Providing cognitive and metacognitive awareness information to support regulation in individual and collaborative learning settings

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Better together

Writing acknowledgements is probably the most rewarding task when writing a dissertation, but also one of the hardest. This (rather than the abstract) is where it all comes together. On the object-level, this dissertation is about metacognition and collaborative learning. However, from a meta-level perspective (although not quite in the sense intended by Thomas O. Nelson and Louis Narens), this dissertation was all about collaboration. It would not have been possible without the valuable support of many people, some of whom I want to point out explicitly. To better structure this part, I will differentiate support within two spaces: the content space and the relational space (I hope Jeroen Janssen and Daniel Bodemer forgive my crude usage of these terms as I am going to take a lot of conceptual leeway here). Simply put, activities within the relational space aim at establishing group well-being while activities within the content space aim at acquiring content-related knowledge (Janssen & Bodemer, 2013). Of course, both spaces overlap greatly and activities within both are assumed to jointly affect not only group performance, but also individual achievement – in this case: mine.

The people most relevant to the relational side of things were obviously my family, including my Germany-based family (Jana Schnaubert, Ulrike Rautenberg, Gert Schnaubert, and all the Grimms and Schönherrs as well) and – of course – my European family (Yurika and Marek Schönherr). Without you, Yuri and Marek, I would not have been able to do this and your support and understanding for me not being around much made this whole project work. Additionally, you helped me take my mind off this dissertation when I needed it most and in turn also helped me focus when I had to. Above all, you make me happy. Thank you, I love you both to bits! Apart from my family, there were many friends that supported me along the way. However, I decided to just name one in particular, because she made me believe in my academic abilities before I even knew I wanted to go there: Thank you Julia Kreis!

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Publication Notes

All studies included in this dissertation have been published in international peer-reviewed journals (studies 1, 3 and 4) or conference proceedings (study 2). All manuscripts are attached in the Appendix section.

Study 1: Schnaubert, L., & Bodemer, D. (2017). Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments. *Learning and Instruction*, *49*, 251–262. https://doi.org/10.1016/j.learninstruc.2017.03.004

[Schnaubert, L., & Bodemer, D. (2018). Corrigendum to "Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments". *Learning and Instruction, 54,* 47. https://doi.org/10.1016/j.learninstruc.2018.01.010]

Study 2: Schnaubert, L., & Bodemer, D. (2016). How socio-cognitive information affects individual study decisions. In C.-K. Looi, J. Polman, U. Cress, & P. Reimann (Eds.), *Transforming learning, empowering learners: The International Conference of the Learning Sciences (ICLS) 2016* (pp. 274–281). Singapore, SG: International Society of the Learning Sciences.

Study 3: Schnaubert, L., & Bodemer, D. (2019). Providing different types of group awareness information to guide collaborative learning. *International Journal of Computer-Supported Collaborative Learning*. https://doi.org/10.1007/s11412-018-9293-y

Study 4: Schnaubert, L., & Bodemer, D. (2018). What interdependence can tell us about collaborative learning: a statistical and psychological perspective. *Research and Practice in Technology Enhanced Learning*, *13*(1), 1–18. https://doi.org/10.1186/s41039-018-0084-x

Zusammenfassung

Selbstreguliertes Lernen und (computerunterstütztes) kollaboratives Lernen sind zentrale Felder pädagogisch-psychologischer Forschung. Beiden ist gemein, dass sie untersuchen, wie Lernende relevante Lernentscheidungen treffen. Forschung zur metakognitiven Selbstregulation beschäftigt sich damit, wie Lernende ihre eigenen Kognitionen beim Lernen überwachen und steuern. In der kollaborativen Lernforschung wird zusätzlich angenommen, dass Lernende Informationen über Kognitionen ihrer Lernpartner zur Lernprozesssteuerung benötigen. Wissensbezogene Group Awareness-Tools werden hierbei eingesetzt, um entsprechende Informationen zu erfassen, zu transformieren und den Lernenden zur Verfügung zu stellen, mit dem Ziel, implizite Handlungsempfehlungen zu geben. Diese Dissertation zielt auf eine Integration beider Forschungsbereiche ab, indem (a) Awareness-Mechanismen zur Unterstützung der metakognitiven Selbstregulation auf individuelle Lernsettings übertragen werden und (b) ein Metakognitions-Framework genutzt wird, um wissensbezogene Group Awareness-Informationen systematisch zu differenzieren und deren Effekte auf Regulationsprozesse und Lernergebnisse zu untersuchen. Hierzu wurden vier empirische Studien durchgeführt. Die ersten beiden Studien beschäftigen sich mit individuellen Lernszenarien und untersuchten den Einfluss metakognitiver Selbst-Informationen (Studie 1) sowie kognitiver und metakognitiver Partnerinformationen (Studie 2) auf Regulationsprozesse und Lernergebnisse. Die folgenden zwei Studien beschäftigen sich mit kollaborativen Lernszenarien und untersuchten den Einfluss kognitiver und metakognitiver Group Awareness-Informationen auf Regulationsprozesse und Lernergebnisse (Studie 3) mit einem zusätzlichen Fokus auf die dyadische Datenstruktur (Studie 4). Die Studienergebnisse zeigen übereinstimmend, dass Regulationsprozesse durch die Bereitstellung kognitiver und metakognitiver Awareness-Informationen in individuellen wie kollaborativen Lernszenarien unterstützt werden können. Ferner scheinen Lernende alle verfügbaren kognitiven und metakognitiven Selbst-, Partner- und Gruppeninformationen in ihre Lernentscheidungen einzubeziehen. Dabei wird zwar die Sicherheit in eigenes Wissen beeinflusst, jedoch nicht der Wissenszuwachs. Allerdings scheinen insbesondere metakognitive Awareness-Informationen die dyadische Datenstruktur zu beeinflussen. Die hier durchgeführte Forschung liefert wichtige Erkenntnisse für Forschung und Praxis und zeigt, wie Metakognitions- und Group Awareness-Forschung sich gegenseitig ergänzen können, um individuelle wie kollaborative Lernprozesse zu untersuchen und zu unterstützen.

Abstract

Contemporary research fields in educational psychology include research on self-regulated learning and (computer-supported) collaborative learning. While both have different research traditions, they have in common that learners have to make important decisions about their learning processes. From a metacognitive self-regulation perspective, learners have to monitor their own knowledge and cognitions to make adequate control decisions. From a collaborative learning perspective, learners additionally have to monitor each other's knowledge and cognitions to structure and coordinate their learning process together. Knowledge-related group awareness tools are designed to assess, transform and visualise such data to guide collaborative learning processes. This dissertation aims at integrating both research traditions by (a) adopting awareness mechanisms in individual settings to foster metacognitive self-regulation and by (b) using a metacognition framework to systematically distinguish different types of knowledge-related group awareness information and analyse how they affect regulatory processes and learning outcomes. In a series of four empirical studies, these issues were investigated. The first two studies were conducted in individual settings and analysed the impact of assessing and providing metacognitive self-information (study 1) and cognitive and metacognitive partner information (study 2) on regulatory processes and learning outcomes. The second two studies were conducted in dyadic learning settings and analysed the impact of cognitive and metacognitive group awareness information on regulatory processes and learning outcomes (study 3) with an additional focus on the dyadic data structure (study 4). The results of these studies consistently show that providing cognitive and metacognitive awareness information supports regulatory processes in both individual and collaborative settings. Moreover, learners seem to integrate available cognitive and metacognitive self-, partner and group information when making study decisions. This seems to affect the learners' confidence in their knowledge, but not knowledge gain itself. However, especially metacognitive awareness information seems to interfere with the dyadic data structure. The research conducted yields various relevant implications for research and practice and shows how metacognition research and group awareness research can complement each other to analyse and foster learning within individual and collaborative learning settings.

Table of Contents

List of Tables

List of Figures

1 Introduction

21st century learning requires a set of different skills that enable learners to self-regulate their learning process, including their use of internal and external resources to plan, monitor and evaluate their progress. Additionally, learning becomes increasingly social, not only with the rise of information and communication technology, but also because research, practice and even politics recognise the merit of social interaction and pooling resources for the development of individual knowledge and skills. Central research areas concerned with these developments are self-regulated learning and computer-supported collaborative learning.

Self-regulated learning has been extensively researched within the last decades, to the point that it is sometimes described as one of the most important research areas within educational psychology (e.g., Panadero, 2017). A central concept with regard to self-regulated learning is agency, i.e., taking charge of own learning processes by monitoring and strategically steering learning (see Hacker, Dunlosky, & Graesser, 2009). Agency thus not only places individual learners into the research focus, but rather the learners' perspective on their own learning. This learner-centred view is closely related to the concept of metacognition, i.e., cognitions about own cognitive states and processes (Flavell, 1979). These include aspects of up-to-date self-awareness, but also declarative knowledge about the functioning of cognitive processes and skills to implement strategies to control cognition (Efklides, 2008). Such meta-level information and processes are the heart of metacognition research, that is concerned with how learners monitor and control their own learning during self-regulated learning (Nelson & Narens, 1990).

Additionally, educational research and practice has increasingly recognised the role of the social environment for learning as well as the merits of computer support. Thus, another contemporary line of research within educational psychology is computer-supported collaborative learning. Broadly speaking, computer-supported collaborative learning "refers to the activity of peers interacting with each other for the purpose of learning and with the support of information and communication technologies" (Suthers, 2012, p. 719) and thus includes different educational practices centring around peer interaction (Dillenbourg, Järvelä, & Fischer, 2009). To counteract challenges of collaborative learning, (cognitive) group awareness tools provide learners with knowledge-related information about the group members implicitly guiding them towards beneficial learning processes (Bodemer, Janssen, & Schnaubert, 2018). By building on the learners' self-regulatory

skills, such guidance mechanisms work on the premise of *guiding without governing* and thus foster learning without undermining the learner's agency (Hesse, 2007).

While there are current trends to merge self-regulated learning and computer-supported collaborative learning (especially within research on socially shared regulation, e.g., Järvelä et al., 2016, 2015), both areas still underestimate each other's potentials in investigating and fostering individual and collaborative learning processes, especially with regard to metacognition. Thus, this thesis is dedicated to combining theoretical and methodological approaches of both fields with a specific focus on metacognition and group awareness research. By using mechanisms drawn from group awareness research to support metacognitive self-regulation and in turn using a metacognition framework on group awareness tools, this thesis aims at fostering our understanding of individual and collaborative learning processes and providing intelligence informing instructional support.

To reach this goal, we[1] conducted a series of four experimental studies on university students, in which we varied the provision of metacognitive and cognitive awareness information on the self, partner or the group in individual and collaborative learning settings, and analysed the effects on learning processes (metacognitive and conflict-based regulation) as well as learning outcomes (knowledge and confidence).

The research conducted is based on two main theoretical pillars: self-regulated learning with a focus on metacognition and collaborative learning with a focus on group awareness research. The second section thus gives an overview over self-regulated learning research relevant for this thesis (section 2), with a specific focus on metacognitive self-regulation (section 2.1). Additionally, it comprises information about socio-cognitive influences on metacognitive regulation (section 2.2). The third section provides an overview over relevant aspects from collaborative learning research (section 3). In this part, I will introduce collaborative learning and especially group awareness tools (section 3.5) as a means to support collaborative learning processes. The goal of this theoretical introduction is to make the reader familiar with the most relevant foundations of this work and uncover gaps within the current research in both main research areas. Afterwards, I will summarise and integrate the preceding sections (section 4) and specify the goal of this thesis and empirical research questions (section 5).

[1] Please note that the plural "we" used within this thesis refers to the work I conducted together with Daniel Bodemer especially in preparation of the publications. As it is not always possible to clearly distinguish this from work I conducted independently and to acknowledge the valuable input of Daniel Bodemer, I used a rather liberal decision criterion favouring the plural form when deciding upon an adequate personal pronoun.

The next parts are then concerned with the empirical research conducted. Section 6 gives and overview over the empirical studies and section 7 discusses the methods used by pointing out similarities and differences between the studies.

The last sections then discuss the results of the research. While section 8 integrates the main results of the empirical studies in response to the research questions, section 9 gives an overview over main implications for research and practice in the field of metacognition (section 9.1) and collaborative learning (section 9.2) in response to the overarching goals of the thesis. The last section contains a brief conclusion (section 10).

The respective research papers can be found in the Appendix section.

2 Self-regulated learning

End of last century, humans were increasingly seen as having an agentic part in self-regulating their behaviour. Going back to Bandura (Bandura, 1991, 1999), this has had a strong influence on how learners are viewed within education (e.g., OECD, 2003) and educational psychology (e.g., Zimmerman, 1989, 2002). This trend has been continued and made increasingly relevant with the information age decentralising learning processes, intensifying the need for learners to plan, monitor and evaluate their learning without explicit help of educators. Even within formal educational settings, like school or university education, a great amount of the actual learning processes is deferred to unsupervised environments fostering the need for learners to self-regulate their learning process (Bjork, Dunlosky, & Kornell, 2013). It is thus not surprising, that there is a growing research body concerned with how learners do (and should) self-regulate, to the point that self-regulated learning has been repeatedly claimed to be one of the most important research areas within educational psychology (e.g., Panadero, 2017). However, it is still understood that learners face severe problems when self-regulating their learning, especially with regard to metacognitively monitoring and controlling their learning activities (e.g., Bjork et al., 2013).

2.1 Metacognitive regulation

Although there are different research traditions with regard to self-regulated learning, for example the socio-cognitive perspective building largely on Zimmerman's work (e.g., 1989, 2000) or a motivational perspective put forward by Pintrich (e.g., 2000), metacognition is seen as a key concept throughout the field. Metacognition in itself is in the core of many models of self-regulated learning (e.g., Efklides, 2011; Winne & Hadwin, 1998; see also Panadero, 2017) and is conceptually closely related to self-regulating learning, to the point that the concepts are often not adequately differentiated (Dinsmore, Alexander, & Loughlin, 2008). Conceptualised in the 70s as "cognitions about cognitive phenomena" (Flavell, 1979, p. 906), the term incorporates many concepts and processes related to the knowledge a person has about cognitions and cognitive processes, the experiences a person is aware of while performing cognitive operations by monitoring cognition, and the use of strategies to control cognition by planning, activating and regulating learning efforts (Efklides, 2008). The basic functions of metacognition are to

monitor and control the learning process. These functions are in the centre of Nelson and Naren's metamemory framework (Nelson & Narens, 1990). The framework describes cognitive processes being split into (at least) two levels: the object-level containing memory processes and the meta-level containing a dynamic model of the object-level (see Figure 1), thus solving the paradox of a learner being the observer and observed at the same time (Nelson, 1996). The levels are connected via monitoring processes (meta-level is informed by the object-level) and control processes (meta-level modifies the object-level). Monitoring describes the self-assessment of own cognitive processes and knowledge to form the meta-level, while control describes the regulation of cognitive processes and behaviour to initiate changes on the object-level (Nelson & Narens, 1990, 1994; see also Schnaubert & Bodemer, 2017).

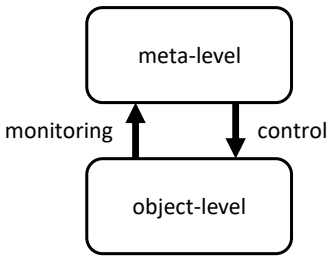

Figure 1. Metacognitive regulation
(adapted from Nelson & Narens, 1990)

Theoretically, the distinction between the two levels is crucial as both serve different functions during learning. Germane learning processes and outcomes are situated on the object-level and thus, this level is the focus of most research on learning and cognition. From a self-regulation perspective, however, the meta-level is crucial as it controls the learning processes based on a subjective assessment of the situation. To be able to initiate learning processes, information from the object-level needs to be compared to some kind of goal or standard (Winne & Hadwin, 1998) and thus, the meta-level is assumed to contain such a goal state (de Bruin & van Gog, 2012; Nelson, 1996). It is assumed that, based on monitoring processes, learners evaluate their current state of learning and compare it to their learning goals (Nelson & Narens, 1990). If this comparison is not satisfactory, they initiate (or continue) learning processes until they reach their goal. These internal evaluation processes thus use an internal standard to allow the outcome of the monitoring process (i.e., metacognitive judgments) to serve a feedback function that can initiate further learning attempts (Butler & Winne, 1995; Winne & Hadwin, 1998). Without this evaluation, no (intrinsic) need for learning may arise. Although the meta-level also contains

cognitions, their target are object-level cognitions; hence, I will in the following refer to meta-level cognitions as metacognitions and object-level cognitions as cognitions.

Apart from theoretical views on metacognition, there is also a vast amount of empirical research especially concerned with analysing monitoring (usually in the form of monitoring judgments made by learners during learning; see section 2.1.2) and control processes (for example study decisions or allocation of study time; see section 2.1.1) and their relationship. This relationship between monitoring and control processes has been observed in many studies (e.g., Metcalfe & Finn, 2008; Nelson, Dunlosky, Graf, & Narens, 1994; Nelson & Leonesio, 1988; Thiede, 1999; Thiede, Anderson, & Therriault, 2003; Thiede & Dunlosky, 1999) and while the cause-and-effect direction may be debated (Koriat, Ma'ayan, & Nussinson, 2006), there is consensus that these processes are inherently linked (see also Schnaubert & Bodemer, 2017). This link between monitoring and control is frequently called "regulation" (I will refer to it as "metacognitive regulation" to distinguish it from other forms of regulation) and measured by a correlation between measures of metacognitive monitoring and control (e.g., Thiede, 1999; Thiede et al., 2003).

The meta-level not only monitors cognition but – due to the cyclic nature of the self-regulatory process – may exercise feedback control to change the object-level and thus cognition (comparable to a control process view on cognition; Carver & Scheier, 1990). Consequently, theoretically, metacognitive regulation is closely connected to learning processes and outcomes. The underlying assumption is that even though this cyclic process is far from perfect (there are restrictions based on inaccurate monitoring as well as inadequate implementation of control processes; see Schnaubert & Bodemer, 2017), learners get valuable insights from monitoring their cognitions and may thus be able to control their learning in a beneficial way. Empirical research has since connected metacognitive regulation to performance (e.g., Kornell & Metcalfe, 2006; Nelson et al., 1994; see also Metcalfe, 2009), especially when accurate monitoring enabled a differentiation between material well and not-well learned (e.g., Thiede, 1999; Thiede et al., 2003).

Because monitoring and control processes are in the centre of metacognitive regulation, we will first take a closer look on control (section 2.1.1) and monitoring (section 2.1.2) before looking more closely into one distinct concept related to metacognitive monitoring: confidence in assumptions (section 2.1.3).

2.1.1 Control

During learning, learners have to make important decisions about their learning process, for example, what to study, whether to continue studying and how much time to allocate to specific aspects of the learning material (Nelson & Narens, 1990). Thus, while controlling learning processes, learners interact with learning material (Figure 2). While the cognitive processes involved are not directly observable, decisions like re-visiting specific parts of the learning material or allocating study time often are. Thus, a great deal of research on metacognitive regulation is concerned with the selection of material to study and the time spend studying this material (e.g., Metcalfe & Finn, 2008; Thiede, 1999; Thiede et al., 2003; Thiede & Dunlosky, 1999).

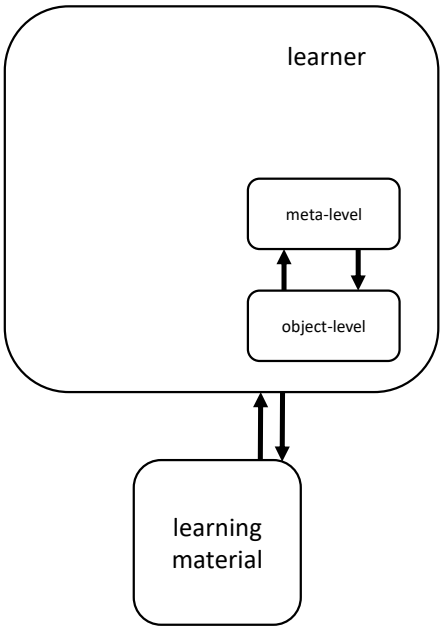

Figure 2. Metacognitive regulation and interaction with learning material

Metcalfe and Kornell (2005) define two main stages of control decisions: choice and perseverance. Choice is thereby defined by the selection of material that needs further attention and a prioritisation of the material connected to the order of processing (i.e., sequencing). Thus, how learners choose material to study and how this relates to metacognitive monitoring has received some attention in the last years (e.g., Koriat, 2012; Koriat et al., 2006). After material is chosen and sequenced, learners allocate a certain amount of study time to it (perseverance; Metcalfe & Kornell, 2005). Theoretically, ongoing monitoring will determine when learners cease studying selected material (e.g., Nelson & Narens, 1990). Empirically, this relationship between monitoring and control is

also well established (e.g., Kornell & Metcalfe, 2006; Nelson et al., 1994; see also Schnaubert & Bodemer, 2017).

