning phase. For example, for the first task, member 1 received three variable costs, for the second task three fixed costs and the profit margin, and for the third task, price and the produced number of things. For the high information density groups, no step could be performed without each member communicating his/her items to others and coordinating their calculations. To avoid confusion during the learning processes, members were given different examples of fixed and variable costs with the formula for the break-even point in units (see Step 6 of Table 2).

Short-term and Delayed Retention Tests.

Six high-complexity problems were used for testing. The problems were similar to the learning tasks, but the business situation and cost names were varied. Participants received three tasks a day after the learning tasks (i.e., short-term retention test), and the other three seven days after the learning tasks (i.e., delayed retention test). Each problem included a table with seven rows to write down the calculations for each step of the task's solution.

Measurement

Performance.

Performance was measured in the learning, short-term retention test, and delayed retention test phases. The total number of points that could be scored for all the three learning tasks was 3, 1 per task, if an answer was correct. If an answer was incorrect, the task scored was 0. For each of the three short-term retention test tasks, 7 points could be awarded. These points were based upon the 7 calculations required to determine the break-even point. Each calculation was scored individually when considering whether correct values and mathematical operations were used. A correct step's calculation received 1 point and an incorrect step's calculation 0. This resulted in a maximum score of 21 points and a minimum of 0. If a step was partially correct, a proportional score was given. The same scores were applied to the delayed retention test's tasks. The scores were transformed into proportions.

Cognitive Load.

Cognitive load was measured after the third task of the learning phase and after each task in the short-term and delayed retention test phases using a subjective 9-point mental effort scale (Paas, 1992). The collaborative cognitive load of the learning phase was calculated averaging the mental effort scores of the members. Individual scores for mental effort were used in the other phases.

Efficiency.

Efficiency (E) refers to the quality of learning as result of combining performance and mental effort (Paas & Van Merriënboer, 1993). A high efficiency denotes relatively high performance in combination with relatively low mental effort. By contrast, low efficiency means relatively low performance with relatively high mental effort. Efficiency was computed by standardizing each of the participant's scores for task performance and the mental effort. For each participant, z-scores were calculated for effort (R) and performance (P) using the formula $E = [(P - R)/2^{1/2}]$.

Results

Data was analyzed with 2 (group experienced: experienced vs. inexperienced group) x 2 (information distribution: high information density vs. low information density) multivariate analyses of variance (MANOVA) and analyses of variance (ANOVA). Dependent variables were performance, mental effort, and efficiency, which were measured and independently analyzed for the learning, short-term retention, and delayed retention phases. Descriptive statistics are shown in Table 3. Partial eta-squared was used to determine the effect size with values of .01, .06 and .14, corresponding to small, medium and large effects respectively (Cohen, 1988).

Learning Phase

MANOVA revealed significant main effects for group experience, $F(2, 60) = 10.40$, Wilks' $\Lambda = .74$, $p < .001$, $\eta_p^2 = .26$, and information distribution, $F(2, 60) = 3.33$, Wilks' $\Lambda = .90$, $p = .04$, $\eta_p^2 = .10$, which indicate that these variables affect a combination of performance, mental effort, and efficiency scores. The interaction between these effects was nonsignificant, $F(2, 60) = .67$, Wilks' $\Lambda = .98$, $p = .52$, $\eta_p^2 = .02$.

Two-way ANOVAs were conducted to examine the variables separately (see Table 4).

Table 3

Mean and Standard Deviations for Dependent Variables of Study Phases

Dependent Variable	*Learning Phase*				*Short-term Retention Test Phase*				*Delayed Retention Test Phase*			
	Experienced Group		*Inexperienced Group*		*Experienced Group*		*Inexperienced Group*		*Experienced Group*		*Inexperienced Group*	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Performance (0-1)												
High information density	.43	.42	.12	.22	.44	.23	.23	.27	.45	.32	.23	.21
Low information density	.65	.40	.13	.21	.46	.21	.38	.29	.47	.28	.34	.29
Mental Effort (1-9)												
High information density	7.78	1.98	8.09	0.96	5.86	2.70	5.39	2.26	4.94	1.96	4.81	2.69
Low information density	6.58	2.11	7.05	1.36	7.08	2.17	5.62	2.81	5.75	2.70	4.58	2.34
Efficiency												
High information density	-0.07	1.26	-0.73	0.54	0.18	0.92	-0.27	0.84	0.19	0.84	-0.31	0.66
Low information density	0.78	1.12	-0.30	0.69	-0.08	0.75	0.07	0.85	-0.01	0.83	0.01	0.79

Table 4

Two-Way Analyses of Dependent Variances for Each Phase

Source	*Learning Phase*				*Short-term Retention Test Phase*				*Delayed Retention Test Phase*			
	MS	*F*(1, 61)	*p*	η_p^2	*MS*	*F*(1, 174)	*p*	η_p^2	*MS*	*F*(1, 177)	*p*	η_p^2
					Performance							
Group experience (G)	2.59	21.12	<.001	.26	0.96	15.62	<.001	.08	1.39	17.23	<.001	.09
Information distribution (I)	0.21	1.68	.20	.03	0.33	5.35	.02	.03	0.17	2.05	.15	.01
G × I	0.17	1.35	.25	.02	0.16	2.52	.11	.01	0.10	1.19	.28	.01
Error	0.12				0.06				0.08			
					Mental effort							
Group experience (G)	2.33	0.75	.39	.01	39.83	6.30	.01	.04	18.11	3.09	.08	.02
Information distribution (I)	19.15	6.18	.02	.09	22.47	3.56	.06	.02	3.64	0.62	.43	.00
G × I	0.09	0.03	.87	.00	10.26	1.62	.20	.01	11.51	1.97	.16	.01
Error	3.10				6.32				5.85			
					Efficiency							
Group experience (G)	11.62	11.26	<.001	.16	0.88	1.24	.27	.01	2.51	3.98	.05	.02
Information distribution (I)	6.24	6.05	.02	.09	0.07	0.10	.76	.00	0.18	0.28	.60	.00
G × I	0.69	0.67	.42	.01	3.80	5.35	.02	.03	2.96	4.69	.03	.03
Error	1.03				0.71				0.63			

Concerning performance, ANOVA revealed that experienced groups ($M = .52$, $SD = .42$) outperformed inexperienced groups ($M = .13$, $SD = .21$). For mental effort, groups with low information density ($M = 6.80$, $SD = 1.80$) perceived lower mental effort than groups with high information density ($M = 7.89$, $SD = 1.68$). For efficiency, experienced groups ($M = 0.32$, $SD = 1.26$) were more efficient than inexperienced groups ($M = -0.48$, $SD = 0.65$) and low information density ($M = 0.29$, $SD = 1.09$) was more efficient than high information density ($M = -0.30$, $SD = 1.11$).

Short-term Retention Test Phase

MANOVA revealed a significant main effect for group experience, $F(2, 173) = 9.07$, Wilks' $\Lambda = .91$, $p < .001$, $\eta_p^2 = .10$, and information distribution, $F(2, 173) = 3.60$, $p = .03$, Wilks' $\Lambda = .96$, $\eta_p^2 = .04$. This suggests that both independent variables affect performance, mental effort, and efficiency simultaneously. The interaction between these effects was nonsignificant, $F(2, 173) = 2.69$, Wilks' $\Lambda = .97$, $p = .07$, $\eta_p^2 = .03$.

For performance, ANOVA (see Table 4) revealed that experienced groups significantly outperformed ($M = .45$, $SD = .22$) inexperienced groups ($M = .31$, $SD = .29$). It also showed that groups with low information density ($M = .42$, $SD = .25$) outperformed high information density ($M = .36$, $SD = .27$). Concerning mental effort, experienced groups ($M = 6.47$, $SD = 2.51$) reported more mental effort than inexperienced groups ($M = 5.53$, $SD = 2.58$). Regarding instructional efficiency, the significant interaction between main effects indicated that for the task with high information density, experienced groups are more efficient than inexperienced groups, ($p = .02$, $\eta_p^2 = .03$). However, for the task with low information density, experienced groups and inexperienced groups are not significantly different ($p = .37$, $\eta_p^2 = .01$).

Delayed Retention Test Phase

MANOVA yielded a significant main effect for group experience, indicating that this variable affects performance, mental effort, and efficiency, $F(2, 176) = 8.64$, Wilks' $\Lambda = .91$, $p < .001$, $\eta_p^2 = .09$. The main effects for information distribution, $F(2, 176) = 1.07$, Wilks' $\Lambda = .99$, $p = .35$, $\eta_p^2 = .01$, and the interaction between these effects, $F(2, 176) = 2.34$, Wilks' $\Lambda = .97$, $p = .10$, $\eta_p^2 = .03$, were nonsignificant.

For performance (Table 4), the analysis revealed that experienced groups ($M = .46$, $SD = .30$) outperformed inexperienced groups ($M = .29$, $SD = .26$). For instructional efficiency, experienced groups ($M = 0.09$, $SD = 0.83$) were more efficient than inexperienced groups (*M* = -0.12, *SD* = 0.75). The significant interaction between main effects indicated that for the task with high information density, experienced groups are more efficient than inexperienced groups, ($p = .01$, $\eta_p^2 = .04$). However, for low information density, experienced and inexperienced groups are not significantly different ($p = .90$, $\eta_p^2 = .00$).

Discussion

The goal of this study was to examine the effect of prior collaborative experience (i.e., experienced vs. inexperienced groups) and collaborative intensity related to task information distribution (i.e., high information density vs. low information density) on test scores and cognitive load during collaborative learning. We discuss the result for each hypothesis.

It was hypothesized that groups with prior collaborative experience would obtain higher test scores (Hypothesis 1) and lower cognitive load resulting in increased efficiency (Hypothesis 2) than inexperienced groups. Results confirmed the expectation for increased test scores following prior collaborative experience in all phases and increased efficiency in the short-term and delayed retention tests. These are the primary results of this experiment.

The results suggest that prior collaborative experience in similar tasks was transferred to new complex learning tasks (Kalyuga, 2013) and helped to optimize the cognitive load associated with transactional activities (P. A. Kirschner et al., 2018). Acquiring collaborative schemas based on similar tasks permitted groups to deal with the high cognitive load of high information density. It seems that working memory resources invested in transactional activities were used to construct high-order schemas of the learning tasks (Van den Bossche et al., 2011). This result is in line with Fransen et al. (2013) in the sense that experienced groups developed group and task schemas. In contrast, inexperienced groups could not handle the high cognitive load leading to the construction of poor knowledge of the tasks. An interesting result is that inexperienced groups reported a lower mental effort in the short-term retention phase which significantly decreased efficiency in experienced groups. One possible explanation for this result is that their lower knowledge level may have reduced their assessment of the complexity of tasks, overestimated their current performance which in turns decreased their mental effort ratings (Nugteren, Jarodzka, Kester, & Van Merriënboer, 2018a).

Concerning information distribution, we expected that low information density decreases cognitive load because learners require fewer transactional activities amongst themselves, leading to higher test scores (Hypothesis 3) and efficiency (Hypothesis 4) than high information density. Results supported these hypotheses for performance in the short-term retention test and for efficiency in the learning phase. It seems that the advantage of some group members being able to solve part of the problem individually affected transactional activities during the learning phase increasing efficiency. But this benefit only improved the performance in short-term (i.e., the short-term retention test), and faded out in the delayed retention test.

As the distribution of the amount of information alters intrinsic cognitive load (Sweller et al., 2011), it is intriguing that differential information distribution did not achieve the same impact as the prior collaborative experience (see effect sizes in MANOVAs). This result might be explained by the positive interdependence acquired by the experienced groups. A relevant study that may support this explanation is provided by D. W. Johnson, Johnson, Ortiz, and Stanne (1991) who compared the impact of positive goal interdependence and resource interdependence. They found that groups with positive goal interdependence exhibited better results than groups with positive resource interdependence. Our data seems to coincide with their results in the sense that shared schemas on how to work on relevant tasks may have more decisively affected collaborative learning than the interdependence based on information distribution.

Regarding the expected higher test scores (Hypothesis 5) and efficiency (Hypothesis 6) of experienced groups in tasks with higher rather than lower information density, the results did not yield evidence for performance. However, the experienced groups were more efficient in the short-term and delayed retention tests. The higher efficiency suggests that task-based collaboration schemas could be activated and transferred to the learning tasks. Although inter-individual activities under high information density conditions were more intense (i.e., more communication and coordination activities), it seems that experienced groups optimized the cognitive load and learned to solve problems more efficiently. The lack of significant results in the learning phase suggests that the advantages of collaboration are not always observable immediately (Soderstrom & Bjork, 2015). Subsequent individual post-tests revealed the benefits of having acquired collaboration schemas.

Concerning the reduction in the difference in similar test scores (Hypothesis 7) and efficiency (Hypothesis 8) between experienced and inexperienced groups when learning with low information density, results supported this expectation in all phases of the study with no significant differences on these measures. Data suggest that prior collaborative experience may be redundant when tasks have a low level of complexity in terms of inter-individual activity. Learners may have devoted working memory resources to harmonizing their schemes of working together with the low information density that required less group interaction. The experience of sharing each item and performing shared calculations for each problem step may have interfered with individual calculations. This could have unnecessarily increased the amount of inter-individual activities and the cognitive load impairing performance and efficiency.

The results of this study allow us to conclude that prior collaborative experience on relevant tasks and how the interacting information is distributed amongst learners are promising research lines that can improve our knowledge about collaborative learning. Data supported the assumption that grouping learners does not necessarily lead to better learning. For this reason, providing collaborative schemas using relevant tasks may help to improve group performance and member learning. This group advantage is crucial in learning situations where the tasks are complex (i.e., high level of element interactivity) and information distribution among group members demands a high level of intra-group activity.

Instructional design of collaborative learning should consider interacting information elements of a task and the cognitive load associated with transactional activities. Cognitive load theory assumes that any learning task is divisible into meaningful elements, and its distribution in collaborative settings may result in fundamental differences at group and individual level. For this reason, given that the goal of learning was to solve problems individually, firstly it is important not lose sight that the performance and efficiency of collaborative learning must be evaluated in terms of individual learning of group members (F. Kirschner et al., 2009a). Accordingly, collaborative learning is better when it promotes better individual learning.

Secondly, students who learn in groups with high-interactivity level tasks require relevant group work schemas (Zambrano R. et al., 2019b). Learning tasks needed to be solved with all information elements provided to group members, and information distribution was varied to test its effects on inter-individual activities. From cognitive load theory, transactional activities are complex meaning-making cognitive operations whose load in working memory may foster or inhibit the acquisition of schemas in long-term memory (Tindale & Kameda, 2000). As coordination and communication activities during learning may impose a high cognitive load, it seems that task-based group schemas help groups to better guide their actions to achieve higher effectiveness.

Our findings have important instructional implications when learning from collaborative high-complexity problems. If learners are novices, learning tasks are complex, and information distribution demands high inter-individual activity, teachers should prepare group members prior to collaboration using similar problems that are already known to them so that they learn to work together. During the learning phase, members should receive the conceptual and procedural knowledge to solve the problems. The distribution of information should be balanced among all group members so that everyone has the same opportunity to process all types of information elements. Because each member has only a part of the information, communication and coordination processes help students to acquire better mental representation of the tasks. If task information does not demand high interactivity among group members, it is not necessary for the teachers to prepare the learners to collaborate.

