Beyond Knowledge: The Legacy of Competence

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Meaningful Computer-based Learning Environments

Springer

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Contents

Beyond Knowledge

The Legacy of Competence in Meaningful Computer-Based Learning Environments

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Beyond Knowledge: About the Content of this Book

Learning and instruction with computers is intrinsically tied to current educational practice in schools, universities, the corporate world and informal settings of learning. However, integration of technology in the practice of education is a sensitive task that has to be well planned in order to meet the needs of learners and teachers . Current changes in European education stress the role of competencies and educational standards; thus, fostering both within the practice of education is eminently important. Meaningful computer-based learning environments contribute to the achievement of learners' acquisition of competence and directly address the superordinate standards of education. They stimulate active learning by providing students with control over learning environments and offer realistic problems with which to practice – environments that can simulate conditions impossible to mimic in the real world, and environments that can embed learning scenarios within the structure of interactive and highly motivating games (Merrill, 2002; Reigeluth, 1999; Van Merriënboer & Kirschner, 2001). Furthermore, the environments also provide the capability of leveraging vast information resources within a myriad of modality-specific deployments – for example, texts, auditory fragments, and animations.

This book presents a highly select compilation of research dedicated to these environments – empirical research (both basic and applied) aimed at the analysis, understanding, and promotion of learning by computer-based and other instructional state-of-the-art approaches.

Section one of this book is dedicated to approaches of competence-based instruction in mathematics and science. By definition, competence is characterized by integrativity, specificity, and durability. Integretivity refers to the combination of knowledge, skills and attitudes as well as aptitudes of students; specificity, refers to the idea that competence is always bound to a context that is either highly specific (e.g., a profession) or more general (e.g., a career); durability relates to the notion that competence does not rely exclusively on tools, working methods or technologies per se (Van Merriënboer, Van der Klink, & Hendriks, 2002). Thus, competence-based instruction requires a holistic approach, consisting of whole tasks that address the coordination and integration of knowledge, skills and attitudes (Van Merrienboer & Kester, 2008). From this perspective, the chapters in this section address the question of how scientific thinking, and epistemological beliefs, in the context of a science classroom, can be extended and enriched by digital learning environments as well as innovative approaches of instructional design.

Part two of this book explores current approaches aimed at analyzing and fostering collaborative learning. As such, these approaches consider collaborative learning under the auspices of information and communication technologies (ICT) in addition to issues of knowledge sharing. The social and communicative aspects of learning are addressed in addition to suggestions for enhancing collaborative transactions of learners in group-based instruction.

The third section is dedicated to issues of e-Learning and mobile learning in general. There is little doubt that when using mobile devices, the opportunity to learn alone or in groups comes with unique and special requirements. These requirements refer to the issue that technical devices, like mobile phones, iPods and other mobile appliances need to be handled as learning tools – tools that must be able to negotiate the ubiquity of open learning environments that are, by comparison to traditional environments, significantly more amorphous. That means the environments in which students learn need to be prepared by the learners themselves so that the learning processes are appropriately initiated and properly controlled by continuous metacognitive processes. The research in this section addresses these issues directly, especially with regard to the innovative applied approaches to support and design meaningful and competence oriented learning environments as they are exploited by the use of mobile tools.

Computers as learning tools, and tool support for computer-based learning, are the focus of the fourth section of this volume. Rich computer-based learning environments enable a qualitatively different way of learning compared to traditional learning environments. By comparison to typical school classrooms, computer-based learning environments allow for non-linear learning by giving students control over the instructional material they are intending to learn. Thus, students are allowed to select information, tasks, instructional formats (e.g., video, audio, graphics, or text), interface properties, and content (e.g., analogies) in their preferred order and at their own pace (Merrills & David, 1994). Although learner control can be highly motivating (Gray, 1987; Lawless & Brown, 1997; Lou, Abrami, & d'Apollonia, 2001), its effect on learning outcomes is not unequivocally supported (Fry, 1972). Thus, the use of support tools in computer-based learning might be an important means to enhance the learning outcomes of students in control over their own learning; however, at present the complexity of these environments renders them currently vulnerable to outcome efficacy debate. Answers to questions about the nature and surplus value of learning support devices, as well as outcome oriented instructional design approaches are major themes that guide the contributions in this section.