While there is some discussion about the strategies learners use to control their learning, especially if they foremost choose items that are least well learned (discrepancy-reduction view, e.g., Thiede & Dunlosky, 1999) or items that are almost learned (region-of-proximal-learning view, e.g., Metcalfe & Kornell, 2005) or if this depends on the uptake function of the learning curve (e.g., Son & Sethi, 2006), the common view is that learners discard items that are perceived as already learned well enough (Schnaubert & Bodemer, 2017). Dunlosky and colleagues (Dunlosky & Ariel, 2011; Dunlosky, Ariel, & Thiede, 2011) propose an integrative framework to explain control decision in light of contradictory evidence. This framework stresses additional factors such as personal agendas, goals and incentives (Ariel, 2013), but also available time (Ariel, Al-Harthy, Was, & Dunlosky, 2011; Ariel, Dunlosky, & Bailey, 2009; Ariel & Dunlosky, 2012) and even the presentation of materials (Dunlosky & Thiede, 2004) as they may ease or complicate the initiation or execution of agendas (Ariel et al., 2009; Dunlosky & Thiede, 2004). To effectively control learning processes, learners thus have to monitor their current state of learning and make an informed decision choosing some material over other (Dunlosky & Ariel, 2011). This involves not only monitoring learning progress item-by-item or text-by-text, but also comparing the outcome (Ariel et al., 2009; Dunlosky & Ariel, 2011). This can be an effortful process and thus, learners may fall back to habitual strategies (like addressing the material in reading order disregarding their monitoring judgments; e.g., Ariel et al., 2011; Ariel & Dunlosky, 2012) when monitoring-based control becomes too challenging (see Schnaubert & Bodemer, 2017).

In conclusion, learners have to make important control decisions during learning, for example, what material to study when and how much time to allocate to it. To optimise their learning process, they thus need to be aware of how well they already mastered different aspects of the learning material and use this information strategically to control learning. However, this can be challenging and thus, these processes often need additional support (Schnaubert & Bodemer, 2017).

2.1.2 Monitoring

Within theories on metacognitive self-regulation, it is widely assumed that learners control their learning processes based on monitoring their cognitive processes (monitoring-based

control; Son & Schwartz, 2002). Thus, metacognitive monitoring has a key role within such theories and has been widely studied (Dinsmore et al., 2008).

Originally more described as a passive process (e.g., Nelson & Narens, 1990), the notion of the necessity of active and conscious efforts has become more prevalent (Efklides, 2008; Nelson, 1996; Van Overschelde, 2008) as learners are assumed to analyse various cues to form their metacognitive judgments (e.g., de Bruin, Dunlosky, & Cavalcanti, 2017; Koriat, Lichtenstein, & Fischhoff, 1980; Koriat, Nussinson, Bless, & Shaked, 2008). But learners not only need to monitor their current state of learning, they additionally need to compare it to a pre-set standard or goal. These goals are assumed to be part of the meta-level model and allow to derive actions based on target-performance comparisons (de Bruin & van Gog, 2012; Nelson, 1996; Nelson & Narens, 1990). These processes can be challenging especially when the learning situation is challenging in itself (Valcke, 2002). This may be one reasons why learners often do not spontaneously monitor their learning or do so insufficiently (Schnaubert & Bodemer, 2017).

Monitoring is usually assessed by asking learners to judge their current state of learning or experiences during learning on some form of rating scale (Dinsmore et al., 2008). Thus, the measurement requires an explicit behaviour of the learners as opposed to control decisions that often refer to the (observable) interaction with external learning material. Self-report is the inherent approach to assessing monitoring, because the subjective view on own cognitions is assumed to be part of the concept assessed as opposed to measurement error (Nelson & Narens, 1990). However, like any instruction, asking learners to rate their monitoring outcomes on a given scale is potentially reactive and research has found these judgments to impact study time allocation (Mitchum, Kelley, & Fox, 2016) and memory (Soderstrom, Clark, Halamish, & Bjork, 2015). Since such requests may stimulate metacognitive reflecting (a key feature of reflection prompts; Bannert, 2006), they may be viewed as a form of prompt and may be suited to trigger monitoring processes during self-regulated learning (consult Schnaubert & Bodemer, 2017, for further information).

Monitoring judgments have two major characteristics: their magnitude (which is available to the learners' themselves and assumed to affect learning via control processes) and their accuracy (their relationship to an external criterion like performance, which is not directly accessible to learners; Nelson, 1996). Both serve different functions during learning. The magnitude ties in with the learners' experiences during learning and can be compared to a goal to initiate, continue or terminate study efforts (Nelson & Narens, 1990).

Additionally, this information can be used to select adequate learning tactics and strategies (e.g., Winne, 2010; Winne & Hadwin, 1998). Thus, from a learner perspective, this is the relevant characteristic during learning as it may be used to control study efforts. From an outside perspective, however, this information may also be evaluated externally. Monitoring judgments can tie in more or less with objective information about the state of learning (monitoring accuracy or calibration; Schraw, 2009; Schraw, Kuch, & Gutierrez, 2013). There are different conceptualisations of monitoring accuracy, usually relating to them being either an absolute overlap between monitoring outcomes and some state of learning (absolute accuracy) or the relative relationship between monitoring outcomes and more or less mastered material (relative accuracy). Both have in common that low accuracy may have detrimental effects on learning due to over- or understudying (relating to absolute accuracy; Dunlosky & Rawson, 2012) or due to failures to select relevant material to study (relating to relative accuracy; Thiede et al., 2003). For example, if learners judge they have sufficiently learned the material for an upcoming test, they will most probably terminate studying. If this judgment is inaccurate, they may understudy and thus underperform and potentially fail the upcoming test. While usually underconfidence is seen as less problematic (as it will usually lead to overstudying and may hamper efficiency, but not effectiveness, of study efforts), allocating study time to already mastered learning material will in practice mean that these resources cannot be spent on other relevant learning activities. Thus, being able to distinguish between well and not-well learned material is crucial to make adequate study decisions (see Schnaubert & Bodemer, 2017). Consequently, monitoring accuracy is central to metacognitive self-regulation as it moderates the link between metacognitive regulation and performance (e.g., Thiede et al., 2003) and is thus connected to the effectiveness and efficiency of learning processes (Schnaubert & Bodemer, 2017). While both aspects of accuracy are important, I will focus on relative accuracy as this thesis is concerned with the learners' ability to make adequate study choices and distinguish between material more or less learned. Thus, the term "monitoring accuracy" in the following refers to relative accuracy.

In conclusion, monitoring learning processes and outcomes is vital for metacognitive self-regulation. Usually assessed via rating scales, monitoring judgments have two major characteristics: their magnitude, relevant for internal goal-target and inter-item comparisons to make control decisions, and their accuracy, the relationship between the internal perspective and an external standard, relevant for the effectiveness of control

decisions with regard to learning outcomes. To successfully regulate their learning, learners have to actively and accurately monitor their learning processes and outcomes. Because learners not always do so, these processes need to be supported (Schnaubert & Bodemer, 2017).

2.1.3 Confidence

Monitoring is not assumed to be one single process, because it is unlikely that such processing efforts can cover the whole of cognition (Van Overschelde, 2008), especially since metacognitive processes are related to mental effort (Scott & Schwartz, 2007; see also Valcke, 2002). Thus, there are various different aspects of cognition that can be worth monitoring during learning. Nelson and Narens (1990) describe some of the basic judgments used in metacognition research (for an updated version see Dunlosky, Serra, & Baker, 2007). One core metacognitive concept frequently studied is retrospective confidence or response confidence or certitude (in accordance with Sniezek, 1992, I use these terms interchangeably). Response confidence judgments ask learners to evaluate the correctness of a prior performed task, and thus measure the validity of answers as perceived by the learners (Schnaubert & Bodemer, 2017). Due to their close connection to task performance, response confidence judgments indicate performance monitoring (e.g., Dunlosky & Hertzog, 2000; Hines, Touron, & Hertzog, 2009). Consequently, they take specific test performance into account and are thus connected to specific content of cognitions, i.e., question-answer relations (see Schnaubert & Bodemer, 2019).

Especially the formation of these judgments has received attention within metacognition research (e.g., Koriat et al., 1980, 2008). Empirical evidence points towards multiple factors influencing confidence judgments, for example experiencing mnemonic processes or deliberate information processing influenced by declarative metacognitive knowledge (for a review as well as empirical evidence see Koriat et al., 2008). Thus, while processing fluency may influence confidence in responses (e.g., Alter, Oppenheimer, Epley, & Eyre, 2007), it is safe to assume that learners also consciously evaluate supporting and contradicting evidence if prompted to form an explicit confidence judgment (e.g., Griffin & Tversky, 1992; Koriat et al., 1980).

Confidence has also been studied in various other research fields. It is – for example – believed to mediate the relationship between decision making and implementing respective actions (Sniezek, 1992) and thus can be seen as acting to qualify cognitions. Due to this

characteristic, confidence is often seen as an important aspect of knowledge itself (e.g., Hunt, 2003), because without confidence in (the correctness of) certain cognitions, they may not qualify as “knowledge” (these questions have been extensively discussed philosophically; for overviews see for example Lehrer, 1990; Reed, 2011). While this view is useful when using confidence in knowledge assessment (e.g., Leclercq, 1983, 1993), in metacognition research, the object-level cognitions (i.e., knowledge and assumptions) and their meta-level evaluation (i.e., confidence) are usually theoretically separated as this allows the meta-level to monitor and control the object-level (see Nelson, 1996). Empirically, this separation allows to study metacognitive regulation and its relation to cognitive processes and outcomes. However, it is important to keep in mind that confidence in itself is attached to specific responses or assumptions rather than the overall state of learning (see also Schnaubert & Bodemer, 2019).

Feedback research is an educational field that has put extensive work in studying the effects of confidence in responses, largely initiated by Kulhavy and Stocks confidence-based feedback model (Kulhavy & Stock, 1989). This research recognises the importance of confidence in assumptions for processing incoming information and the effect this may have on cognition (e.g., Hancock, Stock, & Kulhavy, 1992; Kulhavy, 1977; Kulhavy, Stock, Hancock, Swindell, & Hammrich, 1990; J. M. Webb, Stock, & McCarthy, 1994). Contrarily to the intuitive assumption that uncertain assumptions may be easier to overwrite, research in this area has found repeatedly that confidently held incorrect assumptions are more often corrected with the help of feedback than those held with lower confidence (e.g., Butterfield & Metcalfe, 2001, 2006). This effect has been largely attributed to differences in feedback processing due to motivational aspects (e.g., Fazio & Marsh, 2009), although there are assumed to be additional processes involved (Metcalfe & Finn, 2011). Thus, confidence influences how incoming information is perceived (Schnaubert & Bodemer, 2016, 2019).

But also in the absence of feedback, response confidence judgments play an important role during learning as they provide information about whether specific content is learned and/or understood sufficiently. Thus, low confidence in correct or incorrect assumptions may act as internal feedback (Butler & Winne, 1995) and trigger learning efforts or re-study decisions, allowing learners to correct faulty assumptions. This stresses the relevance of confidence also within self-regulated learning, because confidently held incorrect assumptions may not be called into question by individuals as they do not prompt further

learning attempts (e.g., Hines et al., 2009). Because these judgments are attached to specific assumptions, they usually require some form of response to testing or self-testing and are theoretically and empirically connected to (re-)study decisions (e.g., Hines et al., 2009; Robey, Dougherty, & Buttaccio, 2017). Since they are post-performance judgments, they are often found to be more accurate than pre-performance judgments (Maki, 1998; Maki, Foley, Kajer, Thompson, & Willert, 1990).

In conclusion, response confidence judgments are connected to specific assumptions (Figure 3). Due to this characteristic, they have been extensively studied in various lines of research such as decision making, feedback processing and metacognition. They are seen as a key metacognitive concept and are theoretically and empirically connected to the regulation of study and have often been found to be rather accurate. Due to their importance in metacognition and their close connection to specific cognitions (e.g., during self-testing), they seem especially suited to guide self-regulated learning processes during studying (see Schnaubert & Bodemer, 2017, 2019).

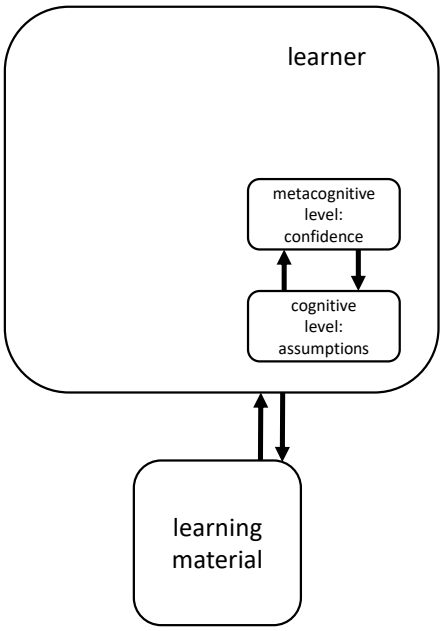

Figure 3. Metacognitive regulation with regard to confidence

2.1.4 Summary

Taken together, metacognitive theories of self-regulated learning assume a causal relationship between monitoring, control and performance (section 2.1). Monitoring processes inform the meta-level about the current state of learning and are thus the basis for metacognitive regulation (section 2.1.2). One key metacognitive concept related to monitoring is (response) confidence, which links metacognitive experiences with specific

cognitive assumptions and is theoretically and empirically connected to control decisions (section 2.1.3). Taking control of the learning process includes decisions about what material needs to be studied and thus, learners need to be aware of how well they already mastered different aspects of the learning material and use this information strategically to control their learning process (section 2.1.1). Because both monitoring and control are the key processes guiding individual learning behaviour, self-regulation will fail if learners don't actively or incorrectly monitor their learning or don't regulate their learning based on the monitoring outcomes (Schnaubert & Bodemer, 2017). While there is some research on how to promote monitoring through prompting (e.g., Bannert, 2006), little research has been done on how to promote the usage of monitoring outcomes to regulate learning (Koriat, 2012). Thus, instructional support is needed that targets triggering monitoring processes and supporting the usage of the outcome during learning (Schnaubert & Bodemer, 2017). Consequently, one aim of this thesis is to develop and apply support mechanisms to promote learners' metacognitive self-regulation without restricting the learners' agency.

2.2 Socio-cognitive information

While self-regulated learning is often studied on an individual level, the socio-cognitive tradition of this research field situates self-regulated learning within a social context (e.g., Zimmerman, 1989, 2000). Theories on metacognition have also recognised the relevance of social processes (e.g., Efklides, 2008; Salonen, Vauras, & Efklides, 2005). However, most theoretical views directly concerned with influences on metacognitive regulation focus on internal mechanisms to inform these processes (e.g., de Bruin et al., 2017; Gigerenzer, Hoffrage, & Kleinbölting, 1991; Koriat et al., 1980, 2008; Nelson & Narens, 1990) and largely disregard external influence. Additionally, empirical research explicitly connecting social influence and metacognitive self-regulation by researching how socio-cognitive information (i.e., information about another learner's cognitive and metacognitive status) affects individual metacognitive processes has only received scarce attention within the field of metacognition (although there are exceptions, see below).

In the following, I will describe how socio-cognitive information may affect metacognitive self-regulation via informing monitoring. Drawing on research from different research areas, I will give an overview, first over research concerned with the impact of cognitive information regarding another learner (with a specific focus on socio-

cognitive conflict; section 2.2.1), I will then look into the impact of metacognitive information (section 2.2.2), and finally address the impact of the individual's own metacognitive status (section 2.2.3).

2.2.1 Information on others' cognitions

Probably the most thoroughly researched area with regard to social influence on individual cognitions deals with the impact of other learners' assumptions about the content, that may directly affect a learners' knowledge base. Especially the effects of social consensus have been extensively studied in the past. Agreeing and disagreeing others may have a great impact on assumptions persons hold as has been dramatically shown in the seminal work of Asch (1951, 1956) and has been consistently observed in the past (for a meta-analysis see Bond & Smith, 1996). Metacognitively speaking, the assumptions of other individuals may serve as external information validating or contradicting own initial assumptions, strengthening or weakening the metacognitive evaluation of these assumptions from an information-processing perspective (Koriat et al., 2008). This type of social influence has been labeled "informational influence" as the information gives evidence about the objective reality as opposed to normative influence, which is based on obtaining social approval (Cialdini & Goldstein, 2004; Deutsch & Gerard, 1955).

While social influence has been predominantly studied within social psychology, how perceiving other learners' assumptions affects own cognitions has also been studied in other fields of psychology, especially with regard to the impact of socio-cognitive conflicts (resulting from confrontation with alternative assumptions put forward by others; Bell, Grossen, & Perret-Clermont, 1985) on learning and cognition. Going back to Piaget (e.g., Piaget, 1977b, 1977a), conflicts are assumed to be a major drive for cognitive development (e.g., Levine, Resnick, & Higgins, 1993; Mugny & Doise, 1978). While much of the work stemming from the Genevan tradition relies on learners actually interacting (see Doise & Mugny, 1984; Doise, Mugny, & Perret-Clermont, 1975), from an informational influence perspective, being confronted with conflicting assumptions may call into question own views on reality and thus affect metacognition (see Schnaubert & Bodemer, 2019). In light of conflicting or consenting evidence, learners may adjust their metacognitive evaluation of their own knowledge or assumptions (e.g., Koriat, Adiv-Mashinsky, Undorf, & Schwarz, 2018; McGarty, Turner, Oakes, & Haslam, 1993) and initiate a search for more information

(Buchs, Butera, Mugny, & Darnon, 2004; Lowry & Johnson, 1981) as would be assumed from a metacognitive regulation perspective (see Schnaubert & Bodemer, 2016, 2019).

In sum, there is evidence from various lines of research suggesting that socio-cognitive information may be perceived as supporting or contradicting evidence and may thus affect object-level knowledge and assumptions and – via monitoring processes – their meta-level evaluation (see Schnaubert & Bodemer, 2016, 2019). Because changes on the meta-level are assumed to initiate control processes (see section 2.1), socio-cognitive information may thus affect the whole metacognitive self-regulation cycle (Schnaubert & Bodemer, 2016).

2.2.2 Information on others' metacognitions

However, not all contradicting (or supporting) evidence is equally likely to affect cognitions. Apart from social consensus (Crano & Prislin, 2006), other source characteristics may determine how persuasive assumptions are perceived. For example, a source judged as reliable and knowledgeable will be more likely to affect an individual's assumptions than a source deemed as not credible at all (for a review see Pornpitakpan, 2004). However, if contextual information about the knowledgeability is missing, learners will need to infer the information based on available information. As the confidence learners' assign to their assumptions is perceived as a good indicator for the accuracy of said assumptions (i.e. knowledge), it seems reasonable to assume that learners' apply the same logic when judging information from others (Schnaubert & Bodemer, 2019). Thus, it stands to reason that content-related information may be evaluated differently if it comes with low or high confidence (as assumed by Buder, 2017). Research done in different research areas, such as research on eyewitness-credibility and advice-taking (e.g., Brewer & Burke, 2002; Cutler, Penrod, & Stuve, 1988; Whitley & Greenberg, 1986), stress the role of source confidence in evaluating incoming information. Eyewitness research, for example, indicates that mock-jurors are most influenced by the witnesses' confidence, rather than their testimonial consistency, when judging the probability that the accused committed a crime (Brewer & Burke, 2002). Thus, incoming information is perceived differently depending on the confidence the source assigns to the information. Additionally, research on source credibility found that source confidence is not only used as a cue to judge the accuracy of information provided, but also to judge the source, i.e., their competence or knowledgeability (e.g., Price & Stone, 2004; Tenney, Small, Kondrad, Jaswal, & Spellman, 2011; Yates, Price, Lee, & Ramirez, 1996). Thus, we can assume that

the confidence with which an assumption is brought forward affects the impact it has on an individual's knowledge base and thus on regulatory processes (Schnaubert & Bodemer, 2016, 2019).