This study has some limitations. It is necessary to identify which specific factors are associated with the prior collaborative experience and the cognitive load they impose during learning (Janssen, Kirschner, et al., 2010). Future research should explore group composition, such as whether the benefits decrease when new groups are formed with members who differ in their experience (Prichard, Bizo, & Stratford, 2011). Further, more investigation is needed during class periods to determine how social factors such as friendship between learners or emotional regulation skills affect information distribution and its cognitive load.

Appendix A

Table A1

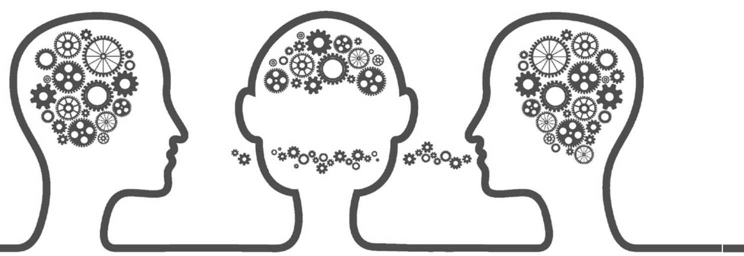
Example of Material used by Individuals in Preparation Phase

STEPS TO THE GROUP WORK	MEMBER 1	MEMBER 2	MEMBER 3
You should identify whether the values of the equation are on the **left side** or **right side** of the equal $=$ sign.	$-10x^2 + 13 =$	$20x - 14x^2 =$	$= -7 + 3x$
You should **communicate** with the other members to identify other similar values. Then, **pass the values** to the left side, changing the sign, and keep the **result in mind**.			
Perform quickly and without error, **all of the operations** that are possible and maintain the **result in your mind**.			
Everyone must share their values with others and **sort** them. **Keep in mind** the results.			
Factor the trinomial with your other partners. Remember to carry out these calculations **mentally**. To avoid forgetting a partial result, each member must have part of the information in his/her mind.			
When **Equal to Zero**, resolve the equations mentally.			
Write down the results on the worksheet:	$x_1 = -\frac{5}{8}$ $x_2 = \frac{4}{3}$		

5. Effects of Prior Knowledge on Collaborative and Individual Learning[4]

Collaborative learning is an extensively used instructional technique by which individuals interact in small groups to learn to solve academic problems. This study aimed to determine the impact of task-specific prior knowledge on individual learners and collaborative groups that were instructed to collaborate. A 2 (individual vs. collaborative group) × 2 (novice vs. knowledgeable learners) factorial experiment with 228 students was carried out to examine the effects of these treatments on performance and mental effort in learning and its outcomes. As expected, knowledgeable individuals and knowledgeable collaborative groups outperformed novice individuals and novice collaborative groups in learning outcomes. Less knowledgeable, collaborating learners outperformed less knowledgeable, individual learners in learning outcomes. While more knowledgeable collaborating and individual learners performed equally well in the learning phase and the delayed test, on the retention test, collaborative groups demonstrated better performance. In general, collaboration benefited learning compared to individual learning in complex tasks, but performance depended on the learner task-specific prior knowledge.

Keywords: cognitive load theory; collaborative learning; individual learning; topic prior knowledge.



[4] This chapter was published as:
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Introduction

Collaborative learning is an extensively used instructional technique. It refers to the process by which individuals interact in small groups to learn to solve academic problems (Slavin, 2014). However, literature indicates that learning in groups is not always associated with better learning compared to individual learning (Clinton & Kohlmeyer, 2005; Morgan & Tindale, 2002; Shibley & Zimmaro, 2002; Tindale, 1993; Weldon, Blair, & Huebsch, 2000).

This article begins with a short discussion of the importance of developing effective collaborative groups (i.e., team formation) and reveals that the results of research in this area are inconclusive. That being said, from an instructional perspective data indicate that providing explicit guidance on how to collaborate on highly demanding tasks may help collaborative groups to take advantage of inter-individual activities for learning. The discussion on developing collaborative groups is followed by a review of collaborative learning research from a cognitive load theory (CLT) perspective (Sweller et al., 2011). The experiment carried out here examined whether, taking prior knowledge into account, collaborative groups are more effective than individual learners when they are prepared to learn collaboratively with highly complex tasks. Groups were prepared for collaboration via explicit guidance on how to work together considering the characteristics of the tasks.

Promoting Successful Collaboration

One way to maximize collaborative learning is to develop collaborative groups to be effective. Research on team development suggests that a collaborative group is effective when it develops shared mental models, mutual performance monitoring, and interpersonal trust (Fransen et al., 2011), positive social interdependence (D. W. Johnson & Johnson, 2009) or social cohesion (Sharan & Sharan, 1992). This assumes that high-performing groups require extensive periods of time (Gersick, 1988; S. D. Johnson, Suriya, Won Yoon, Berrett, & La Fleur, 2002). However, research shows that collaborative group development is not always associated with higher performance. For example, concerning cohesion (i.e., the progressive tendency for a group to stick together in the pursuit of instrumental goals), a meta-analysis showed that the cohesion-performance relationship was stronger for tasks requiring high interdependence such as communication, coordination, and mutual performing monitoring (Gully, Devine, & Whitney, 2012). However, a subsequent meta-analysis reexamining this relationship found that cohesion had a lower effect size with increasing performance, decreasing even further when the measure of cohesion was more general (Castaño, Watts, & Tekleab, 2013).

From an instructional perspective, there is also evidence that suggests that learners can take advantage of collaborative work when they receive guidance on how to collaborate rather than waiting for collaborative groups to develop naturally. For example, Buchs et al. (2015) used 10 min to instruct group members on collaborative skills. They found that learning in dyads with instructional support on how to work together produces better learning outcomes compared to learning individually or collaboratively without instructional support. Prichard, Bizo, et al. (2006) examined the benefits of guiding collaborative members on how to work in groups with three cohorts. In general, they found that the cohort that received instructions on how to collaborate outperformed the cohort that was not trained and that the benefits of the collaboration guide could be lost when the collaborative group members split up into new groups.

Group development and instructional approaches have in common that collaborative groups should have some experience or guidance in working together. A factor in this might be task complexity as a determinant of the effectiveness of learners who have been prepared to collaborate compared to individual learners. Task complexity is a concern that has been extensively studied within a CLT framework.

Collaboration from a Cognitive Load Theory Perspective

CLT is an instructional perspective based on human cognitive architecture (Sweller, Van Merriënboer, & Paas, 2019). It suggests that when acquiring and automating complex knowledge (e.g., school domains) instructors should provide proper guidance keeping task complexity within working memory capacity which can be as low as two elements (Gilchrist & Cowan, 2011) and considering whether long-term memory structures facilitate or impair learning (Kalyuga et al., 2003). Cognitive load refers to the load on working memory when processing information (Sweller et al., 2011). CLT researchers have presented evidence that students learn better when they process task information within the boundaries of working memory (Sweller et al., 2011). If tasks are complex and little knowledge is stored in long-term memory, learners experience overload and performance decays.

Collaborative learning is an emerging research topic in CLT. Under some circumstances group interactions can be a source of cognitive load associated with a collaborative learning task (P. A. Kirschner et al., 2018). However, evidence of the advantages of collaborative learning compared with individual learning is not always consistent. On the one hand, there is evidence that a collaboration-based approach may be more beneficial than individual learning when problems are highly complex and when information is distributed among different working memories. Investigations by F. Kirschner et al. (F. Kirschner et al., 2009b; F. Kirschner, Paas, & Kirschner, 2011; F. Kirschner, Paas, Kirschner, et al., 2011) suggest that groups may be more effective and efficient because members can make use of each other's working memory resources (the collective working memory effect; F. Kirschner, Paas, & Kirschner, 2011). The collective working memory effect holds that collaborative learning is more effective than individual learning when the complexity of the learning material is high (F. Kirschner, Paas, Kirschner, et al., 2011). Sharing information processing of learning materials among the collaborative group members who share working memory resources permits better comprehension and knowledge acquisition of the to be learned tasks. This effect seems to occur when the benefits of reducing cognitive load due to information distribution (i.e., making learners depend on each other's information) are higher than the cognitive costs incurred in communication and coordination activities (i.e., transactional activities). F. Kirschner, Paas, and Kirschner (2011) also found that for low-complexity tasks, collaborative learning was redundant since group members achieved equal or lower performance and efficiency scores than individuals. An interesting result in F. Kirschner, Paas, Kirschner, et al. (2011) is that group members perceived a higher perception of mental effort in the learning phase which was related to a higher performance and efficiency on the posttest.

On the other hand, evidence suggests that collaboration does not improve learning either low- nor high-complexity tasks compared with individual learning. Investigations by Retnowati et al. (2010, 2016) investigated the effect of conventional problems and worked-out examples (worked examples) on individual and collaborative learning. They found that in some high-complexity tasks, individuals performed better than groups. They also found that working in collaborative groups was more beneficial than working alone in problem-solving tasks. In general, Retnowati et al. concluded that at least under some circumstances, especially when using worked examples collaborative learning is not better than individual learning either in high or low complex tasks. Unlike the Kirschner et al. study, task information was not distributed among members in these studies. Curiously, in the learning phase of the second experiment (Retnowati et al., 2016), individual learners outperformed groups in high-complexity tasks with a significantly higher cognitive load.

When considering prior knowledge, there are also mixed results. Zhang et al. (2015) explored collaborative learning when grouping learners by their scores of the previous year. Learners with lower scores were collaboratively grouped and categorized as less knowledgeable learners (with lower prior knowledge), and those with higher score as advanced learners (higher prior knowledge). The latter did not receive instruction on the domain-specific learning task. Researchers found that heterogeneous groups (i.e., groups including novice and advanced learners) favored lower prior knowledge learners, whereas for more knowledgeable learners, homogeneity was redundant. Moreover, individuals with higher prior domain knowledge marginally outperformed homogeneous and heterogeneous groups. Zhang et al. (2016) replicated this study and obtained similar results. These studies are limited because novice and advanced students were not grouped using prior knowledge specifically related to the learning tasks.

Retnowati, Ayres, and Sweller (2018) performed a study manipulating prior knowledge of learning tasks. Participants had either incomplete or complete prior knowledge and compared collaborative groups with individual learning. Interaction analyses revealed that when learners have gaps in their knowledge base, collaborative learning is superior to individual learning. However, when learners have complete prior knowledge, individual learning is superior to collaborative learning. They also found that individual learning condition participants with complete prior knowledge for all learning tasks (individual-complete knowledge condition) outperformed collaboration with complete and incomplete knowledge and individual with incomplete knowledge conditions in transfer tasks. However, the researchers did not compare complex and simple tasks. It is not yet clear whether these results would vary if the complexity of the tasks is increased to the point that individual learners with complete prior knowledge still need to rely on other group members' working memory resources.

Considering prior knowledge in collaborative learning also can pose challenges in predicting cognitive load. If group members are advanced, learning collaboratively may be harmful because transaction activities demand working memory resources resulting in increases in cognitive load. However, if the task has a very high level of interactive elements and peers have partially developed previous knowledge, it can be expected that the collaboration is beneficial. Thus, demands on working memory may increase if collaboration is unnecessary and decrease if collaborating partners have useful knowledge with group members taking advantage of partially developed schemas to refine their knowledge in a learning situation (i.e., reexposure effect; Rajaram & Pereira-Pasarin, 2010). These two opposing effects on working memory demands may counteract each other.

The Present Study

Task complexity, information distribution (member interdependence), and prior knowledge are factors that may explain the advantage of collaborative learning. However, the inconclusive results seem to suggest that grouping learners to collaborate does not necessarily promote better learning (Gillies, 2016). Also, currently there are no data from CLT-based studies about preparing groups to collaborate (see section 1.1).

Instructing students how to work collaboratively on specific tasks may be a category of domain-generalized knowledge (Kalyuga, 2013) at the group level (P. A. Kirschner et al., 2018). Knowledge about how to collaborate may work better when it is built into a domain-specific task. When this type of knowledge is learned in task-specific situations, it may be retrieved from long-term memory and used in similar tasks through analogical transfer (Gick & Holyoak, 1980). For example, a group of learners may better learn problems of linear demand and supply curves in an administration subject if they previously learned to solve problems of linear equations in mathematics compared to another group of learners who did not work on mathematics tasks as a team. Group members may transfer their experience from one task situation to another by finding correspondences through schema induction (Gick & Holyoak, 1980). Generalized domain-knowledge on collaborative work may explain why learners who are prepared to work together are more effective than individual learners (Buchs et al., 2015; Prichard, Bizo, et al., 2006).

This study is a first step to attempt to close this gap. Accordingly, this experiment examined the effect of learning in groups instructed to collaborate vs. learning individually and the effect of prior knowledge level on performance and mental effort with high-complexity problems.

The hypotheses were:

H1. When learning individually, students with more knowledge will outperform and invest less mental effort than students with less knowledge.

H2. When learning in collaborative groups, students with more knowledge will outperform students with less knowledge but the counteractive effects on mental effort when more and less knowledgeable students collaborate cannot be precisely determined.

H3. For learners with less knowledge, collaborative learning groups will outperform and perceive less mental effort than individual learning groups.

H4. For learners with more knowledge, learning in collaborative groups will become detrimental and no advantage to learning in collaborative groups will be found.

Method

Participants

This study was conducted with 228 students (135 females, 93 males) of a large, public high school in Sangolquí, Ecuador. Their average age was 15.87 years (*SD* = .745). The study was part of the mathematics classes and received approval from the local ethical committee. Participants did not have prior knowledge of the learning phase tasks because it is not included in the content of the very strict national curriculum which explicitly prohibits teaching topics not in the curriculum. Further, teachers at the school confirmed that they had not previously taught the content of the learning tasks and that all participants came from the same school. Finally, participants were randomly assigned to the conditions to exclude any systematic prior knowledge differences. Participants were notified of the study and received academic compensation of 10 points for voluntary participation.

Design and Procedure

A 2 (collaborative learning vs. individual learning) x 2 (less vs. more knowledgeable learners) factorial design was used. Dependent variables were performance and mental effort. The study was conducted in five phases: preparation, prior knowledge instruction, learning, retention testing, and delayed testing. Each phase consisted of multiple sessions of 45 minutes. Three instructors and the experimenter guided participants throughout all phases of the study. The experimenter supervised the procedure to guarantee intervention fidelity. All instructions were read aloud.

The five phases entailed:

1. *Preparation*: Construct collaboration schemas using the previously learned domain-specific task of solving quadratic equations and emphasizing collaborative work. Half of the participants formed 3-person collaborative groups (collaborative group condition), and the other half worked individually (individual condition). This phase consisted of four sessions over one week.
2. *Prior knowledge instruction*: Half of each of the collaborative group and individual conditions received instruction on how to calculate a break-even point (BEP). This phase comprised one session on the day following the preparatory phase.
3. *Learning*: All participants received the same learning tasks to calculate the BEP either as individuals or in teams. This phase comprised one session on the day following the prior knowledge instruction phase.
4. *Retention testing*: Similar problems with only the name of the costs and their values varied from the learning tasks were used to evaluate the outcomes of the collaborative and individual learning conditions one day after the learning phase.
5. *Delayed testing:* Similar retention testing problems but seven days after the learning phase.