The topic of the final section of this book is multimedia learning. There are three perspectives on multimedia learning presented by the research in this section. First, the psychological perspective describes memory systems and cognitive processes that explain how people process different types of information and how they learn with different senses. For example, Paivio's dual coding theory (1986; Clark & Paivio, 1991) and Baddeley's working memory model (1992, 1997) form the bases for this perspective. Second, the design of instructional messages identifies multimedia principles and provides guidelines for devising multimedia messages consisting of, for instance, written text and pictures, spoken text and animations, or explanatory video with a mix of moving images with spoken and written text (e.g., Mayer's generative theory of multimedia learning (2001) and Sweller's Cognitive Load Theory (2004; Sweller, van Merriënboer, & Paas, 1998)). Finally, models for course and curriculum design prescribe how to develop educational programs, which contain a mix of educational media including texts, images, speech, manipulative materials, and networked systems. In short, the research in this section explores the three perspectives underlying multimedia in varied and important experimental work.

The chapters in this book provide excellent research having undergone double-blind peer review comprising newly completed investigations in the field. As such, they reflect new data, fresh thinking and new findings in the field. On the other hand, we also decided to include research notes that represent work-in-progress – innovative approaches that might affect future research. These selected research notes also underwent a double-blind process of peer review in order to emphasize the role of current and future processes of instructional design and learning and instruction with computers. We hope to present a valuable resource for the field and thank all contributors for their excellent and outstanding work.

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Part I-I: Collaborative Learning with ICT and Knowledge Sharing

Interdisciplinary Perspectives on Cognitive Load Research as a Key to Tackle Challenges of Contemporary Education

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Abstract In this contribution we argue that challenges of contemporary education require new forms of collaboration and communication across disciplines. Interdisciplinary perspectives are needed to enable us to make truly original and useful contributions to cognitive load theory and practice. Using cognitive load theory as an example, I will show that the cutting edge of cognitive load research lies across the boundaries of disciplines. Four examples will be presented to illustrate how the transfer of methods and findings from exercise physiology, neuroscience, and cognitive aging research have advanced or may advance cognitive load theory: (1) Ratings of perceived exertion from the discipline of exercise physiology have been adapted and successfully used in cognitive load research to measure cognitive load. (2) Findings from recent neuroscience research may further the explanation for why dynamic visualizations are particularly effective when learning tasks involve human movement, and largely ineffective when depicting mechanical, non-human movement. (3) Research on interhemispheric cooperation is used as a model for cognitive load research into the effectiveness of group learning. (4) Cognitive aging research is used to show that age-related reductions in attentional control over information that was not initially relevant can actually lead to superior performance for older adults when this information serves as a solution to subsequent problems.

In this contribution we argue that challenges of contemporary education require new forms of collaboration and communication across disciplines. Research is interdisciplinary when we build on theories and previous research from more than one discipline and use methods for data collection and analysis from more than one research tradition. Using cognitive load theory as an example, it is shown that the cutting edge of cognitive load research lies across the boundaries of disciplines. Interdisciplinary perspectives are needed to enable us to make truly original and useful contributions to cognitive load theory and practice. Four examples will be presented to illustrate how the transfer of methods and findings from exercise physiology, neuroscience and cognitive aging research has advanced or may advance cognitive load theory with regard to the measurement of cognitive load, the effectiveness of learning from dynamic visualizations, the effectiveness of collaborative learning, and a new perspective on age-related distractibility as an opportunity for learning.

(1) Back in the 1950s Gunnar Borg, a Swedish exercise physiologist, introduced the field of perceived exertion. His rating scales of perceived exertion (RPE) are used worldwide in medicine and exercise physiology to produce estimates of exertion that are comparable across people and across tasks. Ratings of perceived exertion are based on the assumption that people are able to introspect on their physical processes. This method of data collection and analysis from the discipline of exercise physiology was first used in cognitive load research in the early 1990s, and assumed that people would also be able to introspect on their cognitive processes. Using a similar RPE scale it was shown that people were capable of giving a numerical indication of their perceived cognitive load. Since then, the cognitive load rating scale has been successfully used in many studies to differentiate between the cognitive load effects of instructional conditions.

(2) Dynamic visualizations such as video or animation have become a popular means of providing instruction on natural processes such as how lightning develops or how the tides work, on technical systems such as the functioning of a bicycle pump or a chemical distillation process, or on abstract processes such as probability calculation. It has been suggested that dynamic visualizations should enhance learning by assisting students to perceive the temporal changes or movement in a system, whereas learning from static visualizations requires students to mentally infer these temporal changes, and inference requires more cognitive effort than simple perception. However, despite their popularity and the fact that dynamic visualizations seem an intuitively superior instructional format for representing change over time than static graphics, research has failed to establish the superiority of dynamic over static visualizations. In this presentation I will report on findings from neuroscience research that can be used to further the explanation for why dynamic visualizations are particularly effective when learning tasks involve human movement, and largely ineffective when depicting mechanical, non-human movement. In the context of cognitive load theory, learning by observing a dynamic visualization of human movement may be less problematic for working memory, since an important part of processing human movement information occurs automatically via a circuit of neurons that deal with the perception and imitation of human movement, i.e. the mirror-neuron system. Several recent studies have provided support for the hypothesis that animations of tasks involving a human-movement component (e.g., paper folding) would lead to better learning than static pictures.