But metacognitive information may also affect learners in the absence of cognitive information. Karabenick (1996) found that learners confronted with other learners having questions indicated higher levels of confusion about the content, presumably due to attributing the questions to task difficulty. Thus, perceiving metacognitive information may directly affect metacognitive monitoring without affecting cognitions about the content itself, but via affecting cognitions about task conditions. Again, in accordance with metacognitive theory, meta-level changes are assumed to affect subsequent learning processes (Nelson & Narens, 1990; see also section 2.1).

2.2.3 Metacognitive evaluations of own cognitions

Last but not least, own metacognitive evaluations may impact how incoming information is processed. Within theories on cognitive conflict, it is assumed that a certain level of confidence in assumptions is needed to experience conflict (Lee & Kwon, 2001; Lee et al., 2003). Largely initiated by Kulhavy and Stock's feedback model (Kulhavy & Stock, 1989), feedback research has recognised the role of confidence in assumptions as an important factor in feedback processing (see also section 2.1.3). This line of research has since studied the impact of confidence in erroneous assumptions on feedback study time (Fazio & Marsh, 2009; Kulhavy, 1977; Kulhavy & Stock, 1989) and error correction (Butterfield & Metcalfe, 2001, 2006; Metcalfe & Finn, 2011) and found clear indications that high confidence fostered both (see also section 2.1.3). Although expert feedback cannot be equated with socio-cognitive information from a source with unknown reliability, this research strengthens the notion of confidence being a relevant factor influencing how incoming information is processed (Schnaubert & Bodemer, 2019). While this research suggests high confidence conflict may be of particular interest for initiating regulatory processes, research on memory conformity suggests that external (i.e., social) information has the highest impact on cognition when learners are uncertain (e.g., Jaeger, Lauris, Selmeczy, & Dobbins, 2012). This is in line with metacognitive theories, which would suggest higher susceptibility to incoming information in case of low confidence, because these indicate a need for more information and a lack of valid information to assure an assumption. From a learning perspective, rising uncertainty might shift the notion of

conflicting assumptions and the need to elaborate different viewpoints towards a lack of knowledge and basic knowledge acquisition processes and may thus benefit learning quite differently. While this sounds reasonable, how metacognitive self-evaluations interact with socio-cognitive information in affecting study decisions remains unclear (see Schnaubert & Bodemer, 2016, 2019).

2.2.4 Summary

As shown in this section, research from various research fields (e.g., social psychology, developmental psychology, cognitive psychology, educational psychology) suggests that socio-cognitive information may impact individual cognitions and metacognitions (see also Schnaubert & Bodemer, 2016, 2019). Thus, while metacognitive monitoring should be the main basis for control processes within individual learning settings (e.g., Nelson et al., 1994; see also Schnaubert & Bodemer, 2017), within social situations, socio-cognitive information may initiate further study efforts when socio-cognitive conflicts occur as a need for further information may arise from conflicting viewpoints challenging initial assumptions (section 2.2.1). However, this may depend on own, pre-existing confidence (section 2.2.3). As metacognitive information on others may be used to validate assumptions put forward and may also indicate task difficulty (section 2.2.2), it seems reasonable to assume that learners integrate available (socio-) cognitive and metacognitive information to inform metacognitive monitoring (i.e., confidence) and thus regulation (Schnaubert & Bodemer, 2016, 2019). However, empirically, the exact nature of this interplay of cognitive and metacognitive self- and other-information and its effect on metacognitive regulation is yet unclear (see also Schnaubert & Bodemer, 2016). Because this is crucial for understanding individual learning processes within a social context, but also because understanding the impact of social information is the basis for understanding individual activities within collaboration, one aim of this thesis is to take a closer look into these mechanisms and analyse how socio-cognitive information affects individual self-regulatory processes (please note that the term “socio-cognitive” may refer to both cognitions and metacognitions of others). Figure 4 (p. 19) integrates information on other learners into the previous model. Please note that I did not specify all possible interaction processes between the types of information as most of them are assumed to be intertwined and this would overburden the graphic.

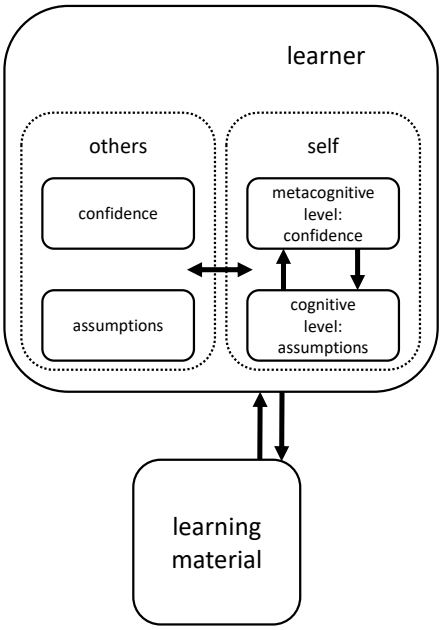

Figure 4. Socio-cognitive influences on metacognitive self-regulation

3 Collaborative learning

While individual learning may be uni-directionally influenced by socio-cognitive information, learning scenarios often include (bi-directional) interaction of learners. Collaborative learning has become increasingly important for educational research and practices, to the point that collaborative problem solving became a target skill for the PISA 2015 assessments (OECD, 2017). In the following, I will provide an overview over aspects regarding collaborative learning research relevant for this thesis. I will first introduce collaborative learning, pointing out specifics and challenges (sections 3.1 – 3.4), and then introduce group awareness tools as a means to support collaborative learning processes (section 3.5). For reasons of simplicity and because this thesis is concerned with dyadic learning, I will focus on collaborative learning in dyads.

3.1 Collaborative learning and individual learning processes

According to Dillenbourg (1999), collaborative learning may be understood as a situation which gives rise to inter- and intra-individual activities, which in turn trigger beneficial cognitive mechanisms. Thus, the collaborative context creates affordances with regard to beneficial learning practices, possibly supported by technology (Jeong & Hmelo-Silver, 2016). Inter-individual activities include explaining content or argumentation, both of which are concerned with individual knowledge about and understanding of content-related concepts externalised during interaction (de Vries, Lund, & Baker, 2002). Concerning intra-individual processes, learners may perceive, comprehend and elaborate on content-related information during collaboration (Buder, 2017). For example, learners lacking understanding may receive information or explanations from more knowledgeable peers (Dillenbourg, Baker, Blaye, & O'Malley, 1995; Weinberger & Fischer, 2006), which may benefit especially the helper, but also the helpee (King, 2007; N. M. Webb, Farivar, & Mastergeorge, 2002; N. M. Webb & Palincsar, 1996). To be able to fill in missing information and structure such a discourse efficiently, it is important for learners to have an understanding of what each other knows and where more information might be needed (Dehler, Bodemer, Buder, & Hesse, 2009, 2011; see also Schnaubert & Bodemer, 2018, 2019). But learners may not only possess different levels of prior knowledge, they may also hold alternative views about the content, which may trigger socio-cognitive conflicts within the individuals involved (e.g., Bell et al., 1985). Such epistemic conflicts have been widely

studied with regard to opportunities for learning (e.g., Doise et al., 1975; Mugny & Doise, 1978) as they may trigger a search for information (Lowry & Johnson, 1981) and elaboration processes if learners resolve them in a meaningful way (Buchs et al., 2004; Chan, Burtis, & Bereiter, 1997; Johnson & Johnson, 2009b; Weinberger & Fischer, 2006). However, the potential of conflicting assumptions can only be utilised if learners are aware of them and are thus able to target them during collaboration (Schnaubert & Bodemer, 2019).

3.2 Collaborative learning in an interaction space

Independent of the specific types of interaction, Engelmann and colleagues (Engelmann, Dehler, Bodemer, & Buder, 2009) conceptualise collaborative learning as an interactive process in which learners add or rearrange content-related information in a shared space and process information added to the space by others. Thus, when learners learn together, they collaborate in an interaction space, in which they share resources and information via externalisation and internalisation processes (Beers, Boshuizen, Kirschner, & Gijselaers, 2005; Engelmann et al., 2009). This can be verbal only, but may also involve interacting with or sharing learning material and/or knowledge artefacts (Jeong & Hmelo-Silver, 2016). Such processes can be describes within the knowledge exchange framework by Buder (2017). The framework assumes that individuals perceive observable group-level activities and in turn externalise internal information to make it available to the group. The information exchanged can be content-related, but also contains contextual cues that provide information about the speaker (fostering partner modelling; Sangin, Nova, Molinari, & Dillenbourg, 2007) and may change how the content is perceived (Buder, 2017; Engelmann et al., 2009). For example, an utterance brought forward hesitantly will be perceived very different from an utterance put forward with confidence (Buder, 2017). Based on Engelmann and colleagues (2009), Figure 5 (p. 22) integrates these interaction processes into the current framework, including a second learner and the respective partner model, direct exchange of information and through observable interaction with the learning material (please note that the figure does not differentiate between content-related and contextual information to reduce complexity; however, it is assumed that interaction may contain both).

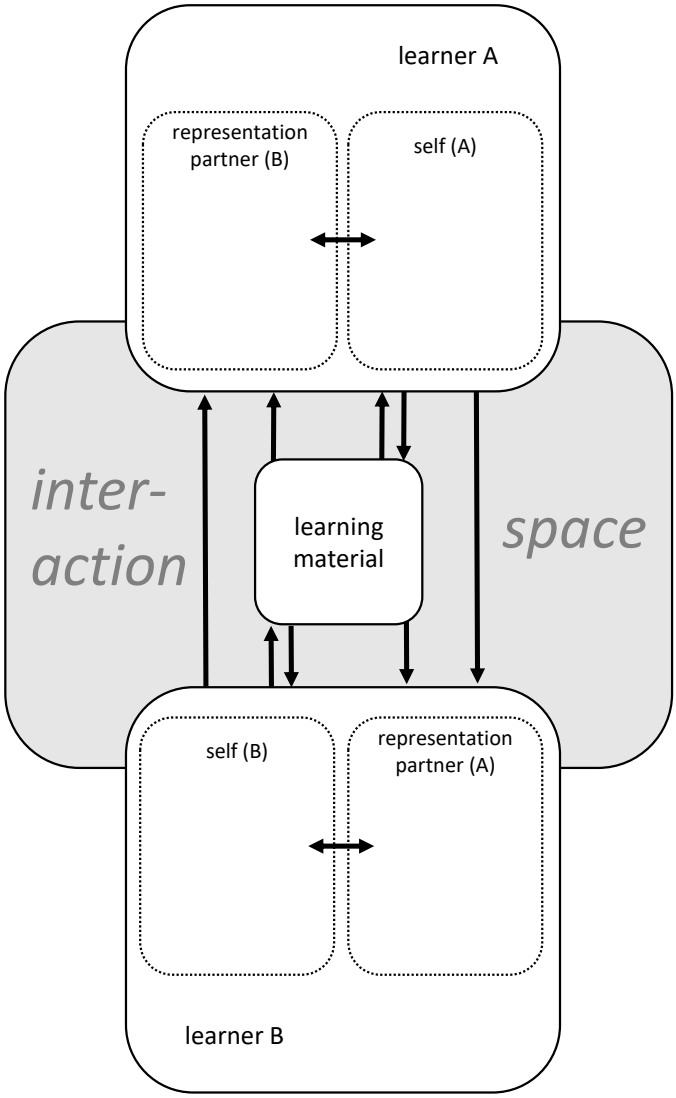

Figure 5. Interaction in an interaction space

3.3 Collaborative interaction and interdependence of learning outcomes

As described above, collaborative learning comprises both (cognitive) activities within a person and activities within an interaction space. Activities in an interaction space may include verbal and non-verbal processes between the learners, but also observable interaction with the learning material (Buder, 2017). While cognitive activities contribute to cognitive (and metacognitive) changes and thus learning (e.g., knowledge gain), activities within the interaction space potentially affect all learning partners involved (e.g., Cress, 2008; see also Schnaubert & Bodemer, 2018). For example, when learners re-arrange aspects within the shared space, these changes lead to unique experiences learners within a collaborating group share (common fate; see Cress, 2008). Moreover, through processes like knowledge sharing and discussing content, learners may actively

influence each other. Such reciprocal influence is considered one of the main causes of statistical interdependence within collaborative learning research (Bonito, 2002; Cress, 2008). Within the context of collaborative learning, statistical interdependence describes a beyond chance similarity of learners (or data retrieved to describe learners) that belonged to a collaborating group. Put differently, this is the variance in data that can be explained by dyad or group assignment rather than individual error or treatment (Gonzalez & Griffin, 2012) (please note that the term interdependence here refers to a post-collaboration phenomenon rather than the characteristic of a collaborative situation (e.g., goal structure) affecting subsequent collaboration as in Johnson & Johnson, 2009a). Conceptually, this interdependence is to be expected in collaborative learning settings, as it is a consequence of collaborative activities (for a more thorough description of how collaborative learning may foster interdependence see Schnaubert & Bodemer, 2018). Figure 6 illustrates the relationship between intra- and inter-individual processes and interdependence of individual learning outcomes within the collaborative learning framework. Since handling interdependence statistically poses a great challenge for collaborative learning research (Strijbos & Fischer, 2007), interdependence is often contemplated statistically rather than conceptually, despite its conceptual relation to (desired) collaborative processes (see Schnaubert & Bodemer, 2018).

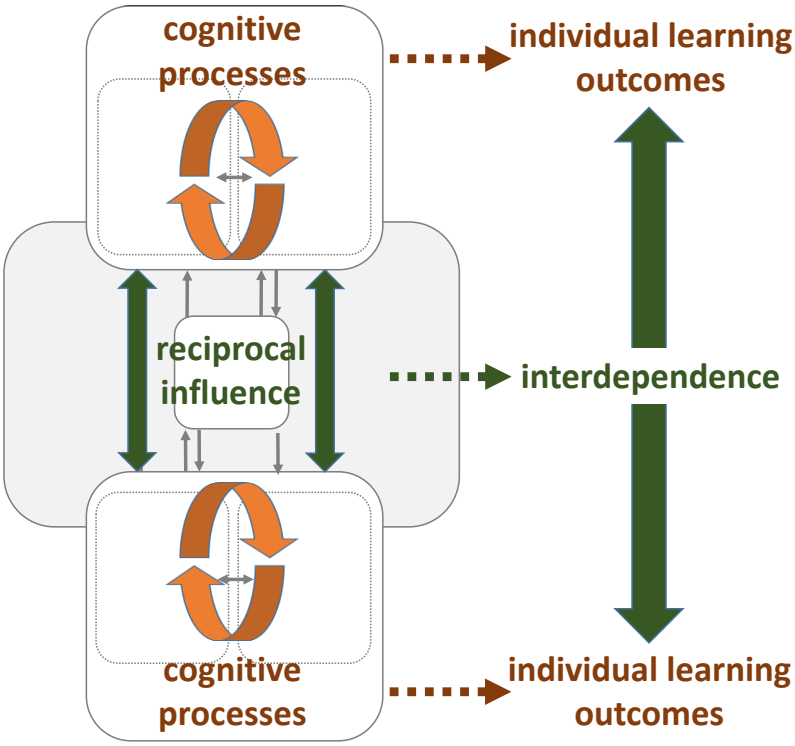

Figure 6. Collaborative learning and interdependence

3.4 Challenges of collaborative learning

Beneficial collaboration processes not always just happen because learners are co-present (Roschelle & Teasley, 1995). While collaborative learning may have many benefits in theory, practically, it poses just as many challenges. Apart from organisational measures like arranging a time and place (if applicable), the collaboration in itself can be highly demanding.

For collaboration to be successful, learners need to coordinate the content as well as their activities within the shared space (Clark & Brennan, 1991; Dourish & Bellotti, 1992; Roschelle & Teasley, 1995). To do so, they have to establish a common ground, i.e., mutual knowledge, assumptions and beliefs that are accepted by both partners (Clark & Brennan, 1991). This common ground acts as a shared frame of reference (G. Erkens, Jaspers, Prangsma, & Kanselaar, 2005) and is thus assumed to be the basis for communication (Clark & Brennan, 1991). Grounding refers to the act of establishing a common ground and relies on an understanding not only of own cognitions but also of the partners' perspective (Beers et al., 2005). Modelling a partners' knowledge in collaboration is important to adapt communicative activities (Clark & Murphy, 1982) and has been found to foster learning gain within collaborative settings (Sangin, Molinari, Nüssli, & Dillenbourg, 2011). If information on the partners' cognitions are missing, learners tend to overestimate similarities (Nickerson, 1999) and may thus fail to detect relevant differences between them (see also Schnaubert & Bodemer, 2019).

Detecting such differences is also relevant from a meta-level perspective, because it can be used to regulate the learning process (Schnaubert & Bodemer, 2019). During collaboration, learners need to decide upon adequate cognitive and collaboration activities (King, 2007). This includes selecting beneficial learning activities and allocating resources, e.g., by choosing to discuss conflicts (Bodemer, 2011) or by attending to content incompletely understood (Dehler et al., 2011). Apart from being aware of and jointly negotiating specific courses of action (see Järvelä & Hadwin, 2013), learners thus need to monitor their own as well as each other's cognitions to choose an adequate strategy and allocate resources (Schnaubert & Bodemer, 2019). This ties in closely with the concept of group awareness, which refers to being informed about relevant aspects of group members or the group as a whole (Bodemer & Dehler, 2011) and describes – amongst others – the salient perception of other learners' knowledge and assumptions (often referred to as "cognitive group awareness"; Bodemer et al., 2018). As cognitions are not directly

observable, attaining cognitive group awareness is assumed to be especially problematic within collaborative situations (Buder, 2011; Janssen & Bodemer, 2013).

The above described communication and coordination activities can be highly demanding (e.g., G. Erkens et al., 2005; Janssen, Erkens, & Kanselaar, 2007) as learners have to make a constant effort to coordinate their language and activities (e.g., Roschelle & Teasley, 1995) but also to decide upon adequate strategies to approach the task (Miller & Hadwin, 2015). This may overwhelm learners – especially when the content in itself is complex (Dillenbourg & Bétrancourt, 2006). But even if learners are able to handle the demand, they may not be aware of relevant aspects of the learning situation to decide upon beneficial courses of action and thus may need support (Schnaubert & Bodemer, 2019).

3.5 Group awareness tools: guidance to support collaborative learning

Guiding collaborative learning attempts can be done in many ways. In general, instructional design is concerned with optimising support towards beneficial learning activities. Within collaborative research, there is often a differentiation between offering very explicit support (e.g., by using collaboration scripts; see Kollar, Wecker, & Fischer, 2018) that potentially inhibits and restricts learners' self-regulation (although this view is not unchallenged and cuts short the great variety of more explicit support mechanisms; see Wise & Schwarz, 2017) and implicit support that constructs a situation in which beneficial activities are likely to happen, but – as it does not give explicit advice – needs to be interpreted by the learners to be transformed into beneficial courses of action. While more explicit advice can be much more directive and support learners with a wide variety of skills and competences (Kirschner, Sweller, & Clark, 2006), implicit support builds on self-regulatory activities and thus preserves the learners' agency (Hesse, 2007).

One prominent way to support collaborative learning by guiding learners rather implicitly is providing learners with group awareness information (e.g., information on their learning partners' knowledge and assumptions) to foster partner modelling and grounding processes but also to tacitly guide their learning activities towards beneficial content and processes (Bodemer et al., 2018; see also Schnaubert & Bodemer, 2019). This is usually done by using specific tools to support group awareness within collaboration (group awareness tools; see Bodemer et al., 2018). These tools are technological auxiliaries, that process awareness information in three consecutive steps: assessing the information, transforming the information, providing the information (see Buder, 2011; Buder &

Bodemer, 2008, for more information including specific challenges for each processing step). From a recipient's perspective, these tools may provide group awareness information on three distinct aspects: information about the learner, information about the partner, and information about the distribution of knowledge within the group (Dehler et al., 2011). All three levels of information are assumed to be especially relevant for comparison processes and may affect learning activities (Dehler et al., 2009, 2011).