The *preparation phase* began in the second week of the new school term, after two months of school vacation, to reduce effects of having previously worked together. Participants were randomly assigned to two conditions: individual learning and collaborative groups. All learners worked on solving quadratic equations. There were no time restraints on the first tasks, but 10 min were allotted to solve the final two tasks from the second session onwards (a digital clock was placed in front of the class); writing was permitted only for the final answer. Instructors encouraged members to interact with each other, to share their values and coordinate calculations among themselves, and discouraged non-task conversations. Participants received the correct answers at the end of each session and were asked to think about how they may collaborate better on the following tasks.

In the *prior knowledge instruction phase*, half of the participants were randomly selected to receive additional instruction. Each learner received a booklet with the concepts of the BEP and a worked example on how to solve a problem (8 min). After studying the booklet, they solved three conventional problems individually (7 min each) using the worked example of the booklet as assistance. After solving each problem, they received the worked example of the three problems and were asked to compare their results and correct their mistakes. Moreover, learners were asked if they had questions to clarify any step for calculating the BEP. Instructors made sure all learners had corrected the errors to foster problem-solving understanding. The other half of the participants received a theoretical class about the topic of the new term, real number properties, which was unrelated to the BEP.

In the *learning phase,* only individuals and groups that had completed the previous phases participated. An a priori analysis with a power of .8 and a medium-size effect (i.e., .06; Cohen, 1988) revealed that the study required 32 individuals for the individual learning condition or 11 triadic groups for the collaborative learning condition to reliably test the hypotheses (see Results section). Collaborative group members remained in their groups to maintain the previous schemas of working together (Prichard, Bizo, et al., 2006). Groups and individuals worked on three tasks to calculate the BEP (9 min for task 1, 8 min for tasks 2 and 3 = 25 min). As in the preparation phase, the instructors encouraged group members to share their values and to coordinate the calculations to solve each problem. If a collaborative group or individual solved the task before the time assigned, that group or individual was required to wait to start the next problem. All problems were solved mentally. Using paper and pencil was only permitted for recording the final answer and indicating the mental effort after completing each task.

In the *retention* and *delayed* test phases, participants were required to individually solve three conventional problems in 30 min, 10 min per problem. They were asked to write the calculations for each step of the problems and scored the amount of mental effort invested in each problem. If a student was absent from the retention test, s/he was allowed to take the delayed test and vice-versa because each test was analyzed independently. No case, thus, needed to be deleted.

Materials

The materials were in the domain of mathematics and economics. The preparation phase consisted of solving quadratic equations, while the remaining phases involved calculating BEPs. All materials were paper-based and presented in booklets.

Preparation phase.

Quadratic equations are compulsory in the national curriculum, and the participants had already received instruction the previous year. All tasks were designed and assigned with a completion strategy scaffolding approach (Van Merriënboer, 1990) as follows: the first session began with an introduction about quadratic equations and two worked examples showing how to solve them using the factoring method during prior knowledge activation. Five rules on how to solve the equations collaboratively were given and explained to the collaborative group condition, followed by a worked example showing how each group member should apply them (see supplementary material), and a conventional task with the correct answer. Examples of the rules are: When it is possible to perform the calculations without the help of others, do it alone and continually rehearse the results to avoid forgetting them. For the collaborative group condition, we manipulated the task information, unpacking the equation values to distribute them among group members (e.g., for $-45x^2$, each member would receive $-15x^2$), requiring each learner to depend on other members to solve the problem. This manipulation also had the purpose of providing prior experience for the information distribution of the learning tasks. Each member received different values for solving the same equation and a table in which they could write down the intermediate steps (see supplementary material). The individual condition participants received the same values and the table.

In the second session, both conditions received the rules of collaboration, two conventional problems with correct answers, and a conventional problem without the correct answer again. The conventional problems had six values, two for each group member; individuals received all values. In the third and fourth sessions, both collaborative groups and individuals received three conventional quadratic equation problems without correct answers, with six to nine values
(e.g., $-10 + 5x^2 - 50 - 50 + 200x = 1x - 50x^2 + 50x + 100x^2$).

Prior knowledge instruction phase.
One way to acquire generalizable domain-specific collaboration schemas may be to use different tasks but with analogous features. Calculating the BEP is a problem with similar characteristics to quadratic equations such as: requiring a combination of several numerical values, using basic mathematical operations, calculating partial answers, holding them in working memory, and finding a single correct answer. The material included a brief explanation of the BEP and a worked example (see Table 1 and steps in Table 2). It also included three conventional problems that were similar to those used in the learning phase, and their corresponding resolution process (worked examples).

Table 1
Example a BEP Problem

Calculate the break-even point of a school chairs business: • Total chairs produced: 50 • Price of each chair: $41 • Office and warehouse rental: $108 • Cost of the wood for the chairs: $155 • Administrator's salary: $119 • Cost of the metal for the chairs: $63 • Profit: $ 52 • Cost of the paint for the chairs: $82 • Electricity, water, telephone, and Internet service: $71

Learning phase.

Each participant received the concepts of the BEP, two worked examples, prompt questions, three learning tasks, and a piece of paper with examples of fixed and variable costs and the BEP in unit's formula (see step 6, Table 2). The booklet explained the BEP and the types of costs (i.e., fixed and variable costs, variable cost per unit, and total costs), the contribution, and the BEP both in units and sales. The worked examples contained a 7-step procedure (see Table 2). Examples of prompt questions were: What was the difference between the BEPs in units and sales? How did you calculate the contribution? Examples of fixed and variable costs were provided to avoid confusion during the learning phase.

Table 2
Process to Calculate the BEP

Steps to solve the problem	*Calculations*	*Interacting elements*	*Temporary answers maintained in working memory*
1. Recognize cost items	Nine items of the problem		
	155, 63, 82, 50, 41, 108, 71, 119, 52	9	
2. Total variable cost	$VC_1 + VC_2 + VC_3 = TVC$		
	155 + 63 + 82 = 300	7	300
3. Variable cost per unit	TVC ÷ amount produced = CU		
	300 ÷ 50 = 6	5	300, 6
4. Contribution	Price – CU = C		
	41 – 6 = 35	5	6, 35
5. Total fixed cost	$FC_1 + FC_2 + FC_3$ + profit = TFC		
	108 + 71 + 119 + 52 = 350	9	35, 350
6. BEP in units	TFC ÷ C = BPU		
	350 ÷ 35 = 10	5	35, 350, 10
7. BEP in sales	BPU × price = BPS		
	10 × 41 = 410	5	10, 410

Note. CV = variable cost; FC = fixed cost; TVC = total variable cost; CU = variable cost per unit; C = contribution; TFC = total fixed cost; BPU = BEP in units; BPS = BEP in sales.

Participants from the collaborative group and individual conditions received the same learning tasks. Task complexity level was determined using the method of Sweller and Chandler (1994), which counts the number of items and operations that must be considered and processed in working memory to solve the task. As presented in Table 2, the 7-step procedure to solve each problem comprised nine items that must be integrated during 8 min to obtain a single correct answer (Table 2). Like the equations of the preparation phase, no step could be solved without all members sharing and working together on their items. Each member needed to depend on other's information. A group member received a fixed cost, a variable cost and any of the other three items that were insufficient to solve each step of the problem. Members had to share all their items, coordinate how to solve each step, and jointly perform calculations using basic mathematical operations. Each step varied in the number of interacting items (column 3 of Table 2), amounting to a total of 45 including mathematical signs. Also, in each step, individual participants and collaborative groups had to perform multiple mental calculations to find many partial answers, hold them temporarily in working memory (column 4 of Table 2), and then integrate them with partial answers computed by others in the group without writing the calculations (i.e., mental arithmetic; DeStefano & LeFevre, 2004). Given these cognitive demands, it was assumed that the tasks were highly complex.

Retention and delayed test phases.

The quality of the task-specific knowledge of each participant was assessed using six similar problems with the same level of complexity as the learning tasks. Participants received worksheets with three tasks one day after the learning tasks (the retention test) and three other similar tasks seven days after (the delayed test). Each problem included a table with seven numbered rows to write the calculations for each step of the solution process.

Measurement

Cognitive load.

Cognitive load was measured subjectively in the learning, retention test, and delayed test phases using a 9-point mental effort rating scale (Paas, Tuovinen, et al., 2003). Mental effort "refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task; thus, it can be considered to reflect the actual cognitive load" (Paas, Tuovinen, et al., 2003, p. 64). The scale is non-intrusive, is sensitive to changes in complexity, and is valid, and reliable for individual learning (Szulewski, Gegenfurtner, Howes, Sivilotti, & van Merriënboer, 2017). Participants were asked to 'Please rate the level of mental effort you invested in this task' on a Likert scale ranging from 1 (very, very low mental effort) to 9 (very, very high mental effort) after each problem to obtain a more precise estimation of the invested load (Van Gog et al., 2012). Cognitive load for each collaborative group for the learning phase was calculated averaging the scores of the members. Individual scores were used in subsequent phases.

Performance.

Performance was measured in the learning, retention test, and delayed test phases. The total number of points for all three learning tasks was 3: 1 point per correct answer or 0 points if the answer was incorrect. For the three tasks of the retention test and delayed test, a total of 7 points could be awarded based on the seven calculations required to obtain the BEP. Each calculation was scored individually based on whether correct values and mathematical operations were used. Correct calculations received 1 point and incorrect calculations 0 points, resulting in a maximum score of 21 points and a minimum of 0. If a step was partially correct, a proportional score was given (e.g., if in steps 4, 6 or 7 an incorrect value was used, ½ point was given). Performance scores on the learning, retention test and delayed test phases were transformed into proportions.

Results

The data were analyzed with 2 (collaborative group vs. individual learning) x 2 (less knowledgeable learners vs. more knowledgeable learners) analyses of variance (ANOVAs). Dependent variables were performance and mental effort, which were measured and analyzed separately for the learning, retention test, and delayed test phases. There were no activities or analyses carried out between the phases. Data exploration revealed outliers. However, the outliers were not excluded because an analysis that excluded outliers showed that they did not alter the pattern of significant results. The results are reported separately, and the means and standard deviations of the dependent variables for all phases are shown in Tables 2, 3, and 4. A summary of all significant results is provided in Appendix A. A significance level of .05 was used for all analyses. Partial eta-squared was used as a measure of effect size, with values of .01, .06, and .14 corresponding to small, medium, and large effects, respectively (Cohen, 1988).

Learning Phase

Two collaborative groups and two individuals were excluded from the analysis after not completing the previous phases. In this phase, 17 three-person novice collaborative groups, 19 knowledgeable collaborative groups, 66 less knowledgeable individuals, and 46 more knowledgeable individuals participated. Table 3 shows descriptive statistics.

Table 3
Means and Standard Deviations for Dependent Variables in the Learning Phase

Dependent variables	Condition			
	Collaborative groups		*Individuals*	
	M	*SD*	*M*	*SD*
Learning performance (0-1)				
Less knowledgeable learners	.51	.31	.25	.29
More knowledgeable learners	.84	.20	.65	.24
Learning mental effort (1–9)				
Less knowledgeable learners	6.27	2.06	6.41	1.58
More knowledgeable learners	6.99	1.68	5.51	1.87

Concerning performance, the ANOVA revealed a significant main effect for condition, $F(1, 144) = 18.391$, MSE = 0.073, $p < .001$, $\eta_p^2 = .113$: collaborative groups ($M = .69$, $SD = .31$) outperformed individual learners ($M = .42$, $SD = .34$). The main effect for knowledge level was also significant, $F(1, 144) = 49.265$, MSE = 0.073, $p < .001$, $\eta_p^2 = .255$: knowledgeable learners ($M = .71$, $SD = .25$) outperformed novice learners ($M = .31$, $SD = .31$). The interaction between main effects was not significant; $F(1, 144) = 0.417$, MSE = 0.073, *ns*.

For mental effort, the main effect for condition was significant, $F(1, 144) = 4.006$, MSE = 3.052, $p = .047$, $\eta_p^2 = .027$: collaborative groups ($M = 6.65$, $SD = 1.88$) experienced more mental effort than individual learners ($M = 6.04$, $SD = 1.76$). However, the main effect for knowledge level was not significant, $F(1, 144) = 0.077$, MSE = 3.052, *ns*. The interaction between these effects was significant, $F(1, 144) = 5.849$, MSE = 3.052, $p = .017$, $\eta_p^2 = .039$. A post-hoc Bonferroni test showed that for participants learning individually, more knowledgeable learners reported less mental effort than less knowledgeable learners ($p = .008$, $\eta_p^2 = .048$). No differences were found for participants learning in collaborative groups. The test also showed no difference for less knowledgeable learners; however, for more knowledgeable learners, collaborative groups reported more mental effort than individuals ($p = .002$, $\eta_p^2 = .063$).

Retention Test

In this phase, 49 novice collaborative group members, 56 knowledgeable collaborative group members, 61 novice individuals, and 46 knowledgeable individuals participated. Table 4 shows the descriptive results.

Table 4

Means and Standard Deviations for Dependent Variables in the Retention Test Phase

Dependent variables	*Condition*			
	Collaborative groups		*Individuals*	
	M	*SD*	*M*	*SD*
Retention test performance (0-1)				
Less knowledgeable learners	.50	.22	.23	.22
More knowledgeable learners	.87	.18	.74	.24
Retention test mental effort (1–9)				
Less knowledgeable learners	6.01	2.50	3.86	2.29
More knowledgeable learners	5.67	1.87	6.12	1.62

The ANOVA for performance found a significant main effect for condition, $F(1, 208) = 46.764$, MSE = 0.047, $p < .001$, $\eta_p^2 = .184$: collaborative groups ($M = .70$, $SD = .27$) outperformed individuals ($M = .45$, $SD = .34$). Concerning knowledge level, $F(1, 208) = 217.926$, MSE = 0.047, $p < .001$, $\eta_p^2 = .512$: more knowledgeable participants ($M = .81$, $SD = .22$) outperformed less knowledgeable participants ($M = .35$, $SD = .26$). The interaction between main effects was also significant, $F(1, 208) = 5.580$, MSE = 0.047, $p = .019$, $\eta_p^2 = .026$. The Bonferroni test showed that for participants learning individually, more knowledgeable learners outperformed less knowledgeable learners ($p < .001$, $\eta_p^2 = .414$); among participants learning in collaborative groups, more knowledgeable participants outperformed less knowledgeable learners ($p < .001$, $\eta_p^2 = .270$). It was also found that among more knowledgeable learners, collaborative groups outperformed individual learners ($p < .001$, $\eta_p^2 = .174$) and, for less knowledgeable participants, collaborative groups outperformed individual learners ($p = .002$, $\eta_p^2 = .044$). The large difference in effect sizes explains the significant interaction.

Regarding mental effort, a significant main effect for condition was found, $F(1, 208) = 8.524$, MSE = 4.443, $p = .004$, $\eta_p^2 = .039$: collaborative groups ($M = 5.83$, $SD = 2.18$) reported more mental effort than individuals ($M = 4.83$, $SD = 2.31$).