(3) In contemporary learning paradigms, collaboration is emerging as one of the promising learning approaches in education. However, while all levels of education are making use of collaborative learning techniques in both traditional and electronic learning environments, either synchronously or asynchronously, either distributed or non distributed, the effectiveness of these types of education/learning has still not been proven. A recent literature review of research comparing the effectiveness of individual learning environments with group-based

learning environments has revealed mixed results. It is still not clear under what circumstances collaborative learning is more effective than individual learning. I will show that neuroscientific research on interhemispheric cooperation can be used as a model for cognitive load research into the effectiveness of collaborative learning. This research has shown that dividing processing across the hemispheres (cf., group learning) is useful when cognitive load is high because it allows information to be dispersed across a larger expanse of neural space. In contrast, when the load is low, a single hemisphere (cf., individual learning) can adequately handle the processing requirements. In this presentation I will show how these results can used to generate new hypotheses about the conditions under which collaborative learning is more effective than individual learning.

(4) There is an abundance of research evidence in the cognitive literature of age-related declines in various functions including speed of processing, selective attention, working memory, long term memory and problem solving. Recent evidence suggests that one source of slowing of processing speed is an age-related increase in distractibility. In this presentation, cognitive aging research of Kim, Hasher, and Zacks (2007) is used to show that age-related reductions in attentional control over information that was not initially relevant can actually lead to superior performance for older adults when this information serves as a solution to subsequent problems. They presented young and old participants first with a reading task in which older adults are differentially disrupted by concurrent distraction and then with a problem solving task, in which some of the items could be solved by words that had served as distractors in the reading task. Their hypothesis that older adults would show greater facilitation or priming from the reading task to the problem solving task was confirmed. I will show how this new way of thinking of Kim et al. may help cognitive load researchers in generating new research questions and find new instructional techniques.

Interpersonal Knowledge in Virtual Seminars

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Abstract Interpersonal knowledge of learning partners plays an important role in collaborative learning. Because of the special characteristics of computer-mediated-communication, it is necessary to investigate the formation and the effects of interpersonal knowledge in virtual learning scenarios. This field study evaluates the formation and the effects of interpersonal knowledge in a virtual seminar. The seminar involved 33 participants who worked together in groups of 3–5 members. At the beginning and end of the virtual seminar, participants were asked about their skill-related interpersonal knowledge and their emotional interpersonal knowledge of other learning partners. Results showed that interpersonal knowledge generally increased during the seminar. While skill-related interpersonal knowledge did not lead to more efficient interaction, socio-emotional interpersonal knowledge was positively related to conflict oriented-consensus building, posing task-related questions and the contribution of ideas. Both skill-related and socio-emotional interpersonal knowledge were positively correlated to participants' satisfaction with, and acceptance of, the seminar.

Objectives and Purpose

Communication between learning-partners plays a crucial role in collaborative learning. Learners not only discuss individual perspectives on tasks and subject matter, but also must coordinate their learning activities in the group. In typical computer-supported learning environments such as virtual seminars, communication becomes even more complex as learners are restricted to asynchronous text-based communication. As a consequence, it is increasingly important to understand the characteristics of interpersonal communication. One important aspect of communication is the interpersonal knowledge that learners develop about other learning partners. Empirical evidence indicates that interpersonal knowledge has an influence on specific learning activities in the reduction of the amount of coordination needed, because members know the strengths and weaknesses of other learning partners (Adams, Roch, & Ayman, 2005). In addition, interpersonal knowledge should also reduce conformity and the suppression of alternative perspectives and judgments (Gruenfeld, Mannix, Williams & Neale, 1996; Shah & Jehn, 1993) which should result in a better performance of collaborative learning groups. This paper addresses two main research questions: First, how does interpersonal knowledge develop in a virtual seminar under the specific conditions of computer-mediated-communication? And second, what effects does interpersonal knowledge have on collaborative learning activities like coordination and critical evaluations as well as on satisfaction with, and acceptance of, a virtual seminar? Context of the study was a virtual seminar "Introduction into Knowledge Management" which was offered by the Virtual University of Bavaria.