Group awareness tools that provide information on cognitive aspects of learning partners or the group have shown promising results in terms of supporting topic selection (e.g., Bodemer, 2011), communication efforts (e.g., Dehler et al., 2011), partner modelling (e.g., Sangin et al., 2011; Schreiber & Engelmann, 2010), but also have been found to benefit knowledge gain (e.g., Bodemer, 2011; Sangin et al., 2011; for a more thorough overview over empirical research on group awareness tools see Bodemer et al., 2018; Janssen & Bodemer, 2013) . These tools differ from other tools processing learner-related information (e.g., within the field of learning analytics) because they target the learners themselves as stakeholders and thus, the information has to be adapted to their specific needs (Schnaubert & Bodemer, 2019).

Figure 7 (p. 27) integrates a group awareness tool into the current framework, specifying the processing steps and placing the information provided within the interaction space, where it can be perceived by the learners. The dotted line indicates that the awareness information provided may be connected to specific aspects of the learning material to ease connecting communication to the learning material (information cueing; Bodemer & Scholvien, 2014). In the following, I will describe the general functions of knowledge-related awareness tools within learning processes.

3.5.1 General functions

The defining function of group awareness tools is to foster the learners' group awareness. While this sounds trivial, this means that the key function is to inform about relevant (social) aspects of the collaborative situation. These tools may thereby facilitate natural formation processes of group awareness by adding an external representation that learners can refer to (Engelmann et al., 2009). Thus, from a cognitive load perspective (e.g., Paas, Renkl, & Sweller, 2003; Sweller, 1994), these tools take processing effort off the learners' shoulders, allowing them to focus their efforts on germane learning processes (Janssen, Erkens, & Kirschner, 2011). Without such support, learners either need to redirect more

resources towards gaining and processing the information or discard the information for study purposes (see also Schnaubert & Bodemer, 2019).

However, group awareness tools not only amplify a natural process, but they may steer this process into an intended direction (e.g., Bodemer, 2011; see also Schnaubert & Bodemer, 2019). By pre-selecting, transforming and presenting information in a specific manner, the information portrayed does not just mirror the collaborative situation but pre-structures it by emphasising certain aspects and suggesting specific processing (Bodemer & Scholvien, 2014). For example, focussing on specific learner characteristics within group awareness tools signals their importance for learning to the learners. On the other hand, transformation processes may constrain the usage of the information, e.g., due to the granularity or its relation to specific content of learning material (e.g., M. Erkens & Bodemer, 2019).

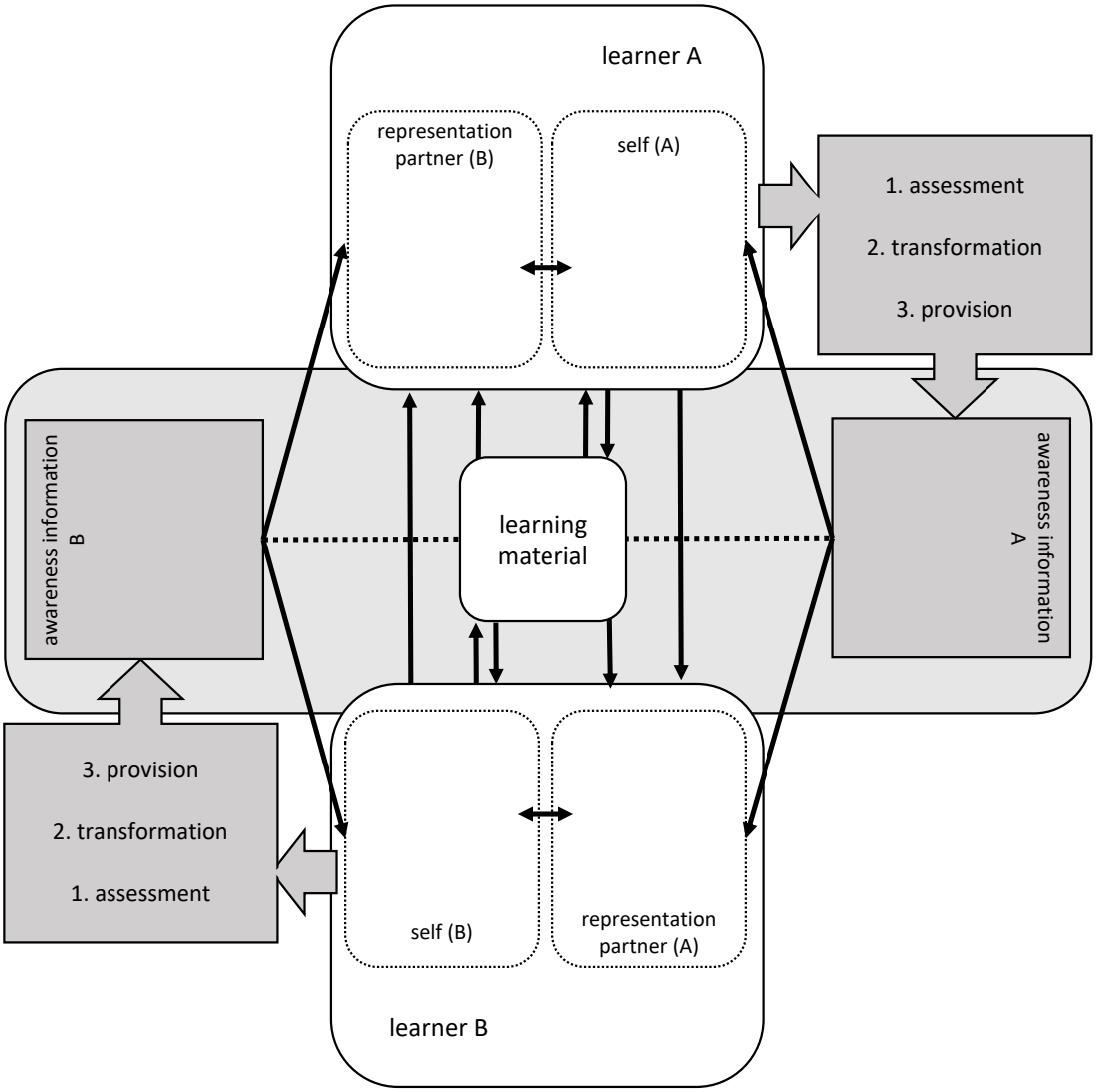

Figure 7. Collaborative learning with group awareness tools

Additionally, the arrangement of the information within the learning environment may suggest specific processing. For example, providing information about learning partners in close proximity may initiate inter-individual comparison processes (Bodemer, 2011; Dehler et al., 2011). Alternatively, carefully arranging information and tying it to specific learning material may also trigger comparison processes between aspects of the learning material (e.g., Dunlosky & Thiede, 2004) or point towards missing information (representational guidance; Suthers & Hundhausen, 2003). If the awareness information is connected to specific learning content, it may point towards relevant parts of the learning material that need further attention (Bodemer & Scholvien, 2014) and thus trigger interaction processes with the material (Schnaubert & Bodemer, 2017) and with a learning partner (Schnaubert & Bodemer, 2019). These functions focussing attention towards specific aspects of the learning material and triggering specific learning activities are subsumed under the notion "guidance", differentiating between the guidance function depending on the learners' active interpretation of the information (informational guidance) and depending purely on their representational arrangement (representational guidance) (Bodemer, 2011). While this differentiation is relevant to distinguish between general (information-independent) and specific (information-dependent) functions, in practice, presentation and information are not completely separable from the recipients' perspective.

In sum, by carefully selecting, assessing, transforming and presenting information, group awareness tools offer an interpretation of the collaborative situation to guide the collaborative learning process into an intended direction (Schnaubert & Bodemer, 2019).

3.5.2 Knowledge-related group awareness information

There is a growing body of knowledge around group awareness tools that provide knowledge-related information about learners in a collaborating group (i.e., knowledge-related group awareness tools[2]). Such tools providing information on cognitive aspects of learning partners or the groups, have shown promising results in terms of supporting topic selection (e.g., Bodemer, 2011; Gijlers & de Jong, 2009), communication efforts (e.g., Dehler et al., 2011), partner modelling (e.g., Sangin et al., 2011; Schreiber & Engelmann, 2010), but also have been found to benefit knowledge gain (e.g., Bodemer, 2011; Sangin et al., 2011; see also section 3.5). For a more thorough overview over

[2] Please note that I will not use the more common term "cognitive group awareness tools" because it confounds cognitive and metacognitive information; see Schnaubert & Bodemer, 2019

empirical research on group awareness tools see Janssen and Bodemer (2013) or more recently Bodemer et al. (2018).

While a great variety of different tools exist, there is little systematic research differentiating between different types of knowledge-related information (Schnaubert & Bodemer, 2019). For example, some tools provide information about the specific content of learners' cognitions (i.e., assumptions) and are thus able to draw the learners' attention towards relevant differences (e.g., Bodemer, 2011). This research can draw on research on socio-cognitive conflict to provoke potentially beneficial learning processes (e.g., Mugny & Doise, 1978). Other tools do not focus on the content of cognitions, but incorporate information of the learners' perception of their knowledge (e.g., Dehler et al., 2009, 2011). This allows learners' to explicitly communicate a need for information (Engelmann et al., 2009). Thus, depending on the group awareness information portrayed, group awareness tools may draw attention to very different aspects of learners' knowledge distributions (e.g., lacks of knowledge or conflicting assumptions) and may induce different collaborative and cognitive processes (Schnaubert & Bodemer, 2019).

3.6 Summary

Taken together, collaborative learning can prove useful for individual knowledge gain. Some beneficial processes like discussing or explaining content are more likely to happen during collaborative than individual learning (e.g., King, 2007). Through such interactions, learners mutually influence each other's learning processes, which may result in statistical interdependence of their learning outcomes (section 3.3). Statistically modelling interdependence takes into account the individual as well as a dyadic perspective. Although it may be interpreted conceptually and provide valuable insight into collaborative dynamics, this is rarely done in collaborative learning research (Schnaubert & Bodemer, 2018). Thus, one aim of this thesis is to introduce a conceptual understanding of (statistical) interdependence in collaborative learning.

Additionally, even though collaborative learning can benefit learners in gaining knowledge, it also holds many challenges. Learners have to jointly regulate their learning processes, negotiating meaning and coordinating activities. This can be highly demanding and learners may fail to implement beneficial learning strategies (see section 3.4). One way to support learners collaborating is by providing knowledge-related information about learning partners or the group to foster group awareness (section 3.5). This may relieve

mental processing effort as the information can be externally represented. Additionally, such information may be transformed to offer a useful interpretation of the learning situation to guide learning processes (section 3.5.1). However, while there is a multitude of different tools available, the field lacks systematic research structuring and comparing effects of different types of knowledge-related group awareness information (Schnaubert & Bodemer, 2019). Apart from the type of information portrayed, the level of information (i.e., self, partner, group) and their specific effects on collaborative processes are often ignored. Thus, another aim of this thesis is to provide and use a framework to analyse and compare different types of knowledge-related group awareness information, while additionally providing first indicators of differential effects of self-, partner and group information.

4 Awareness information to support individual and collaborative learning

In the above paragraphs, I described that individual self-regulation distinguishes between object- and meta-level processes and that both are vital for self-regulated learning. I further differentiated between two central processes (monitoring and control) that are relevant to guide metacognitive self-regulation. One core metacognitive concept evaluating content-related information (like assumptions) is confidence in assumptions. However, the usage of monitoring to control individual learning is understudied and provides a challenge for individual learners (Schnaubert & Bodemer, 2017).

I further discussed that self-regulated learning rarely happens in complete isolation and that there is reason to believe that socio-cognitive information may severely impact metacognitive self-regulation. However, even though social processes seem increasingly important with the rise of socially-oriented information technology (e.g., social media), this area is understudied and it remains unclear how socio-cognitive information uni-directionally affects individual metacognitive regulation processes, especially with regard to socio-cognitive conflict (Schnaubert & Bodemer, 2016).

I additionally focussed on collaborative learning. Collaborative learning may support individual knowledge gain by means of transactive interaction. Such interactions may foster interdependence between learners. However, statistical interdependence, as often observed within data gained from collaborating learners, is frequently ignored, sometimes statistically handled, but seldom conceptually discussed and related to collaborative practices (Schnaubert & Bodemer, 2018).

Because collaboratively coordinating learning processes is challenging, research on computer-supported collaborative learning is concerned with supporting these processes. Group awareness tools are a well-established means to support collaborative learning and to guide collaborative learning processes by providing knowledge-related information on the learners. However, research within this area rarely systematically differentiates between the specific types of knowledge-related information (Schnaubert & Bodemer, 2019) as well as between self-, partner- and group-level effects of these tools.

Merging research traditions on metacognitive self-regulation and research on collaborative learning could provide large benefits for both areas. The concept of awareness and functions of awareness tools may be helpful to support individual learners to monitor their knowledge and assumptions and to use the information to guide study decisions (Schnaubert & Bodemer, 2017). Adding socio-cognitive information would additionally

inform about the social dynamics within individual learning (Schnaubert & Bodemer, 2016). Studying the impact of self- and partner information in individual learning may also help to isolate effects of different levels of awareness information within group awareness tools. On the other hand, using a metacognition framework to differentiate between different types of knowledge-related awareness information used within awareness tools may help to distinguish and specify effects (Schnaubert & Bodemer, 2019). Such an approach can systematise research in this area and also add new methodologies. Integrating individual and collaborative perspectives on learning may further help to understand the effects interventions targeting collaborative practices have on dyadic data (Schnaubert & Bodemer, 2018). Figure 8 thus integrates the metacognitive aspects discussed in section 2 into the collaborative framework (including group awareness tools) discussed in section 3. The following section will elaborate on the integration, further specify the overarching goals of this thesis and derive research questions to be addressed empirically.

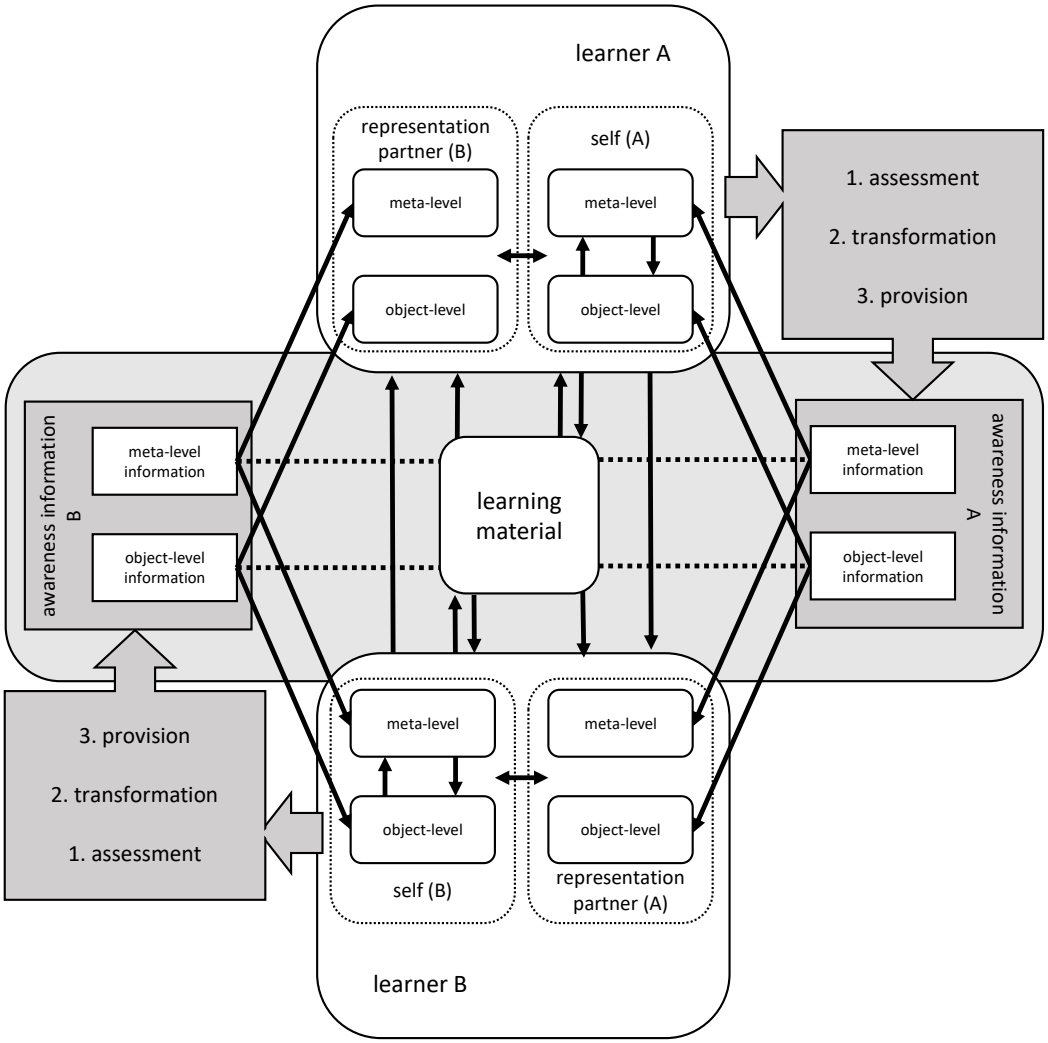

Figure 8. Integration of meta- and object-level information in group awareness tools within collaborative learning

5 Goals and research questions

The overarching goal of this thesis is to study ways to foster individual and collaborative learning by integrating two different research traditions: research on self-regulated learning (i.e., metacognition) and research on collaborative learning (i.e., group awareness). Metacognition research differentiates two levels of cognition, the object-level and the meta-level, that serve different functions within the self-regulated learning process (Nelson & Narens, 1990). On the other hand, research on group awareness describes the benefit of using informational and representational guidance mechanisms to support learning processes (e.g., Bodemer & Dehler, 2011; Suthers & Hundhausen, 2003) while enabling self-regulatory processes (Hesse, 2007). Further, research in this tradition conceptually differentiates three levels of information: information on the learners themselves, information on a learning partner, and information on the distribution of knowledge within a group (Dehler et al., 2011). In the following, I will briefly sketch how combining these traditions may benefit both fields.

5.1 Awareness tools to foster metacognition research and practice

Research on metacognitive self-regulation is predominantly concerned with studying how individuals monitor and control their learning (see section 2.1). This research suggests that learners not always adequately monitor their own learning (see section 2.1.2) or do not use this information strategically to control their learning process (see section 2.1.1; see also Schnaubert & Bodemer, 2017). The functions of group awareness tools facilitate similar processes in collaborative settings as these tools assess learner-related information and feed it back to the learners themselves while carefully arranging it to guide learning efforts (Bodemer et al., 2018). Thus, such an approach may also be applied to individual learners. Assessing metacognitive information may prompt learners to monitor their current state of learning and signals relevance of said information (Schnaubert & Bodemer, 2017). Moreover, transforming and saliently visualising the information in a deliberate manner during learning may ease comparison processes between material well and not-well learned and tacitly guide individual learners into metacognitively regulating their learning process without restricting self-regulatory activities (Schnaubert & Bodemer, 2017). Consequently, within this thesis I will apply awareness mechanisms adopted from group awareness research to individual settings to foster metacognitive regulation.

Additionally, there are strong indications that metacognitive regulation may be impacted by socio-cognitive information (see section 2.2). Having such information saliently available during learning ties in with functions of knowledge-related group awareness tools (Schnaubert & Bodemer, 2019). Thus, using said tools may be suited to investigate the impact of socio-cognitive information on metacognitive regulation to further foster our understanding of individual and collaborative learning (Schnaubert & Bodemer, 2016). Consequently, within this thesis, I will investigate the impact of socio-cognitive information on individual learning, especially metacognitive regulation, by using visualisation mechanisms of group awareness tools.