Knowledge level was also significant, $F(1, 208) = 10.698$, MSE = 4.443, $p = .001$, $\eta_p^2 = .049$: more knowledgeable learners ($M = 5.87$, $SD = 1.77$) reported more mental effort than less knowledgeable learners ($M = 4.82$, $SD = 2.60$). The interaction between these effects was also significant, $F(1, 208) = 19.908$, MSE = 4.443, $p < 001$, $\eta_p^2 = .087$. The Bonferroni test showed that among participants learning individually, more knowledgeable learners reported more mental effort than less knowledgeable learners ($p < .001$, $\eta_p^2 = .126$). There was no significant difference between more and less knowledgeable learners on levels of mental effort when they learned in collaborative groups. In addition, among novice participants, collaborative groups reported more mental effort than individual learners ($p < .001$, $\eta_p^2 = .120$). However, for knowledgeable participants, no difference between individuals and collaborative groups was found, indicating the cause of the significant interaction.

Delayed Test

In this phase, 49 novice collaborative group members, 57 knowledgeable collaborative group members, 65 novice individuals, and 44 knowledgeable individuals participated. Descriptive statistics are shown in Table 5.

Table 5

Means and Standard Deviations for Dependent Variables in the Delayed Test Phase

	Condition			
	Groups		*Individuals*	
Dependent variables	*M*	*SD*	*M*	*SD*
Delayed test performance (0-1)				
Less knowledgeable learners	.39	.14	.26	.20
More knowledgeable learners	.78	.23	.79	.22
Delayed test mental effort (1–9)				
Less knowledgeable learners	3.58	1.42	4.48	1.77
More knowledgeable learners	5.30	1.87	5.66	1.29

For performance, the main effect for condition was significant, $F(1, 212) = 4.467$, MSE = 0.041, $p = .036$, $\eta_p^2 = .021$: collaborative groups ($M = .60$, $SD = .27$) outperformed individual learners ($M = .48$, $SD = .33$). The main effect for knowledge level was also significant, $F(1, 212) = 271.491$, MSE = 0.041, $p < .001$, $\eta_p^2 = .562$: more knowledgeable learners ($M = .78$, $SD = .22$) achieved better performance than less knowledgeable learners ($M = .32$, $SD = .19$). The interaction between effects was significant, $F(1, 212) = 6.861$, MSE = 0.041, $p = .009$, $\eta_p^2 = .031$. For individual learning ($p < .001$,

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$\eta_p^2 = .464$) and for collaborative learning ($p < .001$, $\eta_p^2 = .311$), it was found that more knowledgeable learners outperformed less knowledgeable learners. The Bonferroni test indicated that less knowledgeable participants performed better in collaborative groups than those learning individually ($p = .001$, $\eta_p^2 = .053$); however, there was no significant difference between collaborative and individual groups explaining the significant interaction.

Regarding mental effort, the main effect for condition was significant, $F(1, 212) = 8.553$, MSE = 2.682, $p = .004$, $\eta_p^2 = .039$: individual learners reported more mental effort ($M = 4.98$, $SD = 1.70$) than collaborative groups ($M = 4.50$, $SD = 1.88$). The main effect for knowledge level was also significant, $F(1, 212) = 42.909$, MSE = 2.682, $p < .001$, $\eta_p^2 = .168$: more knowledgeable learners ($M = 5.48$, $SD = 1.65$) reported more mental effort than less knowledgeable learners ($M = 4.09$, $SD = 1.68$). The interaction between these effects was not significant $F(1, 212) = 1.189$, MSE = 2.682, *ns*.

Discussion

The results are discussed following the order of the hypotheses, starting with condition followed by level of prior knowledge. Regarding condition, it was expected that for individual learning, more knowledgeable learners would outperform and invest less mental effort than less knowledgeable learners (h1). In the learning phase, more knowledgeable individuals reported less mental effort than less knowledgeable learners as expected but performed equally well. In retention and delayed tests, more knowledgeable learners outperformed less knowledgeable learners as expected. Knowledgeable learners invested more mental effort in the retention phase and similar mental effort in the delayed test. This suggests that for high-complexity tasks, prior knowledge reduces mental effort during learning without necessarily improving performance during learning. However, as found by Retnowati et al. (2018), the benefits of providing prior knowledge for complex tasks had significant benefits in the performance outcomes (1 and 7 days after). Interestingly, in the retention test, novice individuals experienced a lower cognitive load. One possible explanation may be their lack of knowledge which may have reduced their judgment of the complexity of tasks and overestimated their current performance, which in turn decreased their mental effort ratings (Nugteren et al., 2018a).

We also expected that when students who have prior knowledge learn in collaborative groups, they will outperform less knowledgeable learners, but the counteractive effects on mental effort when more and less knowledgeable students collaborate cannot be precisely determined (h2). As expected, we found evidence for performance both in retention and delayed test phases. Advanced learners could handle the complexity due to their better task-specific knowledge. This result allows us to assume that transactional activities were advantageous for advanced learning groups because the learning tasks had a high level of element interactivity (Retnowati et al., 2018; 2016). This advantage was observed in both individual post-tests. For cognitive load, we found nonsignificant differences. Mental effect results suggest that transactional activities could have interfered with prior knowledge (Retnowati et al., 2018). Seemingly, collaborative groups of advanced learners experienced cognitive load caused by the redundancy of interactions that were unnecessary because group members already had partially developed task knowledge. This cognitive load may be equivalent to the low-knowledge groups' cognitive load. Low-knowledge groups may have performed irrelevant transactional activities (e.g., randomly searching activities) because they lack sufficient schemas that guide their operations in high-complexity tasks (Zhang et al., 2016).

Concerning the effect of prior knowledge, it was expected that when learners are less knowledgeable, collaborative groups outperform and perceive less mental effort than individuals (h3). We found evidence for this hypothesis on performance both in the retention and delayed tests. For cognitive load, surprisingly, less knowledgeable learners that learned in collaborative groups perceived a significantly higher load than individuals in the retention test while no difference was found in the other phases. In line with the collective working memory effect (F. Kirschner, Paas, & Kirschner, 2011), greater cognitive capacity allowed collaborative groups to acquire better mental representations from the complex information. These data suggest that when learners are required to learn from highly demanding problems, collaborative learning may impose a substantial cognitive load, but is more effective than in individual learning, and its benefits are observed in the long term (Soderstrom & Bjork, 2015). The perception of higher mental effort in the retention phase of learners who learned in collaborative groups is interesting ($M = 6.01$), but even more interesting is the substantially lower cognitive load perceived by individual students ($M = 3.86$). It seems, they did not invest a high mental effort because they did not have the appropriate task knowledge (Sweller et al., 2011). It may be necessary to investigate these cases in depth through the analysis of think-aloud protocols (Kalyuga & Plass, 2018).

It was also expected that when learners have prior knowledge, learning in collaborative groups will become detrimental, with no collaborative group advantage (h4). This was confirmed for all phases and measures except the performance in the retention phase of those who learned in collaborative groups. This result might be explained by the activating of prior task schemas when carrying out highly complex tasks. During the learning phase, knowledgeable collaborative group members reported significantly higher cognitive load because they may need to reconcile their own knowledge with externally provided guidance (Kalyuga et al., 2003). Besides, they may have to deal with the transactional activities that were inevitable due to the distribution of information among members which further increased the perception of mental effort.

Interestingly, despite reporting more mental effort during collaborative learning, in the retention phase, more knowledgeable collaborative group members were more effective than more knowledgeable individuals. Seemingly, collaborative learning and prior knowledge for high-complexity tasks did not seem detrimental as the additionally acquired collaborative group knowledge allowed collaborators to outperform individuals the next day. However, this advantage was not long-lasting (i.e., in the delayed test).

Conclusions

In general, the results seem to suggest that collaborative learning may be effective for high-complexity tasks compared with individual learning when learners have domain-generalized knowledge at a collaborative group level (Kalyuga, 2013). Giving learners guidance on how to work together seems to be associated with better performance than just bringing students together to learn new problems (Gillies, 2016; P. A. Kirschner et al., 2018). Seemingly, learners who are prepared to learn collaboratively build task-based collaboration schemas. They may be applied through analogical transfer when these collaborative groups must learn similar tasks (Gick & Holyoak, 1980). It may be reasonable to think that domain-generalizable knowledge for collaboration operates as intergroup guides that take advantage of transactional activities to better learn relatively new tasks.

Furthermore, the effectiveness of collaborative learning is affected by prior task knowledge (Retnowati et al., 2018; Zhang et al., 2016; Zhang et al., 2015). Providing preliminary instruction to construct partially developed domain-specific knowledge before subsequent explicit instruction may produce higher performance in the retention and delayed tests than learning individually without such prior knowledge. Similarly, learning collaboratively with partial knowledge structures yields higher performance than collaborating among less knowledgeable learners. However, when individuals and collaborative groups with this prior knowledge are compared, the advantage of learning in collaborative groups only decreases the mental effort in the learning phase (i.e., due to the advantage distribution) and produces higher performance in the retention test. In the longer term (i.e., delayed test), the performance between collaborative groups and individuals is equal. However, if learners have not received preliminary instruction, learning in collaborative groups is more effective with higher performance than learning individually in the short- and long-term as indicated by the retention and delayed tests respectively.

Practical Implications

This study has educational implications when the learning goal is to learn high-complexity problems, and when high performance needs to be sustained in the longer-term. First, if collaborative learning is used, learners should be provided preparation in learning in collaborative groups through practice on tasks previously learned in the same domain. Once learners have had a collaborative group experience, they will then be able to manage the collaborative cognitive load and transfer this experience to relatively new problems. Also, before giving explicit or full comprehensive instruction for learning to solve quite complex problems, novice collaborative group members should receive preliminary knowledge to guide subsequent acquisition. Instructors can begin instruction by providing guidance using worked examples to first stimulate individual long-term memory elaboration and then promote the construction of better schemas through collaborative learning.

However, if learners have prior task-specific knowledge, learning in collaborative groups may not be more beneficial than learning individually because collaborative groups experience more cognitive load during full guidance (i.e., learning phase) and an advantage in performance is not durable in the long term.

Limitations and Future Directions

Assuming that cognitive load may vary during learning (Kalyuga & Plass, 2018), it is important to develop ways of measuring it during collaboration activities. Making collaborative group activities explicit along with their respective cognitive loads is fundamental. For this, an in-depth analysis of the loads related to transactional activities is required concerning how group members process task information individually and amongst themselves and how learners support each other to overcome task-related difficulties. An evaluation of the impact of transactional activity patterns on performance and mental effort in individual long-term post-tests also is required.

Further, the subjective measurement of cognitive load may not be appropriate for collaborative learning (F. Kirschner, Paas, Kirschner, et al., 2011; Retnowati et al., 2016). Although the mental effort scale appears to be robust for individual conditions, it should be determined if it is valid and reliable for collaborative learning conditions. Other measures of cognitive load that account for the multiple sources and types of cognitive load in collaborative conditions may need to be constructed.

Another limitation of this study is that a pretest was not used. Although the tasks in the learning phase are not easily acquired without being part of a curricular program, students might acquire this knowledge outside the school context. Of course, our use of random allocation to groups should eliminate any systematic biases. A pretest would test whether this is the case.

This study is a first step to uncover the cognitive load factors associated with individual and collaborative learning considering the prior knowledge effect. Future studies should replicate this study to confirm these results and examine the effect of prior knowledge between individual learning, and collaborative learning with and without collaborative preparation. Also, tasks with higher and lower complexity should be used to investigate relations between prior knowledge and complexity.

Appendix A

Table A.1

Summary of Two-Way ANOVAs of the Effects on the Variables

	Dependent Variables	
Conditions	*Performance*	*Mental effort*
Learning phase		
Group vs. individual	>***	>*
Knowledgeable vs. novice	>***	*ns*
Interactions	*ns*	*
Individuals: knowledgeable vs. novice	*ns*	<**
Groups: knowledgeable vs. novice	*ns*	*ns*
Novice: collaborative groups vs. individual	*ns*	*ns*
Knowledgeable: collaborative groups vs. individual	*ns*	>**
Retention test		
Group vs. individual	>***	>**
Knowledgeable vs. novice	>***	>***
Interactions	*	***
Individuals: knowledgeable vs. novice	>***	>***
Groups: knowledgeable vs. novice	>***	*ns*
Novice: collaborative groups vs. individual	>***	>***
Knowledgeable: collaborative groups vs. individual	>**	*ns*
Delayed test		
Group vs. individual	>*	<**
Knowledgeable vs. novice	>***	>***
Interactions	**	*ns*
Individuals: knowledgeable vs. novice	>***	*ns*
Groups: knowledgeable vs. novice	>***	*ns*
Novice: collaborative groups vs. individual	>***	*ns*
Knowledgeable: collaborative groups vs. individual	*ns*	*ns*

* $p < .05$. ** $p < .01$. *** $p < .001$.

Supplementary Material

Example of Material used by Groups in the Preparation Phase

Let's practice a solved example for this equation: $-10x^2 + 13 + 20x - 14x^2 = -7 + 3x$			
STEPS TO THE GROUP WORK	**MEMBER 1**	**MEMBER 2**	**MEMBER 3**
You should identify whether the values of the equation are on the **left side** or the **right side** of the equal= sign.	$-10x^2 + 13 =$	$20x - 14x^2 =$	$= -7 + 3x$
You should **communicate** with the other members to identify similar values. Afterwards, **shift the values** to the left side, changing the sign, and keep the **result in mind**.			$7 - 3x =$
Perform quickly and without error **all the possible operations** and keep the **result in mind**.	$-10x^2 - 14x^2 =$	$20x - 3x =$	$13 + 7 =$
Everyone must share their values with others and **sort** them, **keeping in mind** the results.	$-24x^2 + 17x + 20 = 0$		
Factor the trinomial with your partners. Remember to carry out these calculations **mentally**. To avoid forgetting a partial result, each member must have it in his/her mind.	$(-8x - 5)(3x - 4) = 0$		
When **Equal to Zero**, resolve the equations mentally.	$-8x - 5 = 0$ $3x - 4 = 0$		
Write down the results on the worksheet:	$x = -\frac{5}{8}$ $x = \frac{4}{3}$		

6. General Discussion

This chapter presents the main findings of the research and its theoretical and instructional implications. In addition, its limitations are discussed and opportunities for future research are proposed.

Introduction

Nowadays, more and more voices demand that students learn to solve problems through group work (Griffin & Care, 2015; OECD, 2017). Some of these voices come, for example, from pedagogical perspectives that argue from the assumption that the human being is a social being by nature and that knowledge is an intersubjective construction (Derry, 2013; Freire, 2008; Hakkarainen, Paavola, Kangas, & Seitamaa-Hakkarainen, 2013). The business sector argues from the need to achieve higher efficiency in the processes and organizational results that depend on inter-individual and inter-group activities (Salas, Bowers, & Edens, 2001; Salas, Fiore, & Letsky, 2012). Other voices come from instructional perspectives that assume that collaboration could improve the acquisition of school knowledge (D. W. Johnson & Johnson, 2009; Slavin, 2012). A large number of the views that advocate collaboration (Hmelo-Silver & Chinn, 2015; O'Donnell & Hmelo-Silver, 2013), could fit within a continuum. At one end of that continuum, collaborative learning is seen as a pedagogical method (i.e., learning to be collaborative, independent of the learning task), that is an essential condition for carrying out tasks that are group-based by nature (i.e., learning to collaborate for essentially collaborative tasks). At the other end of the continuum, collaboration is seen as an instructional strategy to assist in learning essentially individual tasks, which is the main approach of this dissertation (Slavin et al., 1985).