Theoretical Framework

According to theories on impression formation and impression management, individuals actively try to manage what they know about their interaction partners and what their interaction partners (should) know about themselves (Fiske, Lin & Neuberg, 1999). In traditional face-to-face-situations, individuals are generally familiar with strategies for managing the formation and development of interpersonal knowledge (e.g. social information seeking, selective self-presentation). However, asynchronous and text-based communication produces a completely different scenario. According to Walther's social-information-processing approach (1996), and his research on impression formation and relationship development in computer-mediated-communication, communication partners can reach the same level of interpersonal knowledge and relationship as in face-to-face settings; they only need more time to adapt to the restrictions of the medium. As interaction is easier with a certain degree of interpersonal knowledge, it is expected that participants do develop a certain degree of interpersonal knowledge about learning partners in the context of a virtual seminar.

With regard to the effects of interpersonal knowledge, research on transactive-memory-systems has shown that skill-related interpersonal knowledge (e.g. knowledge about strength and expertise in certain domains) decreases decision time and coordination effort in groups (Wegner, 1986). With regard to socio-emotional interpersonal knowledge (e.g. knowledge about emotions and feelings), the uncertainty-reduction-theory assumes that individuals who do not possess interpersonal knowledge about a communication partner feel uncertain during interaction (Berger & Calabrese, 1975). As a consequence, individuals try to overcome uncertainty by acquiring interpersonal knowledge about their communication partner, typically by using social-information-seeking techniques like observation or asking questions (Berger & Kellermann, 1994). As empirical studies show, increased interpersonal knowledge about group members particularly affects the social modes of group interaction. It is reported that increased interpersonal knowledge makes individuals more comfortable expressing disagreement (Gruenfeld et al. 1996). Socio-emotional interpersonal knowledge can therefore help reduce the tendency of participants to discuss information which has already been shared amongst the group (Wittenbaum, Hollingshead & Botero, 2004). In another study, Shah and Jehn (1993) found that group members with more interpersonal knowledge asked more questions and were more critical of their decisions regarding candidates. As these are crucial factors for successful collaborative learning, this should result in higher degrees of acceptance and satisfaction with a virtual seminar.

Research Questions

1. How does interpersonal knowledge develop in a virtual seminar?
Because of theories on computer-mediated-communication like the social-information-processing approach (Walther, 1996), it is expected that interpersonal knowledge will generally increase during the seminar.

2. Is there a relationship between interpersonal knowledge and collaborative learning activities?
Studies in the context of transactive-memory-systems (Wegner, 1986) lead to the expectation that possessing skill-related interpersonal knowledge reduces the need for explicit coordination. In addition, it is expected that individuals with more socio-emotional interpersonal knowledge feel less insecure (Berger & Calabrese, 1975) and therefore will: (a) evaluate their learning partners' statements more critically, (b) generate more task-related questions, and (c) contribute more proposals and ideas. Moreover, it is expected that socio-emotional interpersonal knowledge is positively correlated with the amount of social-talk during a group discussion.

3. Is there a relationship between interpersonal knowledge and satisfaction and acceptance with the virtual seminar?
As the effects of interpersonal knowledge are expected to lead to better interaction patterns, it is expected that interpersonal knowledge is generally associated with higher degrees of acceptance and satisfaction with the virtual seminar.

Method

Context and Design

The context of this study was a virtual seminar entitled "Introduction into Knowledge Management". Thirty-three previously unacquainted undergraduate students from seven universities in Bavaria participated in this online seminar in the winter term 2004/2005; most (72%) of the participants were female. Based on the concepts of problem-oriented learning (Mandl, Ertl, & Kopp, 2006), the learning material was structured into six modules. In each module, an anchor case introduced a problematic aspect of knowledge management, e.g. knowledge representation. For each of the six modules groups had to solve different tasks.

Learning Environment

The learning environment consisted of features such as a user interface or HTML pages and threaded discussion boards with the ability for users to upload and download files. Access to the learning environment was provided via the World Wide Web and saved by personal login data. The home page described the basic structure of the seminar with a timetable and news ticker. In addition, communication with the tutor was made possible via a question board.

Data Sources

Interpersonal Knowledge

Interpersonal knowledge was measured via an online-questionnaire after the introduction-phase (t1) and before the beginning of the last learning-module (t2). Because interpersonal knowledge is always two-directional, participants assessed their interpersonal knowledge for each learning partner in two ways. First, participants assessed their own knowledge of their learning partner; then, participants assessed the interpersonal knowledge that the learning partner had about them.

Rating of interpersonal knowledge was divided into skill-related and socio-emotional interpersonal knowledge. In order to measure skill-related interpersonal knowledge, participants were first asked to assess their learning partners' competences in the domains of knowledge management, new media technologies and cooperation. Then, participants were asked to rate their confidence in their assessments (e.g. "How competent is Tim in the domain of knowledge management?

How sure are you with this assessment?" and "How does Tim would rate your competence in the domain of knowledge management? How sure are you with this assessment?"). All questions were based on a 5-point Likert scale with three items ("very competent" and "not competent" / "very sure" and "very unsure"). The degree of skill related knowledge was expressed by the ratings on the confidence scale.