5.2 Metacognition research to foster group awareness research and practice

The role of knowledge-related awareness information has been studied mainly in the field of computer-supported collaborative learning so far. Research in this area suggests clear benefits of such information for collaborative learning (Bodemer et al., 2018). While a multitude of research in this area exists, it remains unclear what type of knowledge-related information may provide most benefits to learners in terms of guiding learning processes but also with regard to learning outcomes (Schnaubert & Bodemer, 2019). As discussed in section 3.5, some group awareness tools provide information about the specific content of learners' assumptions and are thus able to draw the learners' attention towards disagreements (e.g., Bodemer, 2011; Gijlers & de Jong, 2009). This may be beneficial for learners as it may evoke socio-cognitive conflicts and thus potentially advantageous (transactive) learning processes (see section 3.1). From a metacognition perspective, such information is situated on the object-level of cognition (Schnaubert & Bodemer, 2019). Other group awareness tools do not focus on the content of cognitions but incorporate information of the learners' perception of their knowledge (e.g., Dehler et al., 2009, 2011). This allows learners to explicitly communicate a need for information from their perspective (Engelmann et al., 2009). This learner-centred perspective on own cognitions is in the heart of metacognition theory and research, and constitutes information on the meta-level (Schnaubert & Bodemer, 2019). Metacognition research would suggest that, because meta-level information comprises a model of the cognitive status and may thus be indicative of performance (section 2.1), the metacognitive evaluation of specific assumptions may be useful to detect (perceived) lacks of knowledge. These, in turn, are the

basis for regulatory processes (Nelson & Narens, 1990; see also Schnaubert & Bodemer, 2017).

While the differentiation between different kinds of information (object-level information and meta-level information) has not been made systematically within computer-supported collaborative learning research, metacognition research explicitly incorporates these viewpoints (e.g., Efklides, 2008; Nelson & Narens, 1990). Thus, using a metacognition framework to analyse different kinds of knowledge-related awareness information within collaborative settings can provide theoretical and methodological benefits and allows to derive information-specific research questions and hypotheses (Schnaubert & Bodemer, 2018, 2019). Consequently, in this thesis, I will apply a metacognition framework to knowledge-related group awareness information in order to systematically distinguish different types of group awareness information and analyse how they affect learning processes and outcomes.

Combining individual and group-level perspectives could also help to distinguish effects within group awareness tools as such tools may not only serve the function to provide relevant information on the group but may also mirror individual information back to the individuals and provide partner information, all of which may alter learning processes independent of or beyond collaborative processes (Dehler et al., 2009, 2011). Distinguishing between different levels of information (individual and collaborative) is not only necessary when looking into the provision of information, but also when considering learning outcomes. Thus, conceptually relating group awareness interventions to data interdependence (the relation between individual and dyadic sources of variance within outcome data; see section 3.3) may further inform collaborative learning research (Schnaubert & Bodemer, 2018). Consequently, in this thesis, I will investigate the impact of self-, partner, and group information within awareness tools by using individual and collaborative learning settings.

5.3 Empirical research questions

Integrating research on group awareness and metacognition in this thesis thus aims at fostering our understanding of how individual and collaborative learning processes can be supported by providing information on learners' cognitions and metacognitions (guidance) and how this affects learning outcomes. Using individual and collaborative settings will additionally allow us to identify levels of group awareness information (self-information,

partner information, group information) that may be worth considering in future studies. By integrating (group) awareness information and a metamemory framework, we will be able to draw from two separate research areas (computer-supported collaborative learning, especially group awareness, and self-regulated learning, especially metacognition) as well as contribute to both.

In a succession of studies, we thus aimed at answering several empirical research questions. The first one refers to adopting an awareness approach within metacognitive self-regulation research, differentiating self- and partner information:

Research question 1 (RQ 1): How does (cognitive and metacognitive) self- and partner information affect individual self-regulated learning and learning outcomes?

- Can metacognitive awareness information support individual learners' self-regulation and learning outcomes? (esp. Schnaubert & Bodemer, 2017)
- How does partner information affect individual learners' self-regulation and learning outcomes? (esp. Schnaubert & Bodemer, 2016)

The second question refers to using a metacognition framework to systematically study the impact of different types of knowledge-related group awareness information within collaborative learning:

Research question 2 (RQ 2): How does (cognitive and metacognitive) group awareness information affect collaboratively regulating learning in dyads and learning outcomes?

- Can cognitive and metacognitive information in group awareness tools support collaborative regulation of learning and learning outcomes? (esp. Schnaubert & Bodemer, 2019)
- How does this affect data structures of learning outcomes within collaborative settings? (esp. Schnaubert & Bodemer, 2018)

In the following section, I will describe how we aimed at answering these questions, by first giving an overview over the empirical studies conducted (section 6) before describing the methods used in more detail (section 7).

6 Overview over empirical studies

To investigate these questions, we conducted four studies in which we provided learners with different kinds of awareness information. The information itself was either cognitive or metacognitive or both (type of information) and referred to the learner him-/herself, another learner or both learners in a dyad (level of information). Additionally, each question refers to either an individual or collaborative setting.

Studies 1 and 2 focussed on the impact of self- and partner information on individual learning. These studies investigated

(1) the impact of assessing and providing metacognitive self-information during individual learning on individual self-regulation processes and learning outcomes
(2) the impact of providing cognitive and metacognitive partner information during individual learning on individual self-regulation processes and learning outcomes

Studies 3 and 4 took this research to the collaborative level. While in study 2, the partners were silent partners and there was no possibility to interact with them, in these two studies, two learners were able to interact. These studies investigated

(3) the impact of providing cognitive and/or metacognitive group awareness information during collaborative learning on collaborative regulation processes and individual learning outcomes
(4) the impact of metacognitive group awareness information during collaborative learning on learning outcomes with a specific focus on the resulting data structures

Taken together, we investigated the impact of metacognitive self-information (study 1: Schnaubert & Bodemer, 2017) and socio-cognitive information (study 2: Schnaubert & Bodemer, 2016) in individual settings, and the impact of cognitive and metacognitive awareness information in collaborative settings (study 3: Schnaubert & Bodemer, 2019; study 4: Schnaubert & Bodemer, 2018) on the learners' regulation of the learning process and learning outcomes. In the following, I will briefly give an overview over the focus of each empirical study. Each study is accompanied by a depictive representation that shows the relevant variations in terms of independent variables within the framework introduced above. Table 1 (p. 38) provides an overview over the empirical studies conducted and the corresponding publications.

Table 1. Overview over conducted studies and publications

Study	Publication
RQ 1: How does self- and partner information affect individual self-regulated learning?	
1	Schnaubert, L., & Bodemer, D. (2017). Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments. *Learning and Instruction*, *49*, 251–262. https://doi.org/10.1016/j.learninstruc.2017.03.004 [Schnaubert, L., & Bodemer, D. (2018). Corrigendum to "Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments". *Learning and Instruction*, *54*, 47. https://doi.org/10.1016/j.learninstruc.2018.01.010]
2	Schnaubert, L., & Bodemer, D. (2016). How socio-cognitive information affects individual study decisions. In C.-K. Looi, J. Polman, U. Cress, & P. Reimann (Eds.), *Transforming learning, empowering learners: The International Conference of the Learning Sciences (ICLS) 2016* (pp. 274–281). Singapore, SG: International Society of the Learning Sciences.
RQ 2: How does group awareness information affect collaborative learning in dyads?	
3	Schnaubert, L., & Bodemer, D. (2019). Providing different types of group awareness information to guide collaborative learning. *International Journal of Computer-Supported Collaborative Learning*.
4	Schnaubert, L., & Bodemer, D. (2018). What interdependence can tell us about collaborative learning: a statistical and psychological perspective. *Research and Practice in Technology Enhanced Learning*, *13*(1), 1–18. https://doi.org/10.1186/s41039-018-0084-x

6.1 Empirical studies within the framework

Study 1 investigated the impact of prompting and visualising monitoring judgments on metacognitive self-regulatory processes and learning outcomes (see Schnaubert & Bodemer, 2017). Thus, in contrast to the other studies, it focussed not only on the provision of awareness information (red marking in Figure 9), but also on the effect of assessing the information and potentially prompting beneficial processes (green marking). Additionally, it looked more closely into the role of monitoring accuracy within the learning process, but also as an outcome variable. Figure 9 (p. 39) depicts the study within the framework introduced above (variations in terms of independent variable within the study are depicted in red and green).

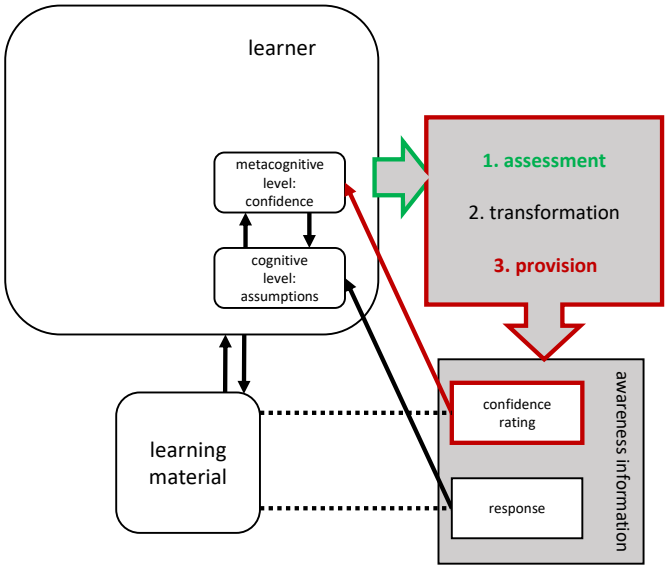

Figure 9. Depiction of study 1 (Schnaubert & Bodemer, 2017)

Study 2 investigated the impact of socio-cognitive information of a bogus learning partner on self-regulatory processes and learning outcomes (see Schnaubert & Bodemer, 2016). The socio-cognitive information consisted of cognitive and metacognitive awareness information and thus allowed us to additionally study how these types of self- and partner information are integrated during self-regulated learning. Figure 10 depicts the study within the framework (variations in terms of independent variable within the study are depicted in green). In comparison to study 1, it adds a social layer.

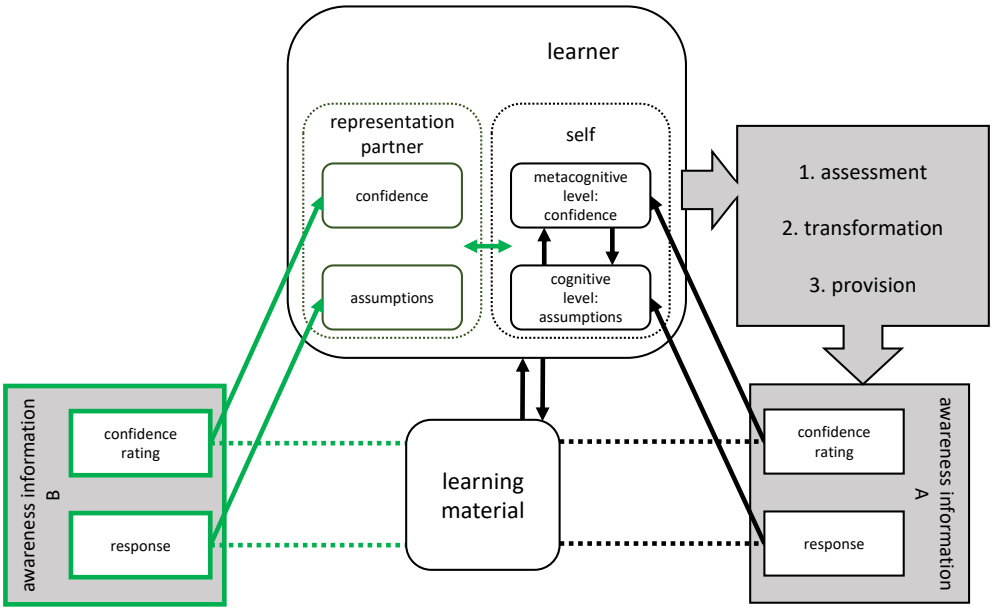

Figure 10. Depiction of study 2 (Schnaubert & Bodemer, 2016)

Study 3 investigated the impact of cognitive and metacognitive group awareness information on joint regulation processes based on metacognitive information and conflicts, as well as on (individual) learning outcomes (see Schnaubert & Bodemer, 2019). Figure 11 depicts the study within the framework. In comparison to study 2, it adds another learner. Thus, the differentiation between self and partner is not possible anymore from an outside perspective. Additionally, this time, cognitive and metacognitive awareness information were varied independently (depicted green and red in the figure), making it a 2 x 2 between-dyads design. This allowed us to study the impact of each type of information separately and additionally how learners integrate the information in a collaborative setting. Furthermore, this study took a closer look at the connection between regulatory processes and learning outcomes.

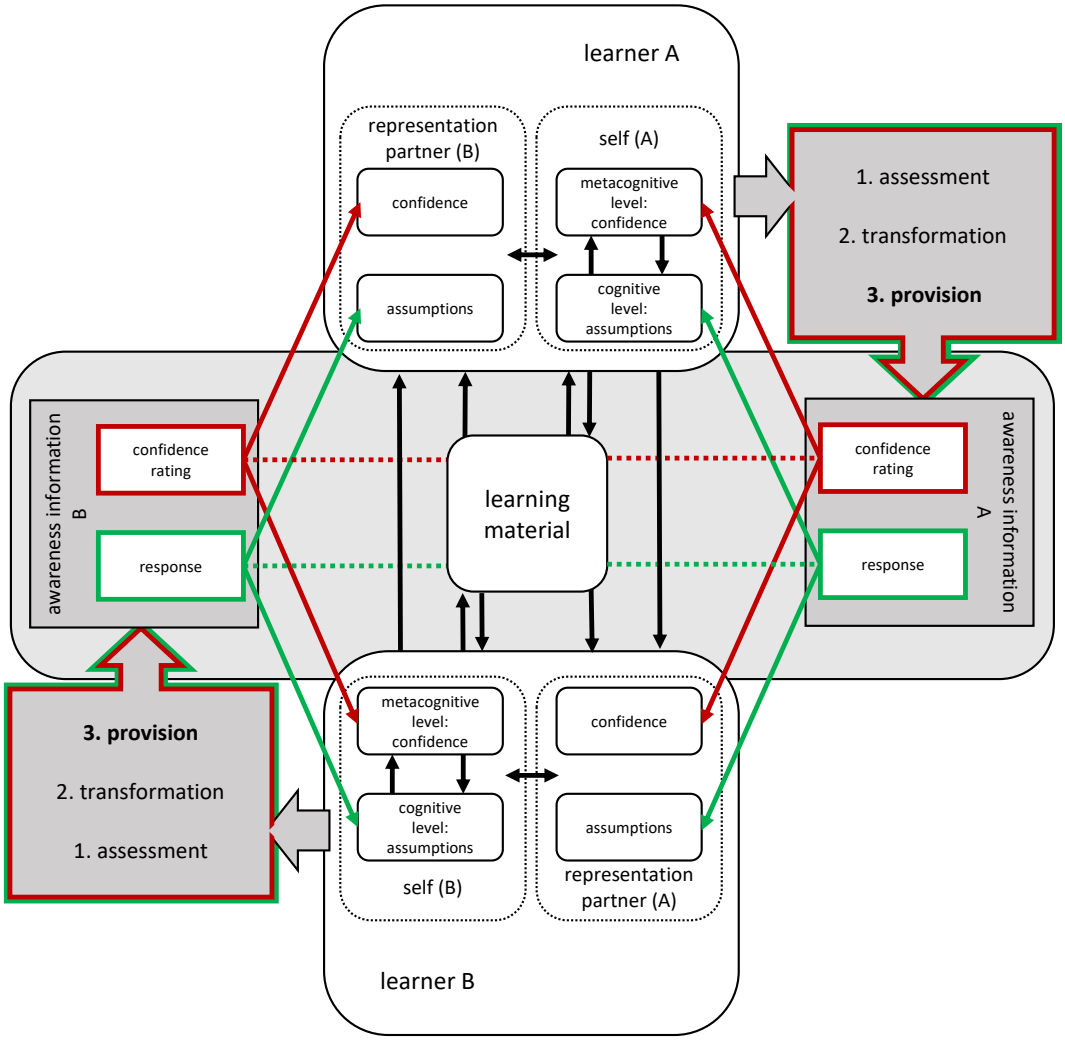

Figure 11. Depiction of study 3 (Schnaubert & Bodemer, 2019)

Study 4 investigated the impact of metacognitive group awareness information (in the presence of cognitive group awareness information) within a collaboration setting. As opposed to study 3, this study focussed on the interdependence of outcome data and did not study regulatory processes (see Schnaubert & Bodemer, 2018). Figure 12 depicts the study within the framework (variations in terms of independent variable within the study are depicted in red). Because outcome data is not explicitly depicted within the figure, it looks rather similar to study 3.

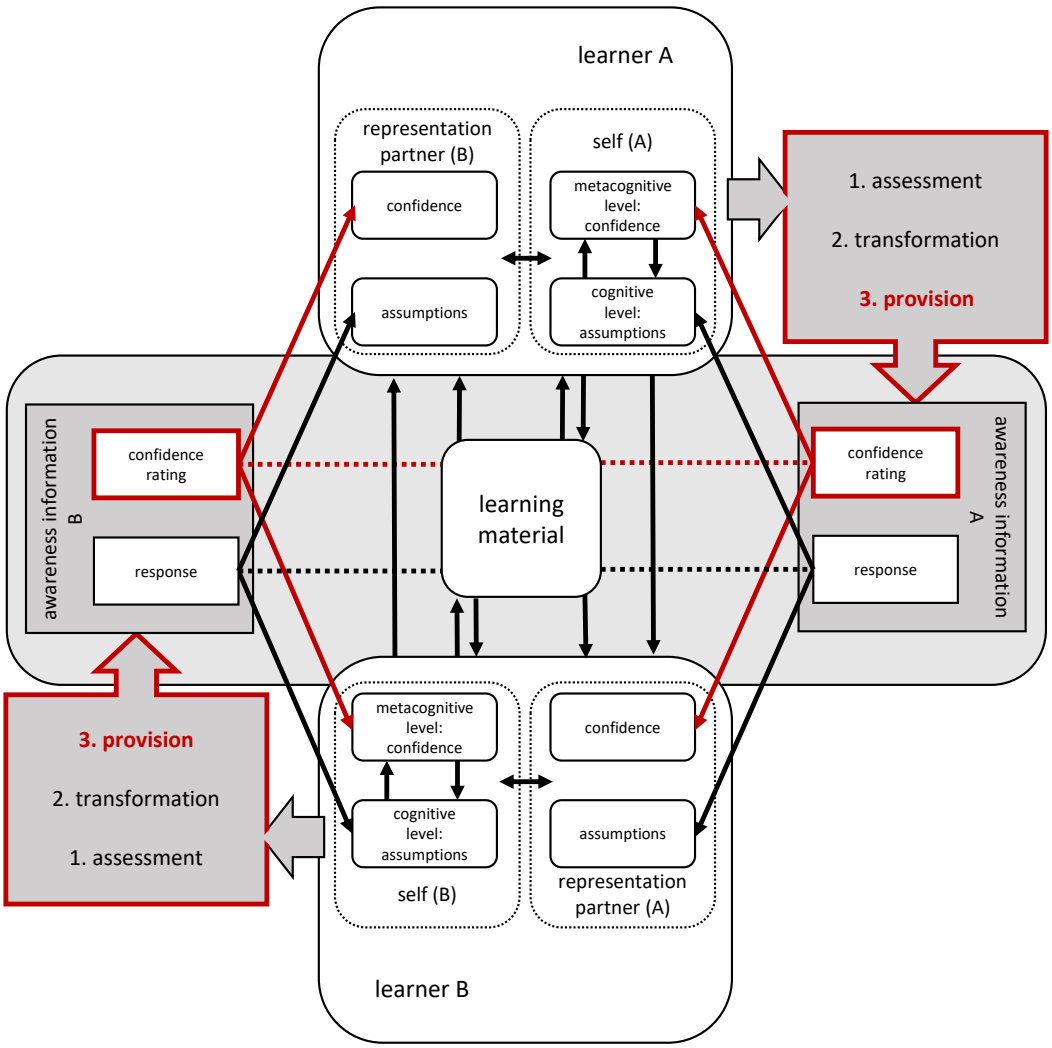

Figure 12. Depiction of study 4 (Schnaubert & Bodemer, 2018)

7 Methods

The studies conducted all followed the same basic pattern. In the following, I will describe the basic information for all studies, pointing out relevant differences and similarities. The specifics of methods used within each study can be found in the respective publications.