Consequently, there is an overwhelming amount of literature on collaborative learning. However, not all studies show that learning in groups is beneficial (Pai et al., 2015; Swanson, McCulley, Osman, Scammacca Lewis, & Solis, 2017). A crucial aspect that could contribute in understanding why and when collaboration is beneficial or harmful is to take into account the characteristics of human cognitive architecture (P. A. Kirschner et al., 2018; Sweller et al., 2011). In other words, researchers and educators should consider the multiple factors that affect information processing in the working memory of group members and the construction of schemas in their long-term memories.

The goal of this research was to explore the consequences of decreasing the cognitive load associated with group interactions in order to improve collaborative learning in highly complex tasks. It was assumed that a collaborative group consists of a cognitive unit (Hinsz et al., 1997) that can simultaneously process more information elements due to the combination of the working memories of its members (i.e., collective working memory) and despite the need to engage in transactional activities (i.e., communication and coordination cognitive processes; F. Kirschner, Paas, & Kirschner, 2011). Transactional activities can be affected by multiple variables, with respect to the individual (e.g., previous task schemas), the group (e.g., intra-group experience in similar tasks or distribution of information among students), or the task (e.g., level of element interactivity) (P. A. Kirschner et al., 2018). Those variables may be optimized to improve task information group processing. By optimizing inter-individual processing during collaborative learning, group members may dedicate more resources from their working memories to build better task schemas in long-term memory.

In this work, it was assumed that a way to optimize the transactional activities and the cognitive load, could be by providing groups with collaborative experience based on relatively similar tasks (i.e., creating experienced groups). Accordingly, a goal was to determine if this group experience allowed learning peers to properly use their transactional activities to learn better, have higher performance, and be more efficient than members of groups without this collaborative experience (i.e., non-experienced groups). Another goal was to examine how the distribution of information amongst group members (i.e., high-density information vs. low-density information) and prior knowledge (i.e., novices vs. advanced learners) affect the results of students learning in experienced and non-experienced groups.

In all studies of this dissertation, members of experienced groups were prepared using math tasks, specifically problems relating to solving quadratic equations which they solved in a group. Non-experienced groups consisted of students who had, just as the others, learned to solve quadratic equations but who solved them individually. Solving such equations was something that the students had already learned in the previous school year. Members of the groups that received guidance on how to collaborate remained in their own groups in the learning phase. Each of the studies was conducted at the beginning of three different school periods in Ecuadorian schools, after two months of vacation (i.e., July and August). As far as possible, students did not have any prior collaborative experience for several weeks before the experiments. Members of the experienced groups received explicit guidance on how to collaborate with previously known tasks (i.e., solving quadratic

equations) whose characteristics were similar to those of the learning tasks (i.e., calculating the break-even point in economics). Finally, the group experience gained in the just described preparation phase was maintained keeping the groups intact in the learning phase. Also, the variables of performance (i.e., learning, short-term retention, and delayed retention), mental effort (i.e., cognitive load) and efficiency were measured in the learning phase and the post-test phases. Efficiency was not measured only in the study reported in Chapter 5. For post-tests (i.e., learning outcomes), short-term retention tasks (i.e., a day later), and delayed retention tasks (i.e., seven days later) were used.

Main findings

The mixed study (*Chapter 3*) examined whether prior collaborative experience based on similar tasks increases effectiveness (i.e., performance), decreases cognitive load and, therefore, increases efficiency in the learning, short-term retention and delayed retention phases. In addition, it examined the differences between experienced and non-experienced groups concerning socio-cognitive, socio-regulatory, and socio-emotional transactional activities as well as task unrelated transactional activities. Results supported expectations regarding the advantage of experienced group members in learning outcomes (i.e., retention and delayed tests). That is, members of the groups that were provided preparation time to gain experience in collaboration with relatively similar tasks performed better, experienced less mental effort, and were more efficient than non-experienced groups on the retention and delayed tests. However, in the learning phase, there were no significant differences on any measures. It seems the preparation of the experienced groups allowed them to acquire group-based information elements that were transferred to learning new tasks. The higher performance and efficiency of experienced groups suggest that the students optimized their transactional activities, which in turn may have contributed to the acquisition of better task schemas. In other words, the cognitive load associated with individual and interindividual processing of task information fostered the acquisition of better schemas in long-term memory.

The superior quality of task schemas was confirmed in the retention tests in which each step of the problem-solving process was measured. Because the results of the learning phase did not show differences between both types of groups, an analysis of the verbal interactions was carried out under the assumption that they impose cognitive load that may promote or inhibit individual learning. During inter-individual processing, each member had to continuously monitor the ongoing conversation, keep their own ideas in their memory, integrate the information presented by others, and continuously update their mental representations (Mojzisch, Krumm, & Schultze, 2014). These transactional activities may impose a high cognitive load (P. A. Kirschner et al., 2018). Therefore, examining the interactions may help to understand the benefits of group experience in terms of cognitive load. An analysis of verbal interactions was made with a sample of five experienced, and five non-experienced groups. It showed that the experienced groups spent more time solving the learning task problems. Also, as expected, experienced groups had more socio-cognitive interactions and fewer socio-regulatory and task unrelated interactions. The number of socio-emotional interactions was not different between both conditions. These data allowed the suggestion that the collaborative work schemas acquired in the preparation phase may have guided inter-individual information processing of learning tasks. The analysis of the subcategories of socio-cognitive interactions showed that groups with previous collaborative experience might have invested less cognitive load in the interpretation of the problem. This result indicates that experienced groups may have found common elements between preparation tasks and learning tasks. The conceptual and procedural information to solve quadratic equations and break-even point problems (the two types of problems used) are different. However, it is possible to assume that experienced groups may realize, for example, that both types of problems required each student to share their information items to understand the situation, or that each member had to process other members' information and integrate it with information which (s)he had in her/his hands to anticipate the procedure to follow.

The number of socio-cognitive interactions devoted to individual and shared calculations, as well as self-correction, may also reveal the advantage obtained by experienced groups. Unlike non-experienced groups, experienced groups performed fewer individual calculations to solve each step of the learning tasks. This result is complemented by the finding that experienced group members had more interactions relating to shared and self-correction calculations during the learning phase. Shared calculations may be a type of transactional communication which involves microcycles of interaction in which one member actively listens (i.e., processes) the information of another member, elaborates other information intrinsically related to what (s)he heard to communicate it to the group, with another member contributing other intrinsically associated elaborations (Noreen, 2013). Transactional communication is a collaborative skill that is associated with better learning (Fransen et al., 2013; Vogel, Kollar, et al., 2016) and is explained by the existence of a shared mental model on how to collaborate (Mohammed & Dumville, 2001). Because transactional communication can be acquired, for example through scripts (Noroozi, Biemans, Weinberger, Mulder, & Chizari, 2013), instructional videos (Jurkowski & Hänze, 2015), or scaffolding strategies as in this study, it seems that experienced groups built schemas of transactive activity during the preparation phase. These schemas may guide the distribution of the cognitive load associated with the calculations to solve the problems. In such schemas, self-correction may be a verbal behavior that exhibits a mechanism of (meta)cognitive monitoring where students evaluate the accuracy of their own working memory processes (Ramdass & Zimmerman, 2008). According to the knowledge categories of Geary's evolutionary educational psychology (Geary, 2005; Sweller, 2008) (see Chapter 2), (meta)cognitive monitoring may be a biologically primary skill because humans have evolved to execute it (Carruthers, 2009). The high cognitive load associated with (meta)cognitive monitoring may be a function of the level of novelty and complexity of the content that student monitors and not of the monitoring itself (Van Gog, Kester, & Paas, 2011). Self-correction may be an indicator of the high cognitive load associated with the calculations of learning tasks. This verbal operation of (meta)cognitive control may be associated with the need to perform more precise mathematical calculations, with fewer errors, and consequently may contribute to better learning and performance (Ramdass & Zimmerman, 2008). Conversely, the lower number of self-correction verbal behaviors of non-experienced group members may indicate that they overestimated the precision of their (meta)cognitive control, and this overestimation may have influenced them in constructing erroneous task schemas in long-term memory.

Another finding in this study was that experienced groups had, as expected, fewer socio-regulatory and task unrelated interactions. According to cognitive load theory, relevant knowledge structures guide behavior and cognition in a relatively familiar environment (Sweller et al., 2011). This principle could be seen in experienced groups because their task-based collaboration schemas may be transferred to the learning tasks, so it was not necessary to invest substantial working memory resources in socially shared regulatory interactions (Vuopala et al., 2019). That is, unlike non-experienced groups, experienced groups seemingly invested less cognitive load both in interactions to organize and coordinate their discussions to solve the learning problems, and in task unrelated discussions. Other studies show that socio-regulatory transactional activities, such as mutual monitoring, are associated with better performance, especially in complex tasks (Näykki et al., 2015). However, it seems that if groups have schemas on how to collaborate, it is likely that they do not need to invest substantial working memory resources in agreeing on how to proceed with the resolution of the tasks. Shared schemas of regulation may have helped experienced group members to focus their mental resources on better inter-individual processing, which may explain their better schemas in retention and delayed tests.

Chapter 4 reports on a study that aimed to examine whether the distribution of information affects the effectiveness and efficiency of groups with and without collaborative experience. For this study, the essential concept of element interactivity level (Sweller, 2010) was applied to group learning. According to cognitive load theory, the more interactive elements to be processed simultaneously (or in a short time scale), the more complex is the task. The more complex the task, the more a learner is required to invest working memory resources (i.e., cognitive load). These premises may also apply to collaborative learning assuming that groups can behave as an information processing unit (Hinsz et al., 1997) and that inter-individual processes (i.e., transactional activities) may be considered as group-based information elements that are not related to the task (i.e., extraneous cognitive load, unless the task is collaborative by nature). Assuming the same amount of time-on-task, it would be expected that the more inter-individual activities amongst group members, the more complex is the collaborative work which requires more working memory resources (i.e., cognitive load). Since transactional activities may depend on multiple factors, for example, how information elements must be interconnected to solve the task, it is to be expected that the way in which task information is distributed among group members may result in different levels of intra-group density. Accordingly, task information used in Chapter 3 was manipulated to create two conditions of distribution: high- and low-density information. The extent to which experienced groups can optimize their working memory resources and have better results in complex tasks (i.e., a high level of task element interactivity) that should be learned with a high level of information density (i.e., group-based element interactivity) was examined.

Evidence for the hypothesis that experienced groups are more efficient than non-experienced groups in tasks with higher information density in retention and delayed tests was obtained. However, no evidence of higher performance and lower mental effort was found in these tests, nor was any significant difference in the learning phase. Another finding was that there was no significant difference between experienced and non-experienced groups in performance, mental effort, and efficiency in all phases on tasks that demanded lower density information. These results suggest that groups that previously worked on analogous tasks acquired relevant schemas of group work and transferred those schemas to learning highly complex tasks. All groups experienced similar performance and mental effort. However, efficiency measures showed that groups with collaborative preparation could optimize their collective working memory resources (F. Kirschner, Paas, & Kirschner, 2011) to deal with the high cognitive demand of inter-individual processing and task information elements.

Chapter 5 reports on a study that aimed to determine the impact of task-specific prior knowledge level (i.e., novices vs. advanced learners) on experienced groups and individual learners. Groups were prepared in the same way as in the previous studies and received the higher information distribution used in Chapter 4. Additionally, half of the students who learned in experienced groups and individually received an additional session that had the purpose of providing specific schemas of the new learning tasks using worked-examples. Regarding learning condition, evidence for the expectation that for individual learning, more knowledgeable learners outperform novice learners in retention and delayed tests was found. This result was not obtained in the learning phase. Mental effort was, as expected, lower in the learning phase, but in the retention test the experienced groups invested a higher mental effort. No difference was found in the delayed test. When students learn in experienced groups, as expected, knowledgeable learners outperformed novice learners in the retention and delayed tests and invested a similar amount of mental effort in all phases. Concerning prior knowledge levels, evidence for the hypothesis that when learners are novices, groups outperform individuals was found in retention and delayed tests, but not in the learning phase. The expectation that experienced groups would invest a lesser amount of mental effort than non-experienced groups was not found in any phase. Instead, those who learned in groups invested more mental effort in the retention phase. Finally, the hypothesis that there is no difference between experienced groups and individuals when students had prior knowledge was confirmed in all phases, except in the retention phase where students in the knowledgeable groups outperformed those in the individual learning condition.

This last study presents evidence that prior task knowledge affects the advantage of having generalizable collaboration schemas for similar tasks. According to the collective working memory effect (F. Kirschner, Paas, & Kirschner, 2011), groups are more effective when tasks are highly complex. However, this effect has not been found in all investigations (Retnowati et al., 2016, 2018). Evidence for this effect was found here, but with the variant that groups received guidance on how to collaborate. In addition to the schemas on how to collaborate, the acquisition of partially developed task information elements explains when collaboration is effective compared to learning individually. When learning tasks have a high level of element interactivity to the point of overwhelming the working memory capacity of novice learners, learning in groups turns out to be more appropriate as long as members have schemas on how to collaborate on the learning task. However, if students already have prior knowledge of the task, having collaborative structures may be redundant. These findings suggest that knowledge structures considerably define the advantage of learning in groups. Students do not learn better if they are only grouped to solve a complex problem. Instead, it may be harmful. Learners should learn to collaborate with each other according to the characteristics of the task. If the task is so complex that it overloads working memory, it is even appropriate to provide both shared work schemas and partially developed schemas of the learning task. It seems that flexible, collaborative knowledge based on relevant tasks combined with task-specific schemas make up structures in long-term memory that optimize group information processing and allow learners to anticipate the missing information elements that must be acquired to solve the learning problems.

Implications

Theoretical implications

A fundamental assumption of cognitive load theory is that extraneous load (i.e., unrelated task information elements) must be reduced when learning new domain-specific tasks (i.e., task information elements). When learners store task elements in long-term memory, they use these elements schematically (i.e., encapsulated) to solve complex problems without affecting the working memory limitations. In turn, previously built schemas form a cognitive structure that allows learners to acquire more complex tasks or mental representations of their environments (see the environmental organizing and linking principles in Chapter 2).

Although cognitive load theory has been developed mainly through studies of individual learning, this research shows that collaborative learning can be improved the cognitive load factors that affect transactional activities are also considered. Previous research has found that groups may construct a collective working memory space (F. Kirschner, Paas, & Kirschner, 2011), which may explain when and why to use collaborative learning. The collective working memory effect holds that group members may share their working memory resources among themselves to better process highly interacting task information elements and construct better mental representations in long-term memory than students who learn individually (F. Kirschner, Paas, & Kirschner, 2011). This research aimed to contribute to this effect by expanding the explanation of how and why learning in groups may be more appropriate considering the cognitive load imposed by transactional activities.