In order to measure socio-emotional interpersonal knowledge, participants assessed their own interpersonal knowledge and their learning partners' knowledge about them on a five-point Likert scale, including items on knowledge of emotions, living-conditions, character and attitudes of the learning partners ("How well do you know Tim with regard to his emotions and feelings?" and "How well do you think Tim knows you with regard to your own emotions and feelings"), anchored with "not well" and "very well".

Satisfaction and Acceptance

Satisfaction and acceptance were measured with an online-questionnaire shortly after the virtual seminar was finished. All items were also based on a 5-point Likert scale, anchored with "Strongly agree" and "Strongly disagree". Satisfaction included six items on efficiency (e.g. "The group discussions were useful and helpful"), four items on satisfaction with knowledge transfer (e.g. "Knowledge of other group members helped me a lot.") and ten items on satisfaction with group cohesion (e.g. "We had a good group climate"). Acceptance was measured on a general level (e.g. "I enjoyed participating in a virtual seminar"). All scales used in this study showed sufficient internal reliability (Cronbach's alpha ranging from 0.78 to 0.88).

Specific Learning Activities

In order to correlate interpersonal knowledge with collaborative learning activities, an interaction analysis was conducted for the last learning-module. Two evaluators counted the statements of coordination, elaboration of perspectives and social-talk. With regard to the social modes, statements were counted that indicated new proposals (those not previously mentioned), task-related questions, and critical evaluations of learning partners' contributions. The inter-rater reliability (ICC) was sufficient ($r>0.78$).

Results

Research question 1: Formation of interpersonal knowledge

Results showed (see Fig. 1) that participants felt more confident in assessing the skills of their learning partners at the end of the seminar as compared to the beginning (m_{t1}=3.43; m_{t2}=3.71; p<0.05; t=-2.38). This effect was not observed with regard to the assessment of learning partners' knowledge about one's own skills. Confidence increased; however, the difference was not significant (m_{t1}=2.84; m_{t2}=3.08, *ns*). Similar results occurred regarding socio-emotional interpersonal knowledge. While the assessment of the socio-emotional interpersonal knowledge of other learning partners increased significantly (m_{t1}=1.9; m_{t2}=2.2, p<0.05; t=-2.23), no significant increase was measured with regard to the assessment of socio-emotional interpersonal knowledge of the learning partners.

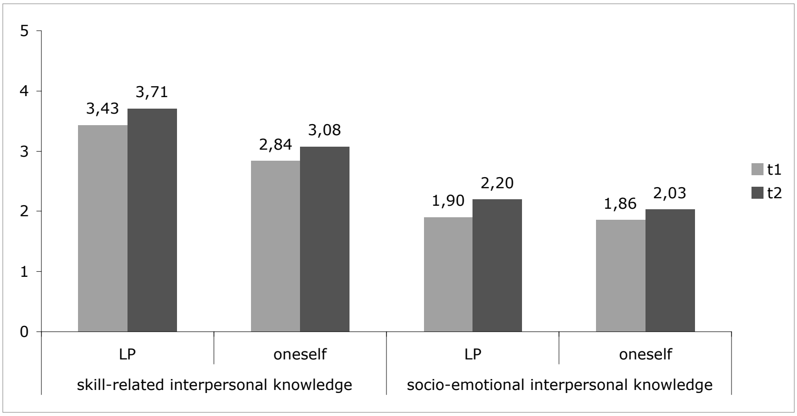

Fig. 1. Formation of interpersonal knowledge.

Notes: LP=Assessment of one's own knowledge of learning partner, oneself = Assessment of learning partners' knowledge of oneself.

Research question 2: Relationship between interpersonal knowledge and collaborative learning activities

On the basis of research on transactive memory-systems, it was expected that higher degrees of skill-related interpersonal knowledge would correspond with more "implicit" coordination. As shown in Table 1, this expectation was not confirmed. The correlation of skill-related interpersonal knowledge and coordination activity was not significant.

Table 1. Correlations between interpersonal knowledge and collaborative learning activities.

	Skill-related interpersonal knowledge		Socio-emotional interpersonal knowledge	
	LP	oneself	LP	oneself
Coordination	0.06	0.08	0.27	0.32
Elaboration	–0.02	0.22	0.56**	0.56**
Proposals	0.04	0.23	0.38*	0.47*
Asking Questions	0.02	0.18	0.33*	0.39*
Critical Evaluation	0.22	0.26	0.32*	0.36*
Social-Talk	0.33*	0.12	0.43**	0.40*

Notes: LP=Assessment of one's own knowledge of learning partner, oneself = Assessment of learning partners' knowledge of oneself. n=33; * p<0.05; ** p<0.01, 1-tailed.