7.1 Sample

Sample sizes of the four studies conducted ranged from 61 to 260 participants (with a range of 29 to 68 participants per separate research condition). Thus, while some sample sizes were borderline, others can be described as rather large for this kind of research (especially the rather elaborate study 3). It is worth noting that for some research questions in the collaborative studies (study 3 and 4), the sample actually did not consist of participants but rather of dyads. Thus, the sample size was considerably smaller for these analyses. The samples of all studies consisted of German university students; the mean age per study raged from 21.00 to 22.09 years. The vast majority of students in all studies studied Applied Cognitive and Media Science towards a Bachelor's degree at the university of Duisburg-Essen, a course of study predominantly consisting of psychology and computer science classes within the faculty of engineering. Within all studies, female participants dominated the samples (they made between 67% and 77% of each sample). When topic specific interest and self-reported prior knowledge with regard to the content domain (see section 7.4.1) were assessed (studies 1 and 3), interest in the topic ranked medium and prior knowledge rather low. Thus, overall, the samples were rather similar and can roughly be described as young, predominantly female adults studying Applied Cognitive and Media Science in higher education with rather low prior knowledge and a mild interest in the topic (the latter is only confirmed for a subsample).

7.2 Design

All four study designs included between-subject (or between-dyad) and within-subject factors. While the main independent variables were varied between subjects (or dyads), some variables were assessed multiple times within the study, usually pre and post learning phases, to assess learning or other changes triggered by the between-subject variations.

In the studies conducted with individuals (1 and 2), participants were randomly assigned to research conditions. In the collaborative studies (3 and 4), dyads were randomly assigned

to research conditions. In the latter studies, participants were allowed to sign up individually or in pairs and thus, some dyads consisted of participants knowing each other and some didn't. While this may contribute to larger error variance in the data (because partner familiarity was not included as a factor within the studies; hence, the resulting variance is unexplained), random assignment to research conditions should ideally minimise the negative effect on internal validity.

7.3 Procedure

The studies all followed the same basic pattern. An overview over the procedure with experimental manipulations (green) and assessment of dependent variables (red) included can be viewed in Figure 13.

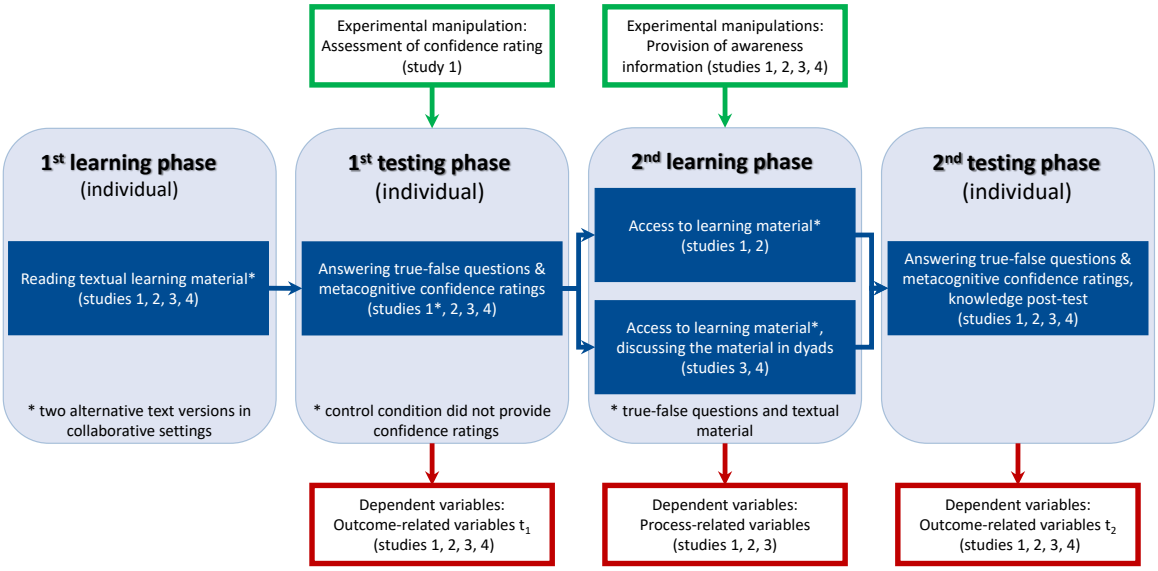

Figure 13. Overview over experimental procedure

First learning phase. After an initial introduction into the procedure, declaration of consent and a demographics questionnaire, learners started with a first learning phase introducing a topic. In this, all participants individually read an expository text on the subject matter (in collaborative designs it was different texts which covered the same basic topic and introduced most relevant concepts but focused on different aspects later on) on blood-sugar regulation and diabetes mellitus (studies 1, 3 and 4) or on immunology (study 2) (see section 7.4.1). Reading was largely self-paced, however, maximum reading times applied.

First testing phase. Then the learners all individually answered some binary true-false questions (learning tasks) about the topic with metacognitive confidence ratings attached

(except for the control condition in study 1, which answered the questions without providing confidence ratings). Confidence ratings were given on a separate binary scale (confident – not confident; see section 7.4.2).

Second learning phase. Afterwards, learners entered a second learning phase. Here, the learners in all studies and conditions were provided with the learning tasks. However, the studies differed in their access to further learning material. In the individual studies (studies 1 and 2), participants were able to access additional learning material (some of it consisted of material studied earlier) on their desktop computers (see Schnaubert & Bodemer, 2016, 2017, for more information); in the collaborative studies (studies 3 and 4) they were able to access material and discuss the issues with a learning partner face-to-face on a multi-touch table top computer (a detailed description of the setup can be found in Schnaubert & Bodemer, 2018, 2019). Learners were able to adjust their ratings in all studies during this learning phase (if the information was provided in the first place). During this phase, the main manipulations took place (except for the prompting in study 1; see section 7.5). In the individual studies, the learners had a fixed maximum time available for the second learning phase, but were able to terminate the learning process early as we were interested in the allocation of study time (studies 1 and 2). In the collaborative studies, they also had a fixed maximum time. However, while participants in study 4 were allowed to terminate the learning process early (although they were discouraged to do so) to allow for more control over the learning process, the time spent in the second learning phase in study 3 was fixed to eliminate the possible impact of learning time as a factor on learning outcomes.

Second testing phase. After the second learning phase, all students answered the questions (learning tasks) individually again from scratch and all provided confidence ratings. Additionally, they all conducted a knowledge post-test assessing transfer (see section 7.4.4). Due to the different focus of study 4, knowledge post-test results were not reported in the respective publication (Schnaubert & Bodemer, 2018).

7.4 Material

The learning material consisted of expository texts and tasks covering biological/medical topics not related to the study courses of the majority of the sample (engineering with a focus on computer science and psychology, see section 7.1; the self-report on prior knowledge confirmed this assumption). Studies 1, 3 and 4 used the same basic material on blood sugar regulation and diabetes mellitus. However, we needed to conduct minor

changes in terms of number of adjunct learning tasks used (study 1: 20, study 3: 16, and study 4: 18) and also adjusted the textual material accordingly. Study 2 used different material, but also covered a medical topic and used 20 learning tasks.

7.4.1 Expository texts and additional information

The subject matter used in the studies 1, 3 and 4 was blood sugar regulation and diabetes mellitus. The basis were two different text versions that both covered the basics on blood sugar regulation but differed especially with regard to the information given on diabetes mellitus. Each text was separated into paragraphs, each paragraph in either one of the texts was paired with a learning task. Each learner only received one text version in the first learning phase. Thus, the initial information only covered parts of the information needed to answer the learning tasks. In the studies 3 and 4, we used the two different versions of the text for the learners in each dyad (A and B). Research on collaborative learning suggests that distributing information may be particularly helpful when learners have a common basis (Deiglmayr & Schalk, 2015). Thus, in the initial learning phase, we provided general information on blood sugar regulation and diabetes to both learners but distributed more specific information among them. Study 1 consistently used one of the text versions (A) for all learners. Thus, in the first testing phase, all learners in these studies lacked information for some learning tasks (see section 7.4.3).

In the second learning phase, all information was available to all learners in some form. In study 1 and 4, learners were able to access the assigned information to each learning task by clicking on a button next to each task (taken together, the information covered both texts A and B). In study 3, each learner had their initial text available on their side of the screen, but they were able to discuss all content and additionally share paragraphs with each other on the shared screen (see Schnaubert & Bodemer, 2019). Thus, in contrast to the other studies, learners in study 3 had to connect the relevant information to the task themselves and depended on each other to share relevant information.

Study 2 used textual material on immunology adapted from Dehler and colleagues (Dehler et al., 2011) as a basis and provided all relevant information already in the first learning phase. Again, each paragraph was paired with one learning task and, like in study 1 and 4, learners were able to access relevant information in the second learning phase by clicking on a button next to each task.

7.4.2 Learning tasks

A key component of the learning environment in all studies was the learning tasks. Learning tasks are part of the instructional material and designed to lead learners to engage with the to-be-learned content (Proske, Körndle, & Narciss, 2012). The learning tasks in this thesis were specifically designed to capture information relevant to understanding the subject matter and each referred to one paragraph within one (or both) of the learning texts. Within the studies, the learning tasks served various purposes: they were used (a) to assess metacognitive and cognitive information (assumptions learners had about the content and their confidence in these assumptions) to inform the awareness tools, (b) for testing purposes (to measure knowledge and confidence pre and post learning phase 2), and (c) to pre-structure the content and learning material. Thus, we use the term "learning tasks" because – from the learners' perspective – the tasks serve an important function within the learning process and the learners may use them to guide their learning (Schnaubert & Bodemer, 2017).

Theoretically and empirically, learning or practice tasks have great potential for learning (see Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013) both directly through retrieval practice and to guide subsequent learning attempts (mediated effects; Roediger & Karpicke, 2006). Thus, they may foster learning by prompting learners to review specific material (for a metaanalysis on the effects on learning outcomes see Hamaker, 1986). Metacognitively speaking, testing can foster monitoring processes and may focus the learners' attention towards specific aspects of the learning material (see Roediger III, Putnam, & Smith, 2011). This thesis draws on this effect by providing learners with self-testing opportunities and the chance to use this information to guide further learning. Additionally, the empirical studies exploited the structuring function of the tasks with regard to the textual material, which allowed to measure how learners regulate their learning (see section 7.6).

The learning tasks in all studies consisted of single statements the learners had to judge as being true or false (see Figure 14, p. 47). Additionally, all learners (except for learners in the control condition of study 1) were asked to judge their confidence in each answer on a binary scale. The answer was spatially coded; confidence was colour coded. Binary scales were used to allow for simple visualisations within the awareness tools for better salience of the information and comparability between learners and within learners between items

(Schnaubert & Bodemer, 2019). Further reasons and implications of using binary measures are discussed in detail in Schnaubert and Bodemer (2017, 2019).

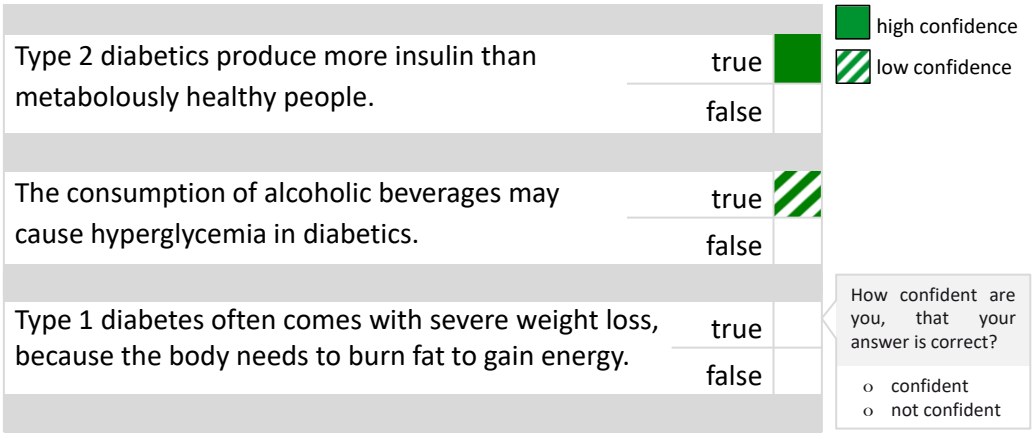

Figure 14. Example of learning tasks with confidence rating (translated from German)

The individual studies (1 and 2) each used 20 tasks to not overburden the learners but also allow for relatively stable within-subject correlations between response patterns and study decisions. However, for the collaborative studies the number of items had to be reduced due to constraints with regard to the dimensions of the multi-touch table top and overall study length (study 4: 18 tasks; study 3: 16 tasks). While this may reduce the stability of the correlation measures used as an estimate for each participant or dyad (Schnaubert & Bodemer, 2019), it is worth noting that the number of observations across learners or dyads should centre the mean correlation value and thus account for some of the negative effects caused by random variations of the single observations (although error variance may be negatively affected).

7.4.3 Relationship between expository material and learning tasks

Instead of assessing the prior knowledge of learners before the experiments, we opted to manipulate prior knowledge by giving learners textual material to familiarise themselves with before the actual treatments started. This enabled us to strategically control the information learners received in the first learning phase with regard to the learning tasks. By only providing partial information in study phase 1 (studies 1, 3 and 4), we ensured incomplete knowledge and thus selective presence or absence of knowledge during first learning task completion. Building on the relationship between the object- and meta-level of cognitions (e.g., Maki, 1998), we were thus able to indirectly manipulate confidence judgments to ensure both certain and uncertain answers. Additionally, within the diabetes material, some tasks covered common misconceptions about the topic (e.g., about the

relationship between obesity and diabetes). While misconceptions may go undetected in individual settings if no clarifying information is provided in the initial learning phase, in the collaborative studies (3 and 4), we provided one learner with accurate information on the subject. This allowed us to manipulate conflict emergence to a certain extent (stemming from common misconceptions on one side and clarifying information received on the other side).

7.4.4 Knowledge post-test and further material

Apart from the main aspects (textual material and learning tasks), we also used further instruments to assess various variables only relevant to some of the studies conducted. The most important were knowledge post-tests, which were administered in all studies but not reported in the publication regarding study 4 (Schnaubert & Bodemer, 2018). These post-tests were designed to assess knowledge about the material provided more elaborately covering information available in either of the learning phases (see also Schnaubert & Bodemer, 2016, 2017, 2019). The tests consisted of 19[3] to 32 items. Each test item referred to specific information within the textual material provided and could thus also be linked to specific learning tasks. Some tasks additionally required transfer and connecting information from different paragraphs and texts (study 1 and 3). All post-tests used a four-answer single choice format and additionally required learners to provide a confidence judgment on a six-point equidistant response scale to allow for a more thorough assessment of knowledge and confidence. We also used a four-item self-report scale to measure self-assessed prior knowledge and interest in the topic in study 1 and 3 (see Schnaubert & Bodemer, 2017, 2019), a one-item self-report scale to assess mental effort in study 1 (see Schnaubert & Bodemer, 2017), and a self-report strategy questionnaire to assess strategic behaviour during collaboration in study 3 (see Schnaubert & Bodemer, 2019). Specifics of these instruments can be found in the referenced publications.

7.5 Independent variables

During the second learning phase, the main manipulations took place (except for the prompting in study 1): the provision of cognitive and/or metacognitive awareness information on the learner him-/herself, a learning partner or the group in a between-subject

[3] We originally used 20 items in study 2; however, one item had to be excluded retrospectively due to a logging malfunction; hence 19 items

(or between-dyad) randomised design. Figure 15 (p. 51) visualises the information provided to each group covering all studies. Table 2 shows how the conditions and studies compare in terms of independent variables. We can see that study 1 is only concerned with self-information and varies metacognitive awareness information only (cognitive information in itself has no inherent standard and is thus not assumed to be particularly relevant for metacognitive regulation, see Schnaubert & Bodemer, 2017).

Table 2. Overview of provision of awareness information (independent variables) per study

setting	study		experimental variations: awareness information provided			
			on self		on partner	
	no.	condition	cognitive	meta-cognitive	cognitive	meta-cognitive
individual	1	control	X	not assessed	-	-
individual	1	prompting	X	**-**	-	-
individual	1	visualisation	X	**X**	-	-
individual	2	no partner information	X	X	**-**	**-**
individual	2	partner information	X	X	**X**	**X**
collaborative	3	cGAI-/mGAI-	**-**	**-**	**-**	**-**
collaborative	3	cGAI-/mGAI+	**-**	**X**	**-**	**X**
collaborative	3	cGAI+/mGAI-	**X**	**-**	**X**	**-**
collaborative	3	cGAI+/mGAI+	**X**	**X**	**X**	**X**
collaborative	4	MC-	X	**-**	X	**-**
collaborative	4	MC+	X	**X**	X	**X**

Note. "X" marks information that was provided, orange cells highlight experimental variations within studies; conditions are named in accordance with the respective publications to facilitate cross connections

Study 2 adds (metacognitive and cognitive) partner information but remains in an individual setting. The visualisation condition in study 1 has identical information provided to the control condition (no partner) in study 2. These conditions mainly differ in the content of the learning materials used (apart from slight other variations; see section 7.4). Thus, similar outcomes should be expected for the overlapping conditions. Because the expected mechanisms of the metacognitive visualisation were similar, dependent variables were also similar between those studies (see section 7.6). Thus, the overlapping conditions may be seen as a structural replication with regard to within-subject (not between-subjects) effects, although not a strict one.

Studies 3 and 4 bring the studies to a collaborative setting. Comparing the information provided between the individual and collaborative studies, we can see that learners in the partner condition in study 2 are provided with the same information as learners in two conditions of the collaborative studies (study 3: cGAI+/mGAI+; study 4: MC+). Due to the different settings used in these studies (individual vs. collaborative), the conditions are not directly comparable as different dynamics have to be expected and the outcomes should vary greatly. However, we are able to see if similar mechanisms apply between the settings, although due to further differences between the studies (e.g., material; see section 7.4), other interfering influences cannot be excluded.

Comparing studies 3 and 4, we can see that study 4 again only varies metacognitive awareness information while study 3 uses a two-factorial between-dyad design to vary the provision of cognitive and metacognitive awareness information independently and thus has the most elaborate study design. Both conditions of study 4 can also be found in study 3 (MC- = cGAI+/mGAI-; MC+ = cGAI+/mGAI+). However, the focus of the research and thus the dependent variables differed considerably between the studies (see section 7.6) and also the collaborative learning environment had slightly different features (in study 4, relevant paragraphs from the texts were attached to the specific learning tasks similar to study 1 and 2, while in study 3 the whole texts were provided to the students and learners had to connect relevant passages to the learning tasks themselves; see section 7.4.1). Thus, while some overlap exists, the collaborative studies complement each other rather than revisit the same questions.

We also assessed some outcome variables twice; hence, time was an additional independent factor throughout the studies.

7.5.1 Visualisations

All studies processed the awareness information in the same way. This covered the way the information was assessed in the first testing phase, transformed, and visualised during the second learning phase. The cognitive and metacognitive data was assessed using binary tasks and confidence ratings on separate scales. The cognitive awareness information (assumptions) was presented by spatial coding (top: true; bottom: false), the metacognitive awareness information (confidence) was colour coded (fully green: confident that answer is correct; hatched white-green: not confident that answer is correct). Thus, using two separate scales and coding systems, it was possible to assess and visualise both types of

information independently. This was crucial for separating the effects especially in study 3 and also enabled learners to easily use both types of information separately.

If information of two learners was portrayed (within studies 2, 3 and 4), the information was in two single columns next to each other for better comparability (see Figure 15). Thus, the design allowed for within- as well as between-learner comparability due to spatial proximity, alignment and salience, and used different coding mechanisms for different types of information. All visualisations are shown in Figure 15.