Assuming that the instructional goal is to acquire domain-specific task schemas that must be executed individually (i.e., after the learning phase), the cognitive load demanded by transactional activities (i.e., group-based information elements) should be categorized as extraneous load. It is possible to consider that transactional activities impose an intrinsic load when the instructional goal is to learn how to collaborate on particular tasks. In any case, inter-individual activities are inevitable, and research should find ways to optimize them to improve individual and group performance.

Cognitive load theory can be expanded to explain the advantages and disadvantages of collaborative learning when examining the transactional activities themselves as well as the factors that affect them. When considering the implications of the essential concept of element interactivity, it can be plausibly assumed that transactional activities can be thought of as interactive elements that may or may not contribute to learning. Interactive elements are roughly defined as "elements that must be simultaneously processed in working memory as they are logically related" (Sweller et al., 2011, p. 58). This concept explains both intrinsic and extraneous loads. In collaborative learning, inter-individual processes are information-processing mechanisms that impose a cognitive load within a group. Therefore, it is possible to talk about group-based interactivity information elements. These processes may impose a cognitive load at individual and group levels and may be related to factors such as prior knowledge on collaborative work (chapter 3), information distribution among members (chapter 4) or prior knowledge of the learning task (chapter 5).

Interacting information elements related to group learning may be reduced or optimized. For example, Chapter 3 shows that experienced groups reduced their regulatory interactions and unrelated task conversations perhaps because members acquired group schemas on how to organize themselves to process information and how to focus their interactions on tasks by avoiding engaging in interactions that do not contribute to learning. Optimization, on the other hand, does not imply reducing transactional activities but improving them. For example, experienced groups carried out more shared calculations and fewer individual calculations. It seems that experienced groups members learned that it is better to share their working memory resources and take advantage of the resources of other members to solve the complex steps of the problem than to try to do this alone. Also, according to the results of the time-on-task analysis of Chapter 3, optimizing collaborative cognitive load may even imply that students invest more time in inter-individual processing to consolidate their schemas in long-term memory.

Another theoretical implication is to consider the flexible, transferable, or generalizable knowledge structures of long-term memory to construct relatively new domain-specific task schemas (Kalyuga, 2013). According to the environmental organizing and linking principle (see Chapter 2), schemas stored in long-term memory guide behavior. From this principle, it can be inferred that collaborative schemas based on relevant tasks may function as a shared central executive (Van den Bossche et al., 2011) that guides inter-individual activities of group members in relatively new tasks. Group schemas may be flexible to the extent that they can be applied to specific or analogical conditions of collaboration, because schemas are acquired and transferred situationally (Cooper & Sweller, 1987; Gick & Holyoak, 1983; Godden & Baddeley, 1975); in this case, with specific tasks and classmates. Under similar conditions of group learning, it seems that students recover their long-term memory group processing strategies required by the task such as group communication, sharing information, mutual coordination to solve specific task steps, organization of member participation, transactive contributions, cognitive monitoring, control of irrelevant interactions, etcetera (P. A. Kirschner et al., 2018; Zambrano R. et al., 2019a; Zambrano R. et al., 2020). These group information processing strategies may be executed through analogical transfer, which involves using processes to solve other similar problems (Gentner et al., 2001; Gick & Holyoak, 1983; Novick, 1988).

The availability of prior collaborative experiences may optimize the cognitive load associated with transactional activities. Solving new and complex learning problems in collaboration may demand a lot of working memory resources without contributing to the acquisition of better task schemas. If there is no prior collaborative experience, resolving complex problems in groups may require students to carry out unnecessary or irrelevant transactional activities (e.g., non-task interactions or discussions to organize themselves, Zambrano R. et al., 2019). These strategies may reduce the time for processing task information and harm group member learning. For this reason, the cognitive load related to collaborative work may be optimized by providing groups guidance on how to work together for their transactional activities to be more efficient and effective.

Another implication for cognitive load theory is the role of prior knowledge in collaborative learning. According to the expertise reversal effect (Kalyuga et al., 2003), advanced students who receive instructional guidance to learn previously acquired information elements may have equal or higher cognitive load and equal performance (i.e., partial expertise reversal effect) or lower performance (i.e., full expertise reversal effect) than novices. It is plausible to assume that this effect may occur under conditions of collaboration (Zhang et al., 2016; Zhang et al., 2015). When the goal of instruction is processing and storing highly complex information relevant to group learning (i.e., high levels of task information elements and group-based information elements), having schemas on how to solve tasks in collaboration may not be sufficient. This research suggests (Chapter 5) that it is better to have collaborative experience in analogous tasks and partially developed schemas of specific learning tasks (i.e., task- and group-based shared schemas; Fransen et al., 2013; Van den Bossche et al., 2011). It seems a combination of generalizable knowledge and specific tasks create a cognitive structure that promotes better information processing during group learning and improves the quality of the schemas to solve learning problems. Providing partially developed knowledge schemas for complex tasks improves learning in both individual learners and non-experienced groups. However, learning how to handle complex tasks improves substantially more when learning groups have collaborative work schemas compared to individual learning.

Learning in groups that have relevant prior task-based experience may or may not decrease cognitive load during learning, but group members may learn better and develop more efficient representations of the task. Instructional design could reduce the cognitive load of the students who learn in groups by managing the complexity of the task, providing prior experience on similar tasks, organizing the distribution of information elements among group members, or ensuring the prior knowledge of the task. However, in principle, it is not possible to eliminate the collaborative cognitive load because it is the result of inter-individual processing without which it is not possible to learn in groups. Consequently, collaborative cognitive load research (i.e., associated with transactional activities) (P. A. Kirschner et al., 2018; Zambrano R. et al., 2020) is a unique field of research that may clarify the advantages and limitations of collaborative learning.

Instructional implications

The research reported here has a number of Important Instructional Implications, namely:

- Groups may learn new, highly complex tasks when they have had previous collaborative experience in similar tasks. Instructors can provide collaboration schemas through tasks with similar characteristics already known by learners (e.g., mathematics with calculus or statistics with economics). During the preparation of learners, instructors should model group work through scaffolding (i.e., fading approach) using cognitive prompts or scripts.
- When collaborative tasks are complex because students have to learn a large number of interactive elements (i.e., task element interactivity is high) through a high level of inter-individual processing (i.e., group-based element interactivity is high), groups should be prepared to collaborate with similar tasks that they have already learned to solve. If the tasks have high levels of task element interactivity but low levels of group-based element interactivity, groups do not require preparation for collaborative learning.
- When tasks are challenging to learn individually because they have very high-level element interactivity, it is better to design collaborative tasks, prepare groups to collaborate on similar tasks, and provide specific schemas about the learning tasks. Instruction on how to collaborate may help groups to adequately communicate and coordinate their inter-individual activities, and the initial instruction of specific learning tasks may help to build the missing schemas to learn to solve the task.

Limitations and future research

This study has several limitations. First, the grading system in the learning phase did not allow evaluation of the collaboration process. Only the final score of each task was considered, but not the score of each step of the task. The reason why this rating process was used was to encourage verbal interaction between collaborating learners and not download working memory through written elaborations (Van Bruggen et al., 2002). In the study reported in Chapter 3, voice recorders were used to identify the types of interactions. Future research may include recordings of both individual and inter-individual written elaborations, as well as non-verbal communication to obtain more information about the collaborative learning process (Martinez-Maldonado et al., 2017).

Another limitation was that no working memory measurement was made to adapt the instruction to individual differences (Mojzisch et al., 2014). This research took advantage of prior knowledge about solving quadratic equations problems to prepare experienced groups, with the purpose of reducing the cognitive load to learn new domain-specific tasks and collaborative skills simultaneously (Fransen et al., 2013). However, this does not imply that individual differences in the processing of numerical, visual, or verbal information do not affect the results of groups (Barnes & Raghubar, 2017). It might be expected that individual working memory capacity affects group performance (Mojzisch et al., 2014). Perhaps students with more working memory capacity require fewer preparation sessions to work in groups than those with lower working memory capacity. It can also be assumed that those with lower working memory capacity benefit more when working in experienced groups with highly complex tasks (i.e., group-to-individual-in-group transfer; Schulz-Hardt & Brodbeck, 2012) than individual students or non-experienced groups with higher working memory capacity.

The advantage of a previous collaborative experience was indicated by the higher performance and cognitive efficiency on the retention and delayed tests. In addition to these measurements, in future investigations, self-report questionnaires on group work (e.g., Fransen et al., 2011) and cognitive load (e.g., an adaptation of Leppink, Paas, Vleuten, Van Gog, & Van Merriënboer, 2013) could be applied to investigate if there is a difference between the perceptions of experienced and non-experienced groups about their own performance, and contrast this perception with the analysis of interactions as was done in the learning phase of Chapter 3.

Future research may replicate the studies reported in this dissertation by comparing the three learning conditions simultaneously. The study would consist of comparing individual learning, experienced groups, and non-experienced groups, with students of high and low prior knowledge about the learning tasks. Because it has been suggested that groups develop across multiple and dynamic phases before effectively collaborating to learn new tasks (Fransen et al., 2013; Tuckman & Jensen, 1977), groups were prepared with familiar tasks. It was assumed that if group members were required to learn to work together with new tasks, they may experience more cognitive load than learning to collaborate with known tasks. Future research may examine whether training groups with new tasks is really harmful. It entails, in turn, assuming that there may be collaboration schemas applicable to different (i.e., non-analogous) domain-specific tasks.

Another future investigation may be to examine the effect of group modeling. In the current investigation, students were prepared to work in groups by combining a scaffolding strategy (i.e., fading and completion) and a script collaboration (i.e., built-in collaboration rules in worked examples) with already known similar tasks. It is possible that video-based collaborative worked-examples can accelerate the preparation of students to collaborate. Rummel and her colleagues (Rummel & Spada, 2005; Rummel et al., 2006) have provided evidence of the effectiveness of this strategy. However, it has not been examined if the advantage of this strategy depends on task complexity and information distribution.

Finally, future research to develop cognitive load measurements that are valid and reliable for collaborative learning is required. In this investigation, cognitive load was measured with the 9-point subjective scale (Paas, 1992). This scale seems to be reliable in individual learning conditions (Paas, Van Merrienboer, & Adam, 1994). However, this measurement and other similar ones (e.g., Leppink et al., 2013) cannot indicate what the cognitive load factors are (e.g., split attention or redundancy) (Sweller, 2018a, 2018b). In conditions of collaboration where many more factors interact, this type of measurement may not be sufficiently specific. A promising way to measure the cognitive load in collaborative learning is to identify the linguistic features during collaborative learning that may be associated with the types of transactional activities and cognitive load (Khawaja et al., 2012, 2013).

Conclusion

This dissertation provides evidence to suggest that collaborative learning may be more effective and efficient by preparing groups to collaborate. The advantage of providing groups with collaboration schemas depends on how the information is distributed among group members and the prior knowledge of the specific domain tasks. The current investigations were designed using cognitive load theory, and mental effort measurements were used. This instructional approach provided a fruitful explanation of the advantage of having flexible collaboration schemas to solve similar learning problems that must be executed individually (i.e., after collaborative learning). It was also possible to explain the advantages of reducing or optimizing group processing of task information, considering that transactional activities are elements of information that impose a cognitive load. In general, the results confirmed that prior knowledge on how to collaborate and on the specific task explains why and when collaborative learning may or may not be effective and efficient.

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Summary

In today's society there seems to be a globally widespread notion that students learn best via collaboration. Additionally, there is overwhelming literature that supposes implicit or explicitly that grouping students to collaborate results in more effective and efficient learning outcomes. However, not all scientific studies show that learning in groups is consistently beneficial. A crucial aspect that may contribute in understanding why and when collaboration is favorable or harmful is considering the human cognitive architecture. This dissertation uses as its foundation the cognitive architecture of the human brain and, thus, by the factors that influence the processing of information in the working memories of members of collaborating groups and how new information is stored in their long-term memories.

The primary goal of this research was to *determine the consequences of decreasing the cognitive load associated with group interactions in order to improve collaborative learning in carrying out highly complex learning tasks*. Collaborative learning groups can be considered as information processing systems that can simultaneously process more information elements due to the combination of the working memories of its members (i.e., collective working memory) and its transactional activities (i.e., communication and coordination processes). Inter-individual activities can be affected by the interaction of multiple variables related to learners (e.g., prior knowledge with respect to the task), groups (e.g., group-member experience in similar tasks or distribution of information among members), or tasks (e.g., level of element interactivity). Manipulating these variables may help to understand how to optimize group information processing and its cognitive load.

In this research it is assumed that transactional activities and its related cognitive load may be optimized providing groups with collaborative experience based on relatively similar tasks (i.e., creating task-based experienced groups). Underlying the primary research goal is to determine if this group experience allows peers to appropriately use their transactional activities to learn better, have higher performance, and be more efficient than members of groups without this collaborative experience (i.e., non-experienced groups). Other goals were to examine how the distribution of information among group members (i.e., high-density information vs. low-density information) and how prior knowledge (i.e., novices vs. advanced learners) affect the results of students learning in experienced and non-experienced groups.

Chapter 2 explore the state of the art of cognitive load theory regarding collaborative learning. Specifically, the principles of human cognitive architecture, knowledge acquired through this cognitive architecture, and the types of cognitive load involved in acquiring new knowledge are discussed. It is suggested that the fundamental theoretical assumptions of cognitive load theory, although it has been built mostly through individual learning research, may apply to understand when and why collaborative learning may be an effective and efficient learning strategy. One way to improve this understanding is to explore the cognitive load factors related to intra-group processing of complex tasks. In other words, research needs to determine the variables that impact the transactional activities during collaboration, and their consequences on individual learning outcomes. It is suggested that mutual cognitive interdependence may be a principle that explains the evolution of human cognitive architecture. However, it does not mean, from an instructional perspective, that collaborating to learn domain-specific tasks will always be appropriate because carrying out learning tasks in groups may impose unnecessary cognitive load associated with transactional activities in addition to the 'normal' load of the task. For this reason, it is proposed to consider the role of generalized domain knowledge concerning group work and prior task knowledge to optimize the working memory cognitive load associated with intra-group processing to acquire better schemas in long-term memory. It concludes with suggestions of a number of research hypotheses which have been derived from this discussion.

Chapter 3 examines whether prior collaborative experience based on having carried out similar tasks increases effectiveness (i.e., performance), decreases cognitive load and, therefore, increases efficiency in the learning, short-term retention, and delayed retention phases. Results suggests that having in task-based group experience improves the learning outcomes. That is, members of the groups that had taken part in the preparation sessions designed to provide experience in collaboration with relatively similar tasks performed better, experienced less mental effort, and were more efficient than non-experienced groups on the retention and delayed tests. In addition, this study examined the differences between experienced and non-experienced groups concerning socio-cognitive, socio-regulatory, and socio-emotional and task unrelated transactional activities. An analysis of verbal interactions conducted with five experienced and five non-experienced groups showed that the experienced groups spent more time solving the learning task problems, had more socio-cognitive interactions and fewer socio-regulatory as well as task unrelated interactions. The number of socio-emotional interactions was not different between both conditions. These data suggest that collaborative work schemas acquired in the preparation phase may guide collaborative learning and optimize the working memory cognitive load devoted by group members to inter-individual information processing of learning tasks.