As expected, socio-emotional interpersonal knowledge was positively associated with the willingness to contribute proposals and ideas to group discussion. Results also showed significant correlations with critical evaluations of learning partners' statements, posing questions and social-talk.

Research question 3: Relationship between interpersonal knowledge and satisfaction and acceptance

As Table 2 shows, expectations regarding satisfaction and acceptance were confirmed. Socio-emotional interpersonal knowledge was strongly correlated with satisfaction pertaining to efficiency, knowledge-transfer, and group cohesion. The more socio-emotional interpersonal knowledge participants possessed about their learning partners, the more satisfied the participants were. Skill-related interpersonal knowledge was positively associated with satisfaction with regards to efficiency and group cohesion.

Table 2. Correlation between interpersonal knowledge and satisfaction / acceptance.

	Skill-related interpersonal knowledge		Socio-emotional interpersonal knowledge	
	LP	oneself	LP	oneself
Satisfaction with efficiency	0.40*	0.16	0.53**	0.45**
Satisfaction with knowledge-transfer	0.27	0.04	0.63*	0.58**
Satisfaction with group cohesion	0.31*	0.37*	0.80**	0.75**
Acceptance of virtual seminar	–0.02	0.08	0.40*	0.36*

Notes: LP=Assessment of one's own knowledge of learning partner, oneself = Assessment of learning partners' knowledge of oneself. n=33;* p<0.05; ** p<0.01, 1-tailed.

Discussion

In general, results confirmed previous research conducted in contexts that were not directly related to computer-supported collaborative learning. Firstly, interpersonal knowledge developed during computer-supported learning. As results indicate, participants showed increasing levels of confidence in assessing the skills of learning partners. In addition, participants were able to better assess the socio-emotional interpersonal knowledge of their learning partners. Consistent with Walther's social-information-processing approach (Walther, 1996), participants seemed to adapt to the restrictions of computer-mediated communication and developed a deeper interpersonal insight, despite the inherent limitations of communication channels.

Consistent with the results of Shah and Jehn (1993), participants with more socio-emotional interpersonal knowledge showed better social modes of interaction with respect to critically evaluating contributions of learning partners, asking task-related questions and making proposals. These are all crucial patterns of successful knowledge construction in collaborative learning. Students with a higher degree of interpersonal knowledge seemed to overcome uncertainty and anxiety as they interacted in a more open manner. However, findings also indicate that interpersonal interaction does not automatically lead to a more efficient interaction. Group members did not automatically develop "implicit" coordination through the awareness of each other's skills and talents. These findings are consistent with experiences in other virtual seminars where coordination efforts did not decrease by the end of the course (Schnurer, 2005). It is likely that students would have needed more time to form a transactive-memory-system with highly efficient coordination processes.

Scientific and Educational Importance

There are several general inferences that can be drawn from the results, which indicate that interpersonal knowledge can develop under conditions of asynchronous text-based communication and that this interpersonal knowledge affects interaction in a positive way. More specifically, results clearly indicate that interpersonal knowledge is an important factor for successful interaction. This lends support to the idea of implementing strategies that foster the development of interpersonal knowledge, especially on a socio-emotional level.

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Individual Versus Group Learning as a Function of Task Complexity: An Exploration into the Measurement of Group Cognitive Load

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Abstract The target of this study is twofold; on the one hand, it is an empirical study into the learning effectiveness of group versus individual learning as a function of task complexity; on the other hand, it is an exploration into the measurement of group cognitive load as a function of task complexity. The effects of individual versus group learning on retention and transfer test performance and mental effort were investigated among 52 high school students performing mathematical tasks. Applying cognitive load theory, groups were considered as information processing systems in which group members, by communication and coordination of information (i.e., transaction costs) can make use of each other's WM capacity. It was hypothesized that, with low complexity tasks, group members would achieve the same test performance, but with higher learning effort than individuals because of the transaction costs. With high complexity tasks, group members were expected to achieve a higher test performance with lower learning effort than individuals, because the transaction costs are minimal compared to the gain afforded by a division of cognitive load. On an exploratory basis, it was investigated how individual-level models can be used as a basis to understand group-level load.

Introduction

The target of this study is twofold; on the one hand, it is aimed at studying group versus individual learning as a function of task complexity; on the other hand, it is aimed at taking a closer look at the development of a method to calculate the cognitive load of a group of collaborative learners by examining the amount of mental effort invested by the individual group members and by the group as a whole.