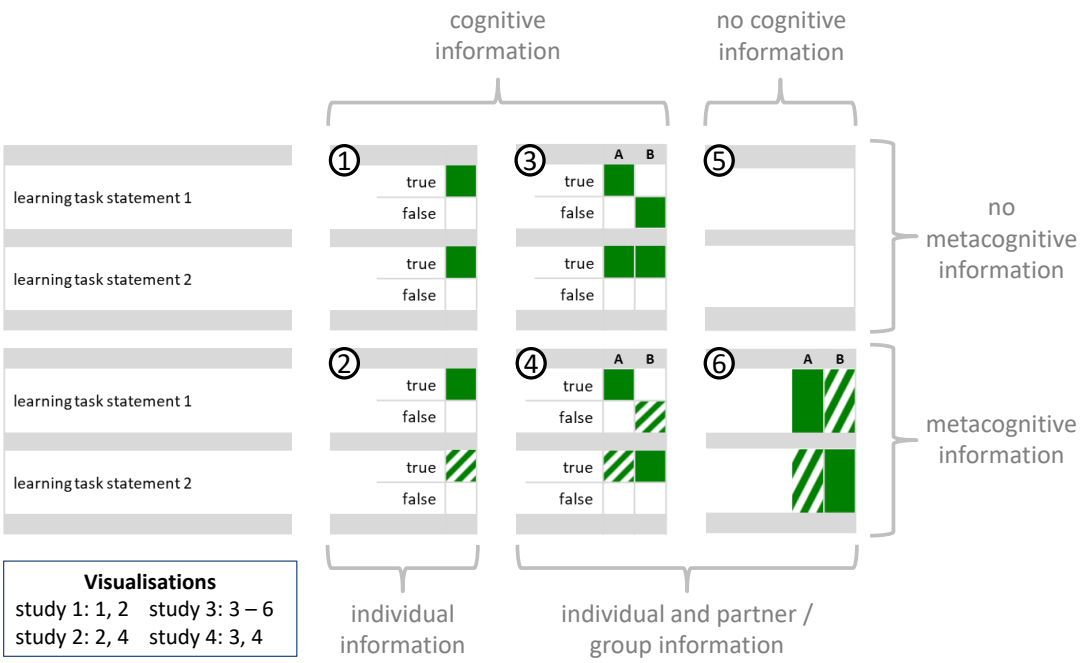

Figure 15. Visualisations of information as used in the studies

7.6 Dependent variables

The main dependent variables with regard to learning processes in the studies were how strongly learners used their own or their group's metacognitive monitoring judgments to choose what learning material to study (metacognitive regulation; studies 1, 2 and 3) and how strongly conflicting assumptions of a learning partner were used to make such study decisions (conflict-based regulation; studies 2 and 3). Metacognitive regulation was operationalised as within-subject (studies 1 and 2) or within-dyad (study 3) correlation between a binary confidence measure assessed in the first testing phase and study decisions in the second learning phase (similar to the procedure used by Thiede, 1999; Thiede et al., 2003); conflict-based regulation was assessed accordingly as within-subject (study 2) or within-dyad (study 3) correlation between conflicting assumptions and study decisions. For

more information on how study decisions were measured, please consult the respective publications. Study 3 used self-report measures to corroborate the behavioural data. Studies 2 and 3 additionally looked into study decisions based on the precise answer patterns (knowledge distributions) of the students combining cognitive and metacognitive awareness information to study in more detail what items received further attention.

Studies 1 and 2 additionally looked into the sequencing of the learning process using mean rank differences of selection order between confidently solved and not confidently solved tasks and additionally between conflicts and consensus (only study 2) to capture time-wise prioritisation of specific learning material (for more details on this algorithm see Schnaubert & Bodemer, 2016, 2017). While other variables such as objective regulation (study 1), study time allocation (study 1 and 2), amount of tasks studied (studies 1, 2 and 3), or mental effort (study 1) were also investigated (see Table 3), metacognitive and conflict-based regulation were the main variables with regard to learning processes.

Table 3. Overview over dependent variables per study

	individual studies		collaborative studies	
	1	2	3	4
Process-related variables				
Metacognitive regulation (confidence-based regulation)	x	x	x	
Conflict-based regulation		x	x	
Objective quality of study decisions	x			
Quantity of study behaviour (number of tasks considered)	x	x	x	
Information requests or discussion rates (per pattern)		x	x	
Allocation of study time (overall, per confidence level)	x	x		
Sequencing of study process (prioritising)	x	x		
Mental effort	x			
Self-report on strategies used			x	
Outcome-related variables				
Knowledge	x	x	x	x
Confidence	x	x	x	x
Monitoring accuracy	x	x		
Data interdependence			x	x

With regard to learning outcomes, we were especially interested if learners gained more knowledge when supported by awareness information and if they also gained confidence;

both aspects were assessed with regard to the learning tasks and the knowledge post-test (for more information, please consult the respective publications). Additionally, study 1 looked in more detail into relative monitoring accuracy (operationalised as within-subject correlation between confidence judgment and performance, see Schraw, 2009; Schraw et al., 2013) as a variable affecting successful learning, but also as a potential learning outcome (the latter was also true for study 2). While the individual studies merely looked into confidence and performance levels in individuals, the collaborative studies (3 and 4) additionally looked more closely into the interdependent data structure of the dyadic data.

7.7 Statistical analyses

To answer our research questions and the specific hypotheses specified in the respective papers, we used various statistical approaches according to design, research question, and data structure. For the individual studies, we mainly used two-sample *t*-tests or Mann-Whitney *U*-tests to test for between group differences, one-sample *t*-tests to compare against a standard, or analyses of variances when within- and between-subject factors were used. Do to the staggered design in study 1, we used one-factorial analyses of variances with Helmert contrasts to disentangle the prompting and visualisation effect. For more thorough analyses of how answer patterns affected study decisions in study 2 and 3, we used two-factorial within-subject analyses of variance. For more complex questions, we used respective analyses, e.g., the moderated mediation model in study 1. For the collaborative studies, we mainly used analyses of variances. However, to estimate the impact of the between-subject design on learning gain mediated by regulation, we used multi-categorical multiple mediation models with simple indicator coding with the condition without awareness information as reference (see Hayes & Preacher, 2014). We also used various approaches to analyse the interdependent data in studies 3 and 4, including a multi-level approach in accordance with Kenny and colleagues (Kenny, Kashy, & Cook, 2006). Since normal distribution could not be assumed for some data throughout all studies, we used bootstrapping or non-parametric tests whenever possible. However, due to the complex designs, we had to use less optimal procedures on occasions. The implications are discussed in the respective papers (for more information on the statistical analyses used, please refer to Schnaubert & Bodemer, 2016, 2017, 2018, 2019).

8 Integrative discussion of results

The purpose of this section is to provide an integrated discussion of the results of the empirical studies (section 8.2). Beforehand, I will give a brief overview over the results study-by-study guided by the research questions (section 8.1). Details on the results of each study can be found in the respective papers. Selected limitations of the studies are discussed throughout this section, but more details can be found in the respective papers.

8.1 Summary of results per study

RQ 1: How does (cognitive and metacognitive) self- and partner information affect individual self-regulated learning and learning outcomes?

Can metacognitive awareness information support individual learners' self-regulation and learning outcomes?

Study 1 found that while prompting monitoring by asking for confidence judgments merely affected quantitative aspects of study behaviour (number of information requests), visualising these monitoring judgments heavily affected metacognitive regulation of study, but also prioritising and study time allocation (although study time allocation was not significantly related to metacognitive judgments). While there were no effects on knowledge gain, post-test knowledge or mental effort, a moderated mediation model showed the effect on knowledge gain was corrupted by the low monitoring accuracy observed in the study and thus, metacognitive regulation did not lead to learners primarily targeting tasks they had solved incorrectly during the first testing phase. However, learners managed to resolve more uncertainties regarding their answers in the learning tasks when provided with the judgements during learning (although this did not affect confidence in the knowledge post-test). Additionally, monitoring accuracy was not affected and quite low in general (for more details see Schnaubert & Bodemer, 2017).

How does partner information affect individual learners' self-regulation and learning outcomes?

Study 2 found that adding (cognitive and metacognitive) information on a learning partner in addition to metacognitive and cognitive self-information shifted some of the focus towards conflicting information. Thus, metacognitive regulation was diminished and conflict-based regulation installed – this was true for material selection in general as well as prioritising. Overall study behaviour (amount of material looked at and time spent

studying) and knowledge gain were not affected. However, confidence increased less when partner information was available during learning (at least when considering the learning tasks rather than the knowledge post-test), but this had no effect on monitoring accuracy. Looking more closely at the rates with which learners provided with socio-cognitive information chose to attend to different patterns or distributions of knowledge-related variables, the data suggests that learners integrate all information available but use information on partner confidence only in conflicting situations, in which they also adapt the usage of own metacognitive information. However, due to low sample size and violations of prerequisites of the analysis conducted, these latter results need to be interpreted with caution (for more details see Schnaubert & Bodemer, 2016).

RQ 2: How does (cognitive and metacognitive) group awareness information affect collaboratively regulating learning in dyads and learning outcomes?

Can cognitive and metacognitive information in group awareness tools support collaborative regulation of learning and learning outcomes?

Study 3 found that the type of awareness information provided guided the selection of material for discussion (metacognitive and conflict-based regulation) in the collaborative setting. This was true for metacognitive awareness information, cognitive awareness information, and their combination. Looking more closely at the material learners discussed per knowledge distribution confirmed these observations. Furthermore, the presentation of metacognitive awareness information seemed to foster confidence gain in the answers of the learning tasks via metacognitive regulation (although partially outweighed by indicators of a direct – albeit not statistically significant – negative effect) and also had a negative impact on the quantity of material that was discussed during collaboration. Questionnaire data showed no signs that learners were aware of the regulatory strategies used (focussing on conflicts or uncertainties). Rather, learners provided with cognitive awareness information reported a more selective strategy but did not differ from learners not provided with the information in terms of reporting using conflicts or uncertainties as a basis for learning decisions. There were no direct effects of the interventions on individual learning outcomes. Descriptively looking into intra-class correlation coefficients between members of dyads, it seems that metacognitive awareness information fostered interdependence on metacognitive outcome measures in the learning tasks but negatively affected interdependence in performance measures (maybe even dependent on cognitive awareness information). These latter observations, however, are merely based on descriptive data and

thus cannot be generalised beyond the sample (for more details see Schnaubert & Bodemer, 2019).

How does this affect data structures of learning outcomes within collaborative settings?

Study 4 focussed primarily on methodological-conceptual aspects of collaborative designs, rather than on answering empirical questions. Thus, empirically, this study merely looked into learning outcomes and the data structures observed. In this study, we found (weak) indications that metacognitive awareness information may foster performance gain. However, intra-class correlations did not suggest enhanced interdependence on this measure, but rather a decrease in interdependence when the information was provided. On the contrary, while metacognitive awareness information did not foster confidence gain, intra-class correlations between confidence levels after collaboration were higher when the information was provided. Although confidence intervals of intra-class correlation measures overlapped and descriptive differences may overstate true differences, variance decompositions indicated different sources of variance at least within this sample (for more details see Schnaubert & Bodemer, 2018).

8.2 Integration of results

The following section integrates and discusses the main results of the studies. To structure this part and to look into similarities and differences between the studies, I will first discuss process-related variables (i.e., guidance effects on regulating learning; see section 8.2.1) and then outcome-related variables (i.e., confidence and knowledge; see section 8.2.2) more closely.

8.2.1 Process-related variables: guidance effects on regulating learning

The following sections describe the guidance effects due to cognitive and metacognitive awareness information on the individual (RQ 1) and group (RQ 2) level. Section 8.2.1.1 will first focus on the effects of metacognitive awareness information on metacognitive regulation while section 8.2.1.2 will focus on added effects of cognitive partner or group information especially on conflict-based regulation as well as the interaction of both cognitive and metacognitive awareness information.

8.2.1.1 Influence of (metacognitive) self-information on regulatory processes

Metacognitive regulation was observed in all studies focusing on learning processes (studies 1, 2 and 3) whenever metacognitive awareness information was provided (see Schnaubert & Bodemer, 2016, 2017, 2019). The studies comparing conditions with and without metacognitive awareness information found that the provision of the information indeed fostered metacognitive regulation and guided learners' learning attempts towards uncertainties both in individual (study 1) and collaborative settings (study 3). This is in line with group awareness research that suggests guidance effects via such visual representations (Bodemer et al., 2018) and has found such effect with regard to indications of (partially) missing information (marginal effect; Bodemer, 2011) or a perceived lack of understanding (Dehler et al., 2011).

Study 1 showed that the provision of metacognitive awareness information via an easy to interpret visualisation had a large effect on what learners chose to study (metacognitive regulation) and in what order (prioritising) and additionally affected how long learners chose to study items (study duration) (Schnaubert & Bodemer, 2017; for details on the effect on metacognitive regulation, please take note of the corrigendum). Thus, it did not only steer the learning efforts towards uncertain tasks, but additionally influenced the time spent on the material perceived as relevant, covering both components of study time allocation as described by Kornell & Metcalfe (2005): choice and perseverance (although the interaction between confidence and condition for study time allocation was not statistically significant). Such a visualisation can thus help learners to overcome a deficit in implementing monitoring-based regulation, that may impede successful learning (Metcalfe, 2009). Study 2 confirmed the prevalence of metacognitive regulation (although to a somewhat lesser extent) and prioritising items based on their metacognitive evaluation if the information was provided for conditions with and without learning partner information available (Schnaubert & Bodemer, 2016). The results of study 3 additionally suggest that the strong guiding effect of metacognitive awareness information may be generalisable to collaborative settings. Although the operationalisation used in this case was somewhat different as uncertainty was interpreted on a group level rather than an individual level (see Schnaubert & Bodemer, 2019) and thus, the magnitude of the indices used are not directly comparable, the strong guidance effect of providing metacognitive awareness information was still clearly visible (Schnaubert & Bodemer, 2019).

Interestingly, while metacognitive regulation was fostered by the provision of the information, it was still observed without this provision in the individual setting (prompting condition study 1), although to a significantly lesser extent (Schnaubert & Bodemer, 2017). While this is in line with metacognition research repeatedly reporting regulation also in the absence of external provision of monitoring judgments (e.g., Thiede & Dunlosky, 1999), this was not observed in the collaborative setting (mGA- conditions study 3; Schnaubert & Bodemer, 2019). In the latter setting, metacognitive regulation did only occur with the information externally provided[4]. Even though regulation coefficients without the information provided in study 1 were quite small and thus this warrants further investigation, it is interesting that metacognitive regulation did not seem to occur at all within the collaborative setting without metacognitive awareness information provided externally, even though the information was assessed prior to the second learning phase (collaboration) like in the prompting condition in study 1. Thus, these learners were likewise prompted to monitor their learning and alerted of the relevance of the information. Consequently, prompting effects should have been comparable between the respective conditions in study 1 and 3.

While possible reasons for this discrepancy could be purely design-related, ranging from differences in time management and general setup (see section 7) to the somewhat different operationalisation of the concept that may have weakened the relationship between (individual) monitoring judgements and (joint) control decisions (see Schnaubert & Bodemer, 2019), another reasonable explanation could be the different dynamics within collaborative settings in general. Within individual self-regulated learning, own metacognitive evaluations are assumed to be the crucial driver of learning (Nelson & Narens, 1994) and the setting used in study 1 was deprived of external influences. However, within social settings and possibly even more so in collaborative settings, internal experiences are only one factor contributing to metacognitive self-evaluations and study regulation (see section 2.2). Social information or collaborative processes may oust or alter

[4] Because we did not explicitly test for this in study 3 (Schnaubert & Bodemer, 2019), I conducted a Wilcoxon signed rank test (conducted due to violations of the normality assumption) like in study 1 to support the interpretation of the descriptive statistics. Like the descriptive data suggested, the test confirmed a significant deviation from zero for the conditions with metacognitive awareness information provided (mGAI+: $Z = 5.86$, $p < .001$), but not for the conditions without the information provided (mGAI-: $Z = -0.13$, $p = .893$). While this is not entirely conclusive, because not detecting differences does not equal identifying equality (Lakens, 2017), it does point towards a lack of metacognitive regulation in the absence of metacognitive awareness information in the collaborative setting.

metacognitive experiences (e.g., Carvalho Filho & Yuzawa, 2001; Koriat et al., 2018; McGarty et al., 1993) and thus enhance the chance that monitoring judgments will be revised in light of the new situation mitigating the relationship between pre-set judgment and control decision, while there is less reason to do so in individual settings (modified monitoring explanation). This could also explain the differences between the measured regulation coefficients (based on initial monitoring judgments) and the self-report data claiming similar regulation based on confidence (possibly based on updated information) throughout conditions within study 3 (this is further discussed in Schnaubert & Bodemer, 2019).

An alternative explanation would be that not the metacognitive experience changes, but that the usage of the information is inhibited during collaborative learning (constituting a production deficiency; Veenman, Kerseboom, & Imthorn, 2000), either due to changed approaches to learning (e.g., pro-actively sharing available knowledge rather than asking others for help) or due to the strain on the cognitive system caused by interfering processes making it more difficult to utilise own monitoring judgments (modified utilisation explanation). Executing metacognitive processes requires cognitive resources (Dunlosky & Thiede, 2004; Valcke, 2002) which may not be available in collaborative situations due to the additional challenges within such situations (Dillenbourg & Bétrancourt, 2006; Kirschner, Sweller, Kirschner, & Zambrano R., 2018). Since the provision of metacognitive awareness information in the collaborative study 3 fostered metacognitive regulation, it seems likely that increased salience of the information leads to a stronger utilisation pointing towards a utilisation deficit without the information. However, this does not discount the modified monitoring explanation because it is entirely possible that the salient visualisation of pre-set judgments inhibits active re-evaluation processes and mends the (re-)formation of monitoring judgments. Thus, without metacognitive awareness information provided, monitoring might be modified quite differently by collaborative processes.

We can conclude that the provision of metacognitive awareness information on confidence judgments strongly guides individual (Schnaubert & Bodemer, 2017) as well as collaborative (Schnaubert & Bodemer, 2019) study decisions and thereby fosters learners' utilisation of their own metacognitive judgments (constituting metacognitive regulation). While metacognitive regulation seems to take place to a limited extent also without the information available during individual learning (Schnaubert & Bodemer, 2017), this

seems not to be true during collaborative learning (Schnaubert & Bodemer, 2019). While this observation could be a methodological artefact, modified monitoring or utilisation processes during collaboration should be further investigated.

8.2.1.2 Influence of partner or group information on regulatory processes

While metacognitive regulation based on (externally available) metacognitive awareness information was strongest in the absence of partner information in the individual settings (study 1: visualisation; study 2: no partner information), conflicting assumptions of a partner became a similar influence on learning efforts when the respective partner information was provided, which by design (i.e., correlation coefficients used) lessened the impact of pre-set metacognitive judgments (Schnaubert & Bodemer, 2016).

When (cognitive and metacognitive) partner information was provided, participants in study 2 focussed on uncertainties as well as conflicts when making study decisions (metacognitive and conflict-based regulation) and deciding on the order of processing (prioritising based on conflict and uncertainties; Schnaubert & Bodemer, 2016). Similar effects were found in the collaborative setting (study 3), where cognitive and metacognitive awareness information led to comparable conflict-based and metacognitive regulation coefficients (Schnaubert & Bodemer, 2019).

Looking more closely into the patterns of cognitive and metacognitive awareness information while differentiating between self- and partner information in study 2, it looks as if learners integrate all information available when deciding what material to study and even seem to take the partner's confidence into account under certain circumstances (although the sample size for these analyses was too small to draw any definitive conclusions, see also Schnaubert & Bodemer, 2016). As opposed to the assumption that certainty in conflicting information may be the strongest force to search for information within individuals (as would be consistent with feedback research, e.g., Kulhavy, 1977; Kulhavy & Stock, 1989; or theoretical assumptions on cognitive conflicts, e.g., Lee & Kwon, 2001; see also section 2.2), our results indicate that maximal uncertainty about the correct answer on group level may trigger most study efforts. This is especially interesting, as in individual settings, group-level certainty should play a subordinate role because individual (not group-level) metacognitive regulation mechanisms are assumed to steer learning processes (Nelson & Narens, 1990, 1994). Thus, from a metacognition perspective, the need for information should be primarily based on individual experiences.

However, if we assume that conflicts trigger uncertainties in individuals (e.g., Buchs et al., 2004; Butera, Darnon, & Mugny, 2010; McGarty et al., 1993; see also Schnaubert & Bodemer, 2016, 2019) and further take note of research suggesting that social information on other learners' performance (e.g., Zhao & Linderholm, 2011) and questions (Karabenick, 1996) changes metacognitive evaluations possibly through task re-evaluations, both conflicts and partner uncertainties may amplify individual uncertainties. Accordingly, they could maximise intra-individual target-performance discrepancies and thus study efforts from a discrepancy-reduction point of view (see Thiede & Dunlosky, 1999), which would be consistent with the data observed. However, as these observations are based on an unsatisfactory evidence base, they need to be further investigated, preferably with more fine-grained and repeated metacognitive judgments allowing to sensitively capture metacognitive changes induced by socio-cognitive information.