Chapter 4 examines whether the distribution of information among learners affects the effectiveness and efficiency of learning for groups with and without collaborative experience. Based on the essential concept of element interactivity level of cognitive load theory, it was assumed transactional activities are a type of group-based information element that imposes cognitive load, and that this may result in different levels of information density. Results suggest that experienced groups optimized their working memory resources and were more efficient in performing complex learning tasks (i.e., a high level of task element interactivity) with a higher level of information density than a lower level of information density (i.e., group-based element interactivity). Also, as expected, no significant difference was found between experienced and non-experienced groups in performance, mental effort, and efficiency, in all three of the measurement moments (study, short-term retention and delayed retention) on tasks that demanded lower information density. It seems that groups that previously worked on similar tasks acquired relevant schemas of group work and transferred them to learn highly complex tasks. These results provide instructional implications for designing efficient collaborative learning environments with respect to team experience and information distribution.

Chapter 5 examines the effect of task-specific prior knowledge level (i.e., novices vs. advanced learners) on students that learned in groups that previously received instruction on how to collaborate (i.e., instructed groups) and individual learners. Advanced learners received an additional session that had the purpose of providing specific schemas of the new learning tasks. Regarding the learning condition, it was found that when students learn individually, advanced learners outperform novice learners in retention and delayed tests as expected. However, learners in the instructed groups invested higher mental effort in the retention test and an equivalent mental effort in the delayed test. When students learn in groups, as expected, more knowledgeable learners outperform novices and invest an equivalent amount of mental effort in the retention and delayed tests. Concerning prior knowledge, when learners are novices, as expected, groups outperform individuals in retention and delayed tests. However, instructed groups invested more mental effort in the retention test and equivalent mental effort in the delayed test. As expected, no difference between experienced groups and individuals was found in all tests when students had prior knowledge, except that in the retention test knowledgeable groups outperformed individual learning condition. It appears that task-based prior collaborative experience (i.e., a type of team expertise) and task-specific schemas (i.e., task expertise) make up structures in long-term memory that optimize group information processing to learn highly complex learning problems.

Chapter 6 presents an overview of the main findings of this research, the theoretical and instructional implications, the limitations of the research, and future studies. This chapter ends by concluding that the evidence found in this research suggests that collaboration may be more effective and efficient for learning highly complex tasks when groups are prepared to collaborate by previously solving other analogous tasks. The advantage of helping groups to acquire collaborative experience based on relevant tasks depends on how the information is distributed among group members and their prior knowledge of the new domain-specific tasks. It was found that the cognitive load theory approach can provide us with comprehensive explanations of the advantage of having acquired collaboration schemas to solve similar learning problems that learners are required to carry out individually (i.e., after collaborative learning). This approach allowed for the explanation of the benefits of reducing or optimizing group processing of task information, considering that transactional activities are elements of information that impose a cognitive load. In sum, it is concluded that prior knowledge on how to collaborate (i.e., a type of team expertise) and on the domain-specific task explain why and when collaborating for learning with highly complex tasks may or may not be effective and efficient.

Previous research on cognitive load and collaborative learning (F. Kirschner et al., 2009a; F. Kirschner, Paas, & Kirschner, 2011; F. Kirschner, Paas, Kirschner, et al., 2011) has taught us that if we are to effectively and efficiently employ collaborative learning we should make use of complex learning tasks to (1) profit from the collective working memory and (2) ensure that the benefits of collaborative learning are higher than the costs of transactive activities involved in collaboration. This research adds that we also must ensure that teams have (3) learned how to collaborate and that the team has experience collaborating on analogous types of tasks (P. A. Kirschner et al., 2018; Zambrano R. et al., 2020), and (4) the necessary prior domain-specific knowledge to work effectively on the tasks (Zambrano R. et al., 2019a; Zambrano R., Kirschner, Sweller, & Kirschner, 2019b; Zambrano R. et al., 2019c).

Samenvatting

In onze huidige maatschappij is er en algemene en wijdverspreide opvatting dat leerlingen het beste leren door samen te werken; samenwerkend leren. Daarnaast is er ook heel veel literatuur die er vanuit gaat - ofwel impliciet ofwel expliciet – dat samenwerkend leren tot effectiever en efficiënter leren leidt. Echter, in meer detail naar deze literatuur kijkend kan geconcludeerd worden dat niet al het samenwerkend leren voordelig is voor leren. Belangrijk is dan ook om te onderzoeken hoe verschillende variabelen van samenwerkend leren het leerproces van de leerlingen beïnvloed. In dit proefschrift zal de cognitieve architectuur van het menselijke brein, en daarmee de factoren die van invloed zijn op het verwerken van informatie in het werkgeheugen van groepsleden en de manier waarop informatie wordt opgeslagen in hun lange termijn geheugen, hiervoor de leidraad zijn. Vanuit dit perspectief kunnen leerlingen die samenwerken om een leertaak te volbrengen worden gezien als informatieverwerkende systemen die meer informatie kunnen verwerken dan individueel werkende leerlingen omdat ze: A) door gebruik te maken van transactionele activiteiten (d.w.z. communicatie- en coördinatieprocessen) B) hun werkgeheugens kunnen combineren (m.a.w. gebruik maken van een collectieve werkgeheugen). Interactie tussen leerlingen die samenwerken kan beïnvloed worden door variabelen met betrekking tot: de leerling (bvb. voorkennis die relevant is voor de leertaak), de groep (bvb. de ervaring van groepsleden met gelijkwaardige leertaken of de verdeling van informatie over deze leden) of de leertaak (bvb. de hoeveelheid interactie tussen de verschillende informatie elementen in de leertaak). Door deze variabelen te manipuleren kan er belangrijk inzicht worden verkregen op hoe de informatieverwerking in groepen en de bijbehorende ervaren cognitieve belasting, geoptimaliseerd kan worden.

In dit onderzoek wordt er verondersteld dat de transactionele activiteiten en hun cognitieve belasting geoptimaliseerd kunnen worden, wat zal resulteren in groepen die ervaring hebben met het samenwerken aan leertaken die relatief gelijkaardig of analoog zijn (d.w.z. het creëren van taak-gebaseerde ervaringsgroepen). *Het onderliggende onderzoeksdoel is om te bepalen of deze groepservaring de mogelijkheid biedt aan hun leeftijdsgenoten om hun eigen transactionele activiteiten op een gepaste manier te* *gebruiken om beter te leren, hun prestaties te verbeteren en hun efficiëntie te verhogen ten opzichte van leden van groepen zonder deze collaboratieve ervaring (d.w.z. niet-ervaren groepen).* Het onderzoek had ook andere doelen, waaronder het bepalen in welke mate de distributie van informatie onder de groepsleden (d.w.z. een hoge informatiedichtheid tegen een lage informatiedichtheid) en een voorkennis (d.w.z. beginnelingen tegen gevorderde leerlingen ten opzichte van een bepaalde inhoud) de resultaten van leerlingen in ervaren en niet-ervaren groepen.

Hoofdstuk 2 zet de huidig theorieën rond cognitieve belasting in relatie tot samenwerkend leren uiteen. Hierbij worden de principes van de cognitieve architectuur van het menselijke brein en de verschillende type cognitieve belasting verbonden aan de verwerving van nieuwe kennis. Er wordt hierbij gesuggereerd dat de fundamentele theoretische veronderstellingen van de cognitieve belastingtheorie, hoewel deze voornamelijk is gebaseerd op individueel leren, gebruikt kunnen worden om te begrijpen wanneer en waarom samenwerkend leren een effectieve en efficiënte leerstrategie kan zijn. Één manier om hier meer inzicht in te verkrijgen is te achterhalen welke cognitieve belastingfactoren gerelateerd zijn aan gezamenlijk leren van complexe taken. Met ander woorden: onderzoek zal de variabelen moeten identificeren die van invloed zijn op de transactionele activiteiten tijdens het samenwerkingsproces, en de gevolgen voor de individuele leeruitkomsten bepalen. Er wordt gesuggereerd dat wederkerige cognitieve afhankelijkheid (EN: mutual cognitive interdependence) een principe kan zijn die de evolutie van de menselijke cognitieve architectuur kan verklaren. Dit betekent echter niet, vanuit een institutioneel perspectief, dat voor het leren van domein specifieke taken samenwerken altijd het meest geschikt zal zijn. Het in samenwerking uitvoeren van leertaken legt immers een bijkomende en onnodige cognitieve belasting op de leerling die geassocieerd wordt met transactionele activiteiten. Deze cognitieve belasting komt boven op de 'normale' belasting van de domein specifieke leertaak. Om deze reden wordt voorgesteld om de rol van gegeneraliseerde domeinkennis betreffende samenwerken in groepen en voorkennis over de domein specifieke taak te onderzoeken. Dit om de cognitieve belasting geassocieerd met het samenwerkingsproces te optimaliseren zodat betere schema's in het langetermijngeheugen gecreëerd kunnen worden. Op basis van deze theoretische inzichten zullen een aantal onderzoekshypotheses worden geformuleerd.

Hoofdstuk 3 onderzoekt of eerdere ervaringen met samenwerkend-leren aan gelijkaardige taken de effectiviteit (d.w.z. de prestaties) bevordert en de ervaren cognitieve belasting vermindert, waardoor de leerefficiëntie en de kennisretentie (d.w.z. leren) op korte en langere termijn ook verbeteren. De resultaten doen vermoeden dat taakgerichte groepservaring een positieve invloed heeft op de leeruitkomsten. Met andere woorden: de groepsleden die aan voorbereidende sessies deelgenomen hadden, die bedoeld waren om een zekere ervaring met het samenwerken aan gelijksoortige taken op te doen, presteerden beter, ervaarde minder mentale inspanning, en waren efficiënter tijdens de korte- en lange-termijn kennisretentietaken, dan de groepsleden die geen ervaring op dit gebied hadden opgedaan. Deze studie onderzocht niet alleen de verschillen in leren en ervaren cognitieve belasting, maar ook de verschillen tussen ervaren en niet-ervaren groepen wat betreft socio-cognitieve, socio-regulerende, socio-emotionele en niet-taakgerelateerde transactionele activiteiten. Een analyse van de verbale interacties uitgevoerd met transcripties van vijf ervaren en vijf niet-ervaren groepen toonde aan dat de ervaren groepen meer tijd besteden aan het oplossen van de problemen verbonden aan de leertaken, en ook meer socio-cognitieve en minder socio-regulerende en niet-taakgerelateerde interacties hadden. Het aantal socio-emotionele interacties was hetzelfde voor beide groepen. Deze data suggereren dat er tijdens de voorbereidende fase kennis is verworven over het samenwerkingsproces, en dat deze kennis het samenwerkend leren op een later tijdstip heeft helpen sturen waardoor de cognitieve belasting geassocieerd met het samenwerkingsproces geoptimaliseerd werd.

Hoofdstuk 4 onderzoekt of de distributie van informatie onder groepsleden van invloed is op de effectiviteit en de efficiëntie van leren voor groepen met en zonder eerdere samenwerkingservaring. Gebaseerd op het essentiële concept van elementinteractiviteit (d.w.z. hoeveel interactie er tussen de verschillende informatie-elementen in een uit te voeren leertaak is) uit de cognitieve belastingstheorie, werd er verondersteld dat transactionele activiteiten een groepsgeoriënteerd informatie-element vormen, dat dus cognitieve belasting kan veroorzaken, waardoor verschillende niveaus van informatiedichtheid mogelijk zijn. De resultaten suggereren dat de ervaren groepen het gebruik van hun beschikbare werkgeheugen optimaliseerden en ook dat ze efficiënter waren bij het uitvoeren van complexe leertaken (d.w.z. leertaken met veel interactiviteit tussen de elementen) bij taken die meer informatiedicht waren dan bij taken die minder informatiedicht waren (d.w.z. groepgeoriënteerde elementinteractiviteit).

Zoals verwacht werd er ook geconstateerd dat er bij taken met een lager niveau van informatiedichtheid er geen significant verschil was tussen de ervaren en de niet-ervaren groepen wat betreft hun prestaties, mentale inspanning en efficiëntie. Het blijkt dus dat groepen die al eerder met gelijkaardige taken gewerkt hadden relevante schema's voor het groepsproces aangeworven hadden, en die konden gebruiken om zeer complexe leertaken uit te voeren. Deze resultaten hebben implicaties voor het ontwerpen van efficiënte samenwerkend leeromgevingen wat betreft ervaring van teamleden werkend met elkaar en informatiedistributie over groepsleden.

Hoofdstuk 5 onderzoekt het effect van het niveau van domeinspecifieke voorkennis (d.w.z. beginners vs. gevorderden in een kennisdomein) op leerlingen in groepen die instructie kregen over samenwerking en individueel lerende. Gevorderde lerende hadden een voorbereidende sessie gevolgd bedoeld om specifieke schema's voor de leertaken te verwerven. Wat betreft het leren in geïnstrueerde groepen vs. individueel leren laten de resultaten zoals verwacht zien dat dat wanneer de leerlingen individueel leren de leerlingen met meer voorkennis (d.w.z. de gevorderden) beter presteren dan de leerlingen met weinig voorkennis (d.w.z. de beginners), zowel voor de korte-termijn als de uitgestelde retentietoets. De geïnstrueerde groepen moesten echter een grotere mentale inspanning leveren tijdens de korte-termijn retentietoets en evenveel mentale inspanning in de uitgestelde rententietoets. Daarnaast presteerden de ervaren groepen met gevorderden, zoals verwacht, beter dan de geïnstrueerde groepen met beginners, en moesten ze evenveel mentale inspanning leveren bij zowel de korte-termijn retentietoets als de uitgestelde. Wat betreft het niveau van domeinspecifieke voorkennis laten de resultaten zoals verwacht zien dat beginners die in groepen leren beter presteren dan individueel lerende bij zowel de korte-termijn- als de uitgestelde retentietoets. Geïnstrueerde groepen leveren echter een grotere mentale inspanning (d.w.z. ervaren meer cognitieve belasting) bij de korte-termijn retentietoets en een equivalente mentale inspanning in de uitgestelde retentietoets. Zoals verwacht, was er geen verschil in beide toetsen tussen de geïnstrueerde groepen en de individuen met veel voorkennis, behalve dat bij de korte-termijn retentietoets de leerlingen in de groepen met meer voorkennis beter presteerden dan de lerende in de individuele leerconditie. Het blijkt dat eerdere ervaring met het taakgerichte samenwerken (d.w.z. het bezitten van een soort gezamenlijke expertise op het gebied van samenwerken) en het hebben van specifieke taak schema's (d.w.z. het bezitten van taakexpertise) helpen om kennis, die de verwerking van groepsinformatie optimaliseren, in het langetermijngeheugen op te bouwen, en met zeer complexe leerproblemen om te gaan.