This study considers groups as information processing systems consisting of multiple working memories (WM). Consequently, it can be argued that groups have effectively more processing capacity available than single individuals with one WM. In a group, the cognitive load can be shared among group members enabling them to deal with more complex problems than individuals. Although there is cognitive load caused by communication and coordination within a group, the so-called transaction costs have to be taken into account. In complex cognitive tasks, these costs are minimal compared to the advantage of being able to share the high cognitive load among group members. This distribution advantage was found in a previous experiment comparing the effects of group and individual learning of complex cognitive tasks on transfer efficiency (Kirscher, Paas, & Kirschner, in press). By making use of each other's processing capacity through sharing of cognitive load imposed by a task, it was possible for group members to more deeply process information elements, and construct higher quality schemata in their long term memory than learners working individually. Another situation occurs with low complexity tasks in which a learner has sufficient capacity to solve a problem individually. That is, solving the problem in collaboration, in terms of experiencing cognitive load, does not have an advantage for an individual group member and can even be disadvantageous. This is so because of the relatively high load caused by the transaction costs within the group. Indeed, research comparing groups to individuals when performing relatively simple recall tasks shows that working in a group can be detrimental (Weldon & Bellinger, 1997). Although groups in all cases outperform individuals in the amount of items recalled, comparing the amount of recalled items by each group member to the amount of items recalled by an individual shows that working in a group hampers performance for the group member because the individual performance is higher. It was therefore hypothesized that with low complexity tasks, group members would have to invest more mental effort in learning to achieve the same test performance than individual learners, because of the relative transaction costs. With high complexity tasks, it was hypothesized that group members could achieve a higher test performance with lower learning mental effort investment than individuals, because the transaction costs are minimal compared to the gain afforded by a division of cognitive load.

Whereas valid and reliable instruments have been developed in the context of individual learning (Paas, Tuovinen, Tabbers, & Van Gerven, 2003), there are no standard methods to determine the cognitive load experienced by groups of collaborating learners. It is not clear if and how these individual measurements can be used to get a reliable estimate of the group's cognitive load – in other words, whether an individual-level model can be used as a basis to understand group-level load. Individual cognitive load measurements represent the load that a specific instructional method imposes on the limited cognitive system of a learner. This load can be anywhere between very high or very low depending on the characteristics of the learner (e.g., age and expertise) and the characteristics of the instructional method (e.g., task format and task complexity). Determining individual cognitive load can be done using a variety of psychological, task- and performance-based, and subjective measurements – all of which have been tested for reliability and validity (see Paas et al., 2003). For measuring group cognitive load, however, such instruments are not available. It is therefore unclear as to how individually based measurements can be used to determine the cognitive load of a group of collaborative learners. The individual subjective rating scale developed by Paas (1992) is based on the assumption that students are able to introspect on their cognitive processes and can report how much effort it took them to solve a problem. This rating scale has been shown to be valid, reliable, non intrusive, and has been used in many studies dealing with cognitive load, providing the opportunity to compare results between studies. In the present study, this rating scale was used to obtain an indication of: (a) group cognitive load by looking at the average of individual group member effort scores, (b) individual group member scores of the effort it took the group as a whole, and (c) a single effort score that was judged collectively by the group. The goal of this part of the study was to explore the impact of task complexity on the amount of cognitive load people experience in a group and how different measurements can be used to measure group cognitive load.

Method

Participants

Participants were 52 second-year Dutch high school students with an average age of 14 years. They participated in the experiment as part of their math curriculum and did not receive any academic or financial compensation. Prior knowledge on math-related subjects was assumed to be the same for all participants, for they all had followed exactly the same math courses during the last 2 years. The students were assumed to be novices on the topic of surface calculation for they were only instructed on how to calculate rectangle surface areas but did not have any prior knowledge concerning the calculation of surface areas of triangles and circles.

Materials

All materials were in the domain of mathematics and concerned the calculation of geometrical surface areas; namely that of the triangle and the circle. Materials were designed for this investigation, consisting of: (a) an introduction on how to calculate geometrical surface areas, (b) learning tasks in which solving geometrical surface calculation problems was the goal, and (c) retention and transfer test tasks on geometrical surface calculation. All materials were paper based.

Introduction

The introduction was based on three subjects or geometrical figures: rectangles, circles and triangles. For every geometrical figure, the theory behind calculating the surface area, as well as a worked out example of how to use this theory when solving a surface calculation problem, were the core of the introduction. The theory, in all three instructions, consisted of an insight in the relevant formulas and shapes of the geometrical figures. The three geometrical figures were treated separately in the order of rectangle, triangle, and circle. In this way, students started with known information to activate their prior knowledge, subsequently extending their knowledge by studying unknown information. The introduction was paper based but also discussed in class by the math teacher.