As mentioned above, results of study 3 showed that the guiding effects of visualising conflicting assumptions can be generalised to collaborative settings (Schnaubert & Bodemer, 2019). Not only did the results confirm the prevalence of conflict-based regulation to a similar extent to metacognitive regulation if the information was provided to dyads, but we also found that dyads with cognitive and metacognitive awareness information available seemed to use both types of information to make study decisions. The results of this study cautiously suggest that, in such cases, conflicts may have an universal effect on dyadic study decisions, but confidence may only guide dyads when there is consensus among learners (for restrictions on data interpretation see Schnaubert & Bodemer, 2019). Beyond this possible interaction effect, the one pattern that stuck out through a considerably lower attention rate was the certain consensus (Schnaubert & Bodemer, 2019). While this is hardly surprising, it indicates that with regard to choosing learning material, learners in collaborative settings may not so much differentiate between the source of the issue (group-level uncertainty or conflict), but rather discard material where there is no reason to attend to it working through almost everything else. However, the data assessed does not allow conclusions about object-level processing and thus, conflicts and uncertainties may provoke very different cognitive (and collaborative) processes unaccounted for in the reported studies (see also sections 9.1.2 and 9.2.2).

Both studies 2 and 3 suggest that learners integrate available cognitive and metacognitive awareness information of self and partner when making study decisions

(Schnaubert & Bodemer, 2016, 2019). However, because the difference between individual and collaborative studies is not merely determined by the setting, but also by the changed perspective on regulatory processes (regulation as a joint activity cannot be viewed through the lens of one specific individual in the collaborative setting as usually done in metacognition research), we were not able to investigate study decisions based on patterns of cognitive and metacognitive awareness information distinguishing between actor and partner in the collaborative study (study 3). Research conducted by Dehler and colleagues (2009, 2011) suggests that self-, partner- and group-level information may be used distinctively for different communicative activities during collaboration. Such results stress the need to include these perspectives also within research on regulatory processes. Thus, how exactly individuals within collaborative settings utilise different types of awareness information to regulate their learning possibly differentiating between self and partner needs to be taken up in further research.

In sum, we can conclude that socio-cognitive information affects metacognitive regulation by putting added attention on conflicting assumptions (Schnaubert & Bodemer, 2016, 2019). Further, learners seem to integrate available cognitive and metacognitive self- and partner information when making study decisions in individual (Schnaubert & Bodemer, 2016) as well as collaborative settings (Schnaubert & Bodemer, 2019), although the exact mechanisms at work during individual and collaborative learning are still unclear.

8.2.2 Outcome-related variables: knowledge and confidence

The following sections describe how (cognitive and metacognitive) awareness information affected meta-level outcome variables (magnitude and accuracy of confidence; see section 8.2.2.1) and object-level outcome variables (knowledge; see section 8.2.2.2) in individual (RQ 1) and collaborative (RQ 2) settings. Additionally, section 8.2.2.3 discusses the effects on the dyadic data structure (i.e., interdependence).

8.2.2.1 Meta-level outcomes: confidence magnitude and accuracy

In terms of meta-level outcome variables, we looked into magnitude and accuracy of confidence judgments both in the learning tasks and the knowledge post-test. While there were no effects on these variables with regard to the knowledge post-test in any of the studies, the effects with regard to the learning tasks were more multifarious.

Results of study 1 suggest that learners gain more confidence during learning when metacognitive awareness information is visualised and learners are thus able to explicitly work through their uncertainties (Schnaubert & Bodemer, 2017). However, partner information seems to diminish the gain in confidence (Schnaubert & Bodemer, 2016) and while the observed effects were not great, it seems logical that particularly cognitive partner information may induce doubt by evoking socio-cognitive conflicts (e.g., Buchs et al., 2004; Butera et al., 2010), especially if learners don't have a chance to clear up the reasons for disagreements because the partner is not available for discussion (study 2 as opposed to studies 3 and 4). While effects of agreeing and disagreeing others on confidence may go both ways, research suggests that the effect of disagreement may be stronger – at least when objective (or physical) information about the reality is restricted (McGarty et al., 1993). While participants in our experiments had access to objective information, the learning material was rather complex and may thus have left enough room for doubt to booster the effects of social disagreement. Explicitly targeting these conflicts may resolve respective uncertainties in theory and may even foster confidence via monitoring positive effects on knowledge (as assumed in models of metacognition, e.g., Nelson & Narens, 1990). However, these resolution processes require active and successful engagement with the respective content. Metacognitive partner information may also foster uncertainties by inducing re-evaluation processes (e.g., Karabenick, 1996; see also section 2.2.2). However, since these effects are assumed to be mediated by task re-evaluations, they may be weaker than the effects of cognitive awareness information.

Restrictions on mutual conflict and uncertainty resolution processes and resulting remainders of uncertainty could explain why partner information diminished confidence gain in study 2, but no overall diminishing effects of awareness information were found in studies 3 and 4, although they also focused attention on conflicts and group-level uncertainties (although the precise effect in itself cannot be reproduced as data of both learners was always varied simultaneously). Additionally, while results from study 1 might even suggest enhanced uncertainty resolution processes when metacognitive awareness information is provided, these effects were not observed in the collaborative studies either (Schnaubert & Bodemer, 2018, 2019). The interdependencies in these studies point towards some mutual engagement affecting the learners' confidence when metacognitive awareness information is provided, but this did not lead to higher or lower confidence levels (Schnaubert & Bodemer, 2018, 2019). The mediation model in study 3 indicates that

metacognitive awareness information only fosters confidence gain if the information is used to regulate the learning process and may even have adverse effects otherwise (Schnaubert & Bodemer, 2019). While these results are in itself not conclusive, they are in accordance with the interpretation that not being able to properly work through uncertainties because the partner is not available for discussion (study 2) or the information is not used (study 3) may even have detrimental effects on confidence, while explicitly working through uncertainties may foster confidence gain.

Additionally, it is worth mentioning that – from an outside perspective on learning – resolving uncertainties is only a valuable goal of educational practices if the underlying cognitions are indeed objectively correct (and thus would qualify as knowledge). Firmly believing in objectively incorrect assumptions (i.e., overconfidence) is especially problematic as the learners themselves will have no reason to re-check such assumptions if not confronted with contradicting evidence, thus hampering effective learning (e.g., Dunlosky & Rawson, 2012). While feedback may correct faulty assumptions in formal education settings (e.g., Shute, 2008), they may stay uncorrected during self-regulated learning because internal feedback mechanisms may fail in light of inaccurate monitoring if the information is not exposed to an external feedback process (Butler & Winne, 1995; Winne & Hadwin, 1998), for example by externalising it within collaborative learning scenarios (Fischer, Bruhn, Gräsel, & Mandl, 2002). Collaborative learning settings may thus be especially fruitful as other learners may challenge individual assumptions and force learners to justify and thereby potentially re-evaluate their assumptions (King, 2007). However, the studies within this thesis looking into monitoring accuracy (studies 1 and 2) found no effects of either visualising metacognitive self-information (Schnaubert & Bodemer, 2017) nor of partner information (Schnaubert & Bodemer, 2016) and thus, neither providing the opportunity to explicitly correct metacognitive evaluations nor external information seems to foster monitoring accuracy (although the partner information may have failed to draw attention to faulty assumptions partly due to the algorithm used to generate the information; see section 8.2.2.2).

It can be concluded that providing metacognitive awareness information fosters confidence gain if this information is used to strategically work through uncertainties (Schnaubert & Bodemer, 2017, 2019). Additionally, such information seems to interfere with the dyadic structure of the learners' confidence (Schnaubert & Bodemer, 2018, 2019; see also section 8.2.2.3). Furthermore, partner information may hamper confidence gain

and although the mechanisms are not entirely clear, it seems reasonable to assume that uncertainty may arise from metacognitive as well as cognitive partner information and prevail if these issues are not (or cannot be) addressed during learning (Schnaubert & Bodemer, 2016, 2019). All of these effects were restricted to the material actually worked with during learning (i.e., learning tasks) and no transfer of the effects to other material (i.e., knowledge post-test) occurred. Monitoring accuracy seems to be largely unaffected by the provision of self- and partner information, invalidating the idea that providing opportunities to explicitly re-evaluate metacognitive assumptions proves useful in terms of correcting a metacognitive error (Schnaubert & Bodemer, 2016, 2017).

8.2.2.2 Object-level outcomes: knowledge gain

In terms of object-level learning outcomes, our studies showed no clear effects of awareness information on knowledge gain neither for proximal variables (performance in learning tasks) nor for more distal variables (performance in knowledge post-test). While in all studies there was a knowledge gain visible from pre- to post-test (learning tasks) within all conditions, the treatments did not have a direct effect on this (apart from the effect of providing metacognitive awareness information in study 4, Schnaubert & Bodemer, 2018; this is discussed below). This is surprising, since the regulation attempts showed very clear re-focusing on potentially fruitful aspects of the learning material like conflicts or uncertainties (Schnaubert & Bodemer, 2016, 2017, 2019) and theory and research suggest positive effects by focussing on conflicts (e.g., Mugny & Doise, 1978) or perceived lacks of knowledge (e.g., Nelson et al., 1994; Nelson & Narens, 1990).

However, when we investigated the relationship between regulation and learning gain in more detail in study 1, we could see clear indications that one major factor limiting the effects of metacognitive awareness information was monitoring accuracy (Schnaubert & Bodemer, 2017). This is in line with theoretical assumptions and empirical findings of low monitoring accuracy preventing regulatory efforts from leading to learning gains (e.g., Thiede et al., 2003). The mediated moderation model showed that the positive effect on learning due to metacognitive regulation was mediated by objectively reasonable regulation (i.e., revisiting tasks incorrectly solved) but also moderated by monitoring accuracy – which had been considerably low in this study (possible reasons for this are discussed in Schnaubert & Bodemer, 2017). Thus, a lack of monitoring accuracy may have diminished potentially positive effects of metacognitive awareness information throughout studies.

Interestingly, we did find indications of an effect of metacognitive awareness information on performance in study 4 (Schnaubert & Bodemer, 2018). However, the results are inconclusive and, since study 3 could not confirm such an effect (Schnaubert & Bodemer, 2019), it remains unclear whether there actually is an underlying effect of the information on performance in collaborative settings and the different results are due to either type-II (study 3) or type-I errors (study 4) or due to differences between the specific settings (e.g., the opportunity to re-check information without having to connect the material autonomously in study 4, but not in study 3).

While the lack of monitoring accuracy may – at least partially – account for the lack of effect of metacognitive awareness information, it is yet unclear why cognitive awareness information on a learning partner (study 2) or the group (study 3) and the resulting focus on conflict did not foster learning gains either (see Schnaubert & Bodemer, 2016, 2019), although they are assumed to trigger beneficial resolution processes (e.g., Bell et al., 1985) and may even lead to cognitive re-organisation (Limón, 2001).

When discussing these issues, we have to differentiate between scenarios with a real (study 3) and a simulated partner (study 2), because the latter did not comprise combined knowledge of a group. The algorithm to generate the partner information in study 2 had no pre-defined or coherent level of knowledge but consisted of a rather random conglomeration of answers (for more specifics see Schnaubert & Bodemer, 2016). Thus, it may be argued that the conflicting assumptions did not point towards faulty assumptions, specifically complex material or tasks that required the integration of different perspectives (as may be particularly fruitful for learning, see Schnaubert & Bodemer, 2019). Rather, it was a random pointer towards or away from the individual's answers, rendering the information it gave rather useless from an outside perspective. While being aware of potentially conflicting assumption may still trigger additional learning efforts (Lowry & Johnson, 1981) and may thus have beneficial effects even with the conflicting information being incorrect (Bell et al., 1985), our analyses did not indicate an increase in non-specific learning efforts (i.e., total number of information requests or study duration per request; see Schnaubert & Bodemer, 2016). Thus, without additional engagement, it may be less surprising that learners did not gain from addressing "random" conflicts pointing equally towards correct and incorrect information.

However, it is surprising that learners did not gain from information fostering the identification of conflicts within settings with actual learning partners (study 3; Schnaubert

& Bodemer, 2019). In real-life settings or real collaborations, it can be assumed that learners have some coherent level of knowledge (prior knowledge or knowledge induced by expository learning material). While the lack of effect of cognitive awareness information in the collaborative study 3 may be partially due to a low sensibility of our test instrument (especially considering the true-false questions and high level of guessing probability and thus random error attached to the results; see Schnaubert & Bodemer, 2017), it obviously may also have reasons relating to the theoretical assumptions rather than the empirical design.

It seems rather implausible that addressing conflicts in a collaborative setting does not have the potential for learning because theoretically sound theories and research provide strong support for this potential (e.g., Buchs et al., 2004; Johnson & Johnson, 1979, 2009b; Mugny & Doise, 1978), although alternative views do exist (as described in Johnson & Johnson, 2009b). However, independent of their theoretical potential, conflicts are not always perceived and resolved in a beneficial manner. Buchs and colleagues (Buchs, Pulfrey, Gabarrot, & Butera, 2010) for example point out that conflicts may be a threat to competence perception of the self and harmful for the learning process especially if they are interpreted on a relational rather than epistemic level. The relevance of the relational aspects of collaboration – unaccounted for in this thesis – is obviously especially relevant in real collaborative settings, where learners interact with each other (study 3 and 4). Additionally, even in individual settings (like study 2), conflicting information may be perceived as a (social) threat and hamper beneficial processing (Quiamzade & Mugny, 2001).

Apart from the perception and interpretation of the conflict itself, Weinberger and Fischer (2006) discuss less beneficial collaboration processes taking place in reaction to a socio-cognitive conflict. For example, they describe *quick consensus building* – a way to resolve the conflict by finding a quick solution without deeper elaboration of the content. Interestingly, Gijlers and colleagues (Gijlers, Saab, van Joolingen, de Jong, & van Hout-Wolters, 2009) found indications that visualisations stressing discrepancies in assumptions may foster quick consensus building activities (although the authors also observed more conflict-oriented and thus potentially beneficial activities) and while the data they present is far from conclusive, it seems plausible that such a strong focus on conflict may encourage some learners to “get rid” of the issue to achieve consensus within the group rather than elaborate on the respective content (see also Schnaubert & Bodemer, 2018, 2019).

In conclusion, despite theoretical and empirical evidence pointing towards beneficial effects of metacognitive and cognitive awareness information for individual and collaborative learning, taken together, our studies did not confirm these effects (Schnaubert & Bodemer, 2016, 2017, 2018, 2019). While the results suggest that a lack of monitoring accuracy contributed to this outcome (Schnaubert & Bodemer, 2017), the question why the focus on (visualised) conflict throughout studies did not translate into cognitive learning gains warrants further investigation. However, this question cannot be solved without looking more closely into collaborative processes.

8.2.2.3 Data structure: interdependence

While it was beyond the scope of this thesis to look more deeply into collaborative processes, statistical interdependence of learning outcomes within dyads after collaboration found in the collaborative studies (studies 3 and 4) point towards changes in collaborative processes initiated by awareness information (Schnaubert & Bodemer, 2018, 2019). Thus, it becomes clear that data gained from dyads may provide further information when interpreted as such.

Consequently, in studies 3 and 4, we looked more closely into the intra-class correlation (see Griffin & Gonzalez, 1995; Shrout & Fleiss, 1979, for more information on this measure) between the individual learners' knowledge and between their confidence after collaboration. While the data in both experiments is not conclusive in itself (the sample sizes are too low to draw definite conclusions, confidence intervals of intra-class correlation coefficients overlap and the comparison between coefficients is rather descriptive in nature; see also Schnaubert & Bodemer, 2018, 2019), combining the results of both studies, a pattern seems to be emerging. While the provision of cognitive awareness information did not seem to interfere too strongly with data interdependence (although there are some possible interaction effects worth looking into in follow-up research; see Schnaubert & Bodemer, 2019), the provision of metacognitive awareness information considerably decreased interdependence in performance measures after collaboration (with regard to the learning tasks) and considerably increased the interdependence of confidence levels in both studies (3 and 4). Considering that interdependence conceptually is assumed to mainly result from interactive processes (Bonito, 2002; Cress, 2008) and can be supported by instructional interventions designed to interfere with collaboration (Schnaubert & Bodemer, 2018), this indicates that the provision of metacognitive awareness information

not only draws attention towards uncertain material but interferes with the dynamics of collaboration.

Surprisingly, while the provision of metacognitive awareness information led to higher interdependencies with regard to post-intervention confidence (possible reasons range from a common exposure view and metacognitive alignment to actively resolving uncertainties or negotiating the meta-level; see Schnaubert & Bodemer, 2018), it seems to have the inverse effect on knowledge (although the data from study 3 indicates that especially the condition with cognitive and metacognitive awareness information available breaks ranks with regard to interdependence). This is particularly interesting, because in study 4 this interdependence coincides with indications for less performance gain. While there are various possible explanations for these differences in interdependence between conditions throughout the studies (for details see Schnaubert & Bodemer, 2018), the observation that metacognitive awareness information seems to interfere stronger with regard to both cognitive and metacognitive learning outcomes is rather surprising. The fact that metacognitive awareness information may be interpreted on individual (intra-individual) as well as dyadic (inter-individual) level and also has an inherent value component (better – worse) while cognitive awareness information is restricted to inter-individual comparisons (at least without effortfully relating the content of different assumptions) without inherent value may contribute to the differential effects of metacognitive awareness information (fostering and hampering positive interdependence) but does not explain why cognitive awareness information does not have a stronger positive impact (for more information on this see Schnaubert & Bodemer, 2018).

Finally, it is worth pointing out that visualising information about learners within a group in order to promote group awareness and partner modelling without the full burden of actively acquiring and processing the necessary information may also lead to alignment processes without the need for active interaction between learners for example via anchoring effects (Zhao & Linderholm, 2011) or re-evaluation of task difficulty (Karabenick, 1996) relating more to the common exposure explanation of interdependence (Schnaubert & Bodemer, 2018). Thus, such awareness information may be reactive and not only affect knowledge of the individuals about the group, but alter said characteristics within the group as a mere by-product of the information independent of the intended guiding effects or adapted interaction processes mostly seen as a key function of group awareness tools (see Schnaubert & Bodemer, 2019).

In conclusion, especially metacognitive group awareness information seemed to interfere with the data structure post collaboration and while there are various possible reasons for this specific observation (see Schnaubert & Bodemer, 2018, 2019), it is important to acknowledge that interventions interfering with the collaboration process such as group awareness interventions may also interfere uniquely with the data structure of learning outcomes (Schnaubert & Bodemer, 2018).

8.2.3 Summary

The studies collectively show that providing information on the self, a learning partner or the knowledge distribution within the group guides individual (RQ 1) and collaborative (RQ 2) learning processes by fostering metacognitive and/or conflict-based regulation. However, effects on learning outcomes were more ambiguous and especially effects on knowledge gain were rare at best.

The conducted research strongly indicates that visualising relevant information on the self, a learning partner or the group implicitly guides learners into responsibly regulating their learning. Learners made aware of their subjective lacks of knowledge may use this information to regulate learning in individual and collaborative settings (Schnaubert & Bodemer, 2016, 2017, 2019) as proposed by metacognition theory (e.g., Nelson & Narens, 1990) and empirical research (e.g., Thiede, 1999; Thiede et al., 2003 see also Schnaubert & Bodemer, 2017, 2019). Socio-cognitive information may further draw attention to conflicts, which may be another source of regulation as proposed by research from collaborative learning (e.g., Bodemer, 2011; Doise & Mugny, 1984; see also Schnaubert & Bodemer, 2016, 2019). Again, this effect can be observed within collaborative and individual settings (Schnaubert & Bodemer, 2016, 2019). Adding socio-cognitive information may thus weaken the link between initial metacognitive judgments and study decisions in an individual setting, proposedly via conflicting assumptions inducing uncertainty (e.g., McGarty et al., 1993; see also Schnaubert & Bodemer, 2016, 2019). Additional analyses on the patterns of information re-visited further suggest that learners integrate all available information and make study decisions accordingly (Schnaubert & Bodemer, 2016, 2019).

Considering the clear effects on regulatory processes throughout the studies, it is surprising that we only observed sparse effects with regard to learning outcomes for individual (RQ 1) as well as collaborative (RQ 2) settings. While there are indications that

confidence