Hoofdstuk 6 geeft een overzicht van de voornaamste bevindingen van voorgaande studies, alsook een samenvatting van de theoretische en instructionele implicaties, de beperkingen van dit onderzoek, en voorstellen voor vervolg onderzoek. Dit hoofdstuk eindigt met de conclusie dat de resultaten van de verschillende onderzoeken suggereren dat samenwerkend leren effectiever en efficiënter is om het leren van zeer complexe leertaken te bevorderen. Dit is echter op voorwaarde dat de groepen de nodige voorbereiding voor het samenwerken krijgen door aan analoge taken te werken. Het voordeel dat een dergelijke voorbereiding kan opleveren is echter ook afhankelijk van hoe de informatie onder de groepsleden verdeeld is en hoe groot hun voorkennis is van de domeinspecifieke taken. Er kan daarnaast worden vastgesteld dat cognitieve belastingstheorie een duidelijke en uitgebreide verklaring kan geven voor het voordeel van samenwerkingsschema's om vergelijkbare leerproblemen op te lossen. Deze cognitieve benadering verklaart ook het voordeel van het reduceren of optimaliseren van het in samenwerking verwerken van taakinformatie, rekening houdend dat transactionele activiteiten cognitieve belasting veroorzaken. Kortom, er wordt vastgesteld dat voorkennis over hoe men moet samenwerken (d.w.z. een soort samenwerkingsexpertise) en over de domeinspecifieke taken (d.w.z. domeinexpertise) bepalend is om te kunnen verklaren wanneer en waarom samenwerkend leren bij zeer complexe taken al dan niet effectief en efficiënt zal zijn.

Uit eerder onderzoek naar cognitieve belasting en samenwerkend leren (F. Kirschner et al., 2009a; F. Kirschner, Paas, & Kirschner, 2011; F. Kirschner, Paas, Kirschner, et al., 2011) weten wij dat wij (1) complexe leertaken moeten gebruiken om voordeel uit het collectieve werkgeheugen te kunnen halen alsmede (2) ervoor moeten zorgen dat de voordelen van samenwerkend leren groter zijn dan kosten van de transactieve activiteiten verbonden aan het samenwerken. Van dit onderzoek kunnen wij hieraan toevoegen dat men ervoor moet zorgen dat de groepen / teams (3) al geleerd hebben hoe ze samen moeten werken en dat ze ook ervaring hebben opgedaan met het samenwerken aan gelijkaardige taken; en (4) over de nodige domeinspecifieke voorkennis beschikken om op een effectieve wijze met de leertaken om te gaan (Zambrano R. et al., 2019a; Zambrano R., Kirschner, Sweller, & Kirschner, 2019b; Zambrano R. et al., 2019c).

Resumen

En la sociedad actual parece haber una noción generalizada de que los estudiantes aprenden mejor a través de la colaboración. Además, existe una literatura abrumadora que supone implícita o explícitamente que agrupar a los estudiantes para colaborar da lugar a resultados de aprendizaje más efectivos y eficientes. Sin embargo, no todos los estudios científicos muestran que aprender en grupos es consistentemente beneficioso. Un aspecto crucial que puede contribuir en la comprensión del por qué y cuándo la colaboración es favorable o perjudicial, es considerar la arquitectura cognitiva humana. Esta disertación usa como fundamento la arquitectura cognitiva del cerebro humano y, por lo tanto, los factores que afectan el procesamiento de la información en la memoria de trabajo de los miembros del grupo y cómo adquieren la nueva información en sus memorias de largo plazo.

El objetivo principal de esta investigación fue *determinar las consecuencias de la disminución de la carga cognitiva asociada con las interacciones grupales para mejorar el aprendizaje colaborativo en la realización de tareas de aprendizaje altamente complejas*. Los grupos de aprendizaje colaborativo pueden considerarse como sistemas de procesamiento de información que pueden procesar simultáneamente más elementos de información debido a la combinación de las memorias de trabajo de sus miembros (i.e., memoria de trabajo colectiva) y sus actividades transaccionales (i.e., procesos de comunicación y coordinación). Las actividades interindividuales pueden verse afectadas por la interacción de múltiples variables relacionadas con los alumnos (e.g., el conocimiento previo con respecto a la tarea), con los grupos (e.g., la experiencia de miembros del grupo en tareas similares o la distribución de información entre ellos) o con las tareas (e.g., el nivel de interactividad de los elementos de información). La manipulación de estas variables puede ayudar a comprender cómo optimizar el procesamiento de información grupal y su carga cognitiva.

En esta investigación se asume que las actividades transaccionales y su respectiva carga cognitiva pueden optimizarse proporcionando a los grupos experiencia colaborativa basada en tareas relativamente similares (i.e., creando grupos experimentados basados en tareas). Un objetivo específico derivado del objetivo principal de esta investigación fue *determinar si esta experiencia grupal permite a los*

compañeros utilizar adecuadamente sus actividades transaccionales para aprender mejor, tener un mayor rendimiento y ser más eficientes que los miembros de grupos sin experiencia de colaboración (i.e., grupos sin experiencia). Otros objetivos fueron examinar cómo la *distribución de información entre los miembros del grupo* (i.e., la información de alta densidad frente a la información de baja densidad) y cómo *el conocimiento previo* (i.e., principiantes versus aprendices avanzados) afecta los resultados de los estudiantes que aprenden en grupos con y sin experiencia.

El Capítulo 2 explora el estado del arte de la teoría de la carga cognitiva con respecto al aprendizaje colaborativo. Específicamente, se discuten los principios de la arquitectura cognitiva humana, el conocimiento adquirido a través de esta arquitectura cognitiva y los tipos de carga cognitiva involucrados en la adquisición de nuevo conocimiento. Se sugiere que los supuestos teóricos fundamentales de la teoría de la carga cognitiva, aunque se han desarrollado principalmente a través de la investigación del aprendizaje individual, pueden aplicarse para comprender cuándo y por qué el aprendizaje colaborativo puede ser una estrategia de aprendizaje efectiva y eficiente. Una forma de mejorar esta comprensión es explorar los factores de carga cognitiva relacionados con el procesamiento intragrupal de tareas complejas. En otras palabras, la investigación necesita determinar las variables que impactan las actividades transaccionales durante la colaboración y sus consecuencias en los resultados de aprendizaje de los estudiantes individuales. Se sugiere que la interdependencia cognitiva mutua puede ser un principio que explica la evolución de la arquitectura cognitiva humana. Sin embargo, no significa, desde una perspectiva de la instrucción, que colaborar para aprender tareas específicas del dominio siempre sea apropiado, porque llevar a cabo tareas de aprendizaje en grupos puede imponer una carga cognitiva innecesaria asociada con actividades transaccionales, además de la carga 'propia' de la tarea. Por esta razón, se propone considerar el papel del conocimiento de dominio generalizado en relación con el trabajo en grupo y el conocimiento de tareas previas para optimizar la carga cognitiva de la memoria de trabajo asociada con el procesamiento intragrupal para adquirir mejores esquemas en la memoria a largo plazo. Se concluye sugiriendo algunas hipótesis de investigación derivadas de esta discusión.

El Capítulo 3 examina si la experiencia de colaboración previa basada en haber realizado tareas similares aumenta la efectividad (i.e., el rendimiento), disminuye la carga cognitiva y, por lo tanto, aumenta la eficiencia en las fases de aprendizaje, retención a corto plazo y retención demorada. Los resultados sugieren que tener experiencia grupal basada en tareas mejora los resultados del aprendizaje. Es decir, los miembros de los grupos que habían participado en las sesiones de preparación diseñadas para proporcionar experiencia de colaboración con tareas relativamente similares se desempeñaron mejor, experimentaron menos esfuerzo mental y fueron más eficientes que los grupos sin experiencia tanto en la retención como en las pruebas demoradas. Además, este estudio examinó las diferencias entre los grupos experimentados y no experimentados con respecto a las actividades transaccionales socio-cognitivas, socio-regulatorias y socio-emocionales y no relacionadas con la tarea. Un análisis de las interacciones verbales realizado con cinco grupos experimentados y cinco no experimentados mostró que los grupos experimentados pasaron más tiempo resolviendo los problemas de la tarea de aprendizaje, tuvieron más interacciones socio-cognitivas y menos interacciones socio-regulatorias y no relacionadas con la tarea. El número de interacciones socio-emocionales no fue diferente entre ambas condiciones. Estos datos sugieren que los esquemas de trabajo colaborativo adquiridos en la fase de preparación pueden guiar el aprendizaje colaborativo y optimizar la carga cognitiva de la memoria de trabajo que dedicaron los miembros del grupo al procesamiento de información interindividual de las tareas de aprendizaje.

El Capítulo 4 examina si la distribución de la información entre los estudiantes afecta la efectividad y la eficiencia de los grupos con y sin experiencia colaborativa. Basado en el concepto esencial del nivel de interactividad del elemento de la teoría de la carga cognitiva, se asumió que las actividades transaccionales son un tipo de elemento de información grupal que impone carga cognitiva, y que esto puede resultar en diferentes niveles de densidad de información. Los resultados sugieren que los grupos experimentados optimizaron sus recursos de memoria de trabajo y fueron más eficientes en la realización de tareas de aprendizaje complejas (i.e., un alto nivel de interactividad de elementos de la tarea) con el nivel más alto de densidad de información que con el nivel más bajo de densidad de información (i.e., interactividad de elementos basada en el grupo) Además, como se esperaba, no se encontraron diferencias significativas entre los grupos con experiencia y sin experiencia en el rendimiento, el esfuerzo mental y la eficiencia en todas las fases cuando las tareas exigían un menor nivel de densidad de la información. Parece que los grupos que previamente trabajaron en tareas similares adquirieron esquemas relevantes de trabajo grupal y los transfirieron para aprender tareas altamente complejas. Estos resultados proveen lineamientos instruccionales para el diseño de ambientes de aprendizaje colaborativo teniendo en cuenta la experiencia grupal y la distribución de la información.

El Capítulo 5 examina el efecto del nivel de conocimiento previo específico de la tarea (i.e., principiantes versus estudiantes avanzados) sobre los estudiantes que trabajaron en grupos que habían recibido previamente instrucción sobre cómo colaborar (i.e., grupos instruidos) y estudiantes individuales. Los estudiantes avanzados recibieron una sesión adicional que tenía el propósito de proporcionar esquemas específicos de las nuevas tareas de aprendizaje. Con respecto a la condición de aprendizaje, se encontró que cuando los estudiantes aprenden individualmente, los estudiantes avanzados superan a los estudiantes novatos en las prueba de retención y demorada como se esperaba. Sin embargo, los estudiantes de los grupos instruidos invirtieron un mayor esfuerzo mental en la prueba de retención y un esfuerzo mental equivalente en la prueba demorada. Cuando los estudiantes aprenden en grupos, como se esperaba, los estudiantes con más conocimientos superan a los novatos e invierten una cantidad equivalente de esfuerzo mental en las pruebas de retención y demorada. Con respecto al conocimiento previo, cuando los alumnos son novatos, como se esperaba, los grupos superan en desempeño a los individuos en las pruebas de retención y demorada. Sin embargo, los grupos instruidos invirtieron más esfuerzo mental en la prueba de retención y un esfuerzo mental equivalente en la prueba demorada. Como se esperaba, no se encontraron diferencias en todas las pruebas entre quienes aprendieron en los grupos experimentados e individualmente cuando los estudiantes tenían conocimiento previo, excepto que en la prueba de retención los grupos con conocimiento previo superaron a la condición de aprendizaje individual. Parece que la experiencia de colaboración previa basada en tareas (i.e., un tipo de experticia basada en el equipo) y los esquemas específicos de la tarea (i.e., experticia basada en la tarea) conforman estructuras en la memoria a largo plazo que optimizan el procesamiento de información grupal para aprender problemas de aprendizaje altamente complejos.

El Capítulo 6 presenta una visión general de los principales hallazgos de esta investigación, las implicaciones teóricas e instructivas, las limitaciones de la investigación y los estudios futuros. Este capítulo termina concluyendo que la evidencia encontrada en esta investigación sugiere que la colaboración puede ser más efectiva y eficiente para aprender tareas altamente complejas cuando los grupos están preparados para colaborar mediante la resolución de otras tareas similares. La ventaja de ayudar a los grupos a adquirir experiencia de colaboración basada en tareas relevantes depende de cómo se distribuye la información entre los miembros del grupo y el conocimiento previo de las nuevas tareas de dominio específico. Se encontró que el enfoque de la teoría de la carga cognitiva puede proporcionar explicaciones apropiadas sobre la ventaja de tener esquemas de colaboración flexibles para resolver problemas de aprendizaje similares que deben ejecutarse individualmente (i.e., después del aprendizaje colaborativo). Este enfoque permitió explicar los beneficios de reducir u optimizar el procesamiento grupal de la información de la tarea, considerando que las actividades transaccionales son elementos de información que imponen una carga cognitiva. En suma, se concluye que el conocimiento previo sobre cómo colaborar (i.e., un tipo de experticia de equipo) y sobre la tarea de dominio específico explica por qué y cuándo colaborar para aprender con tareas altamente complejas puede o no ser efectivo y eficiente.

La investigación previa sobre la carga cognitiva y el aprendizaje colaborativo (F. Kirschner et al., 2009a; F. Kirschner, Paas, & Kirschner, 2011; F. Kirschner, Paas, Kirschner, et al., 2011) ha mostrado que si deseamos emplear el aprendizaje colaborativo de manera efectiva y eficiente, debemos usar tareas de aprendizaje complejas para (1) aprovechar la memoria de trabajo colectiva y (2) asegurarnos que los beneficios del aprendizaje colaborativo sean más altos que los costos de las actividades transaccionales involucradas en la colaboración (F. Kirschner et al., 2009a). Esta investigación añade que también debemos asegurarnos de que los equipos (3) hayan aprendido a colaborar, y que tengan experiencia colaborando en tareas análogas (PA Kirschner et al., 2018; Zambrano R. et al., 2018; Zambrano R. et al., 2020), y (4) los conocimientos previos de dominio específico necesarios para trabajar efectivamente en las tareas (Zambrano R. et al., 2019a; Zambrano R. et al., 2019b; Zambrano R. et al., 2019c).

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Curriculum Vitae

Jimmy Zambrano R. (Jimmy Antonio Zambrano Ramírez) was born in Guayaquil, Ecuador, on February 16, 1979.

Work: He is currently occasional researcher for a program of evaluation of teacher performance in mathematics and language of preschool and primary education Ecuadorian centers. Also, he occasionally trains teachers of educational centers of the Ecuadorian Army about instructional design, school learning, and other related topics. He began his career as educator at the primary school Jerusalén, in 1999, in Milagro. He then worked in higher education and have been educational advisor at the National Institute for Educational Evaluation of Ecuador and the Pontifical Catholic University of Ecuador in pedagogy and teacher assessment respectively.

Education: He finished his secondary education in 1997 with a specialization in Chemistry and Biology at the state high-school 17 de Septiembre, in Milagro. Then he finished his bachelor's degree in Education Sciences with a specialization in Educational Administration in 2007 at the University of the Armed Forces ESPE, in Sangolquí. In 2012, he finished a master's degree in Human Resources and Knowledge Management at the University of León, Spain, and two years later another master's degree in Distance Education at the National University of Loja. At the end of 2018, he received a Doctorate in Education from the Andrés Bello Catholic University of Venezuela (Summa Cum Laude). He has complemented his education with specialized courses about educational technology, theological anthropology, and theory of science.

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