Learning Tasks

Learning tasks were of low, medium and high complexity. For each of these three levels of task complexity, two tasks in the domain of mathematics were developed. In this way, three tasks focused on the calculation of surface areas of triangles, and three tasks on the calculation of surface areas of circles. Task complexity or intrinsic cognitive load was determined by using Sweller and Chandler's (1994) method based on the number of interactive elements in a task and the insight necessary for solving the problem. The tasks were structured in such a way that transaction costs of communication and coordination were kept to a minimum and the information elements could be divided among the members of the group.

Test Tasks

Eight test tasks were designed to determine how much students had learned. Half of these tasks were based on surface calculation of circles and half on triangles. There was a distinction in retention and transfer test tasks, such that four of the tasks (two circle and two triangle) were identical in structure to the ones performed in the learning phase; these were the retention tasks. Four of the tasks (two circle and two triangle) were structurally different from the ones performed in the learning phase; but to solve these problems, the same underlying theory on surface calculation had to be used.

Cognitive-Load Measurement

To measure the participants' cognitive load after each task in the learning and test phase, the subjective 9-point cognitive-load rating scale developed by Paas (1992) was used.

Performance Measurement

Solving learning and test tasks meant correctly calculating the surface area of a geometrical figure. One point was awarded for a correct answer and zero points for an incorrect answer. In the learning phase, this meant that a minimum score of zero and a maximum score of three points could be earned; in the test phase, the minimum score was again zero and the maximum eight points. For the statistical analysis, the performance scores on retention and transfer were transformed into proportions.

Design and Procedure

All students received written instruction on how to calculate the surface areas of rectangles, circles and triangles two days prior to the learning tasks. During this instruction phase, participants had seven minutes to study each geometrical figure by themselves. Then, the teacher had seven minutes to discuss the theory and a worked-out example in class and give clarification answers to questions asked by the students. The total instruction took 50 minutes after which the participants had to hand in the written instructions to the teacher. In the learning phase, because of the within subject design of this study, every participant, at one point, worked on the learning tasks individually as well as in a group. For each participant, the order of individual and group work was counterbalanced, as was the task subject a participant started (i.e., circles or triangles). At the beginning of the learning phase, participants were randomly assigned to the individual or group condition, which meant that twenty-one participants started to work individually on three tasks of three different complexity levels and then worked in triads on three other tasks at these three complexity levels. Twenty-one other participants started to work in triads on these problems and then worked individually. If a participant first, individually or in a group, worked on the calculation of the surface area of a triangle, the second time, being in the individual or group condition, the geometrical figure was a circle. If a participant, individually or in a group, worked on the calculation of the surface area of a circle, the second time, being in the individual or group condition, the geometrical figure was a triangle. The participants had to study and solve each problem and rate their cognitive load on the mental effort rating scale: the individual scale (Paas, 1992). On the same scale, group members additionally had to rate the amount of mental effort they invested to arrive at the solution together: the group member scale, and the group additionally had to give one score of their joint mental effort that was needed to come to the solution: the group scale. In the test phase, all participants had to individually work on four retention and four transfer tasks; this phase was held one day after the learning phase and took 50 minutes in total. Again, after each test task, the participants had to rate their mental effort on the mental effort rating scale.

Results

Because analyzing the data is in progress the results are still preliminary.

Learning Phase

A 2 (learning condition: individual vs. group) × 3 (task complexity: low, medium, high) ANOVA with repeated measures on both factors was used to analyze the data obtained during the learning phase. With regard to performance, the ANOVA revealed main effects of learning condition, $F(1, 48) = 4.811$, $MSE = 1.253$, $p < .05$ and task complexity, $F(2, 48) = 18.606$, $MSE = 3.055$, $p < 0.001$, as well as a significant interaction between learning condition and task complexity, $F(2, 48) = 3.792$, $MSE = 0.610$, $p < .05$. The interaction indicated that groups particularly performed better than individuals on the medium complexity tasks. With regard to mental effort, the ANOVA revealed main effects of learning condition, $F(1, 49) = 12.810$, $MSE = 40.412$, $p < 0.001$ and task complexity, $F(2, 49) = 63.384$, $MSE = 175.847$, $p < 0.001$, but did not reveal a significant interaction between learning condition and type of test, $F(2, 49) = 6.790$, *ns*. These results indicate that at all three complexity level group members rated a lower mean mental effort than individuals.

Test Phase

No significant effects were found in the test phase with regard to performance and mental effort. Performance efficiency was calculated for the transfer tests using Paas and van Merriënboer's (1993; see Van Gog & Paas, 2008) computational approach by standardizing each of the participants' scores for test performance, and mental effort invested in the learning phase. For this purpose, the grand mean was subtracted from each score and the result was divided by the overall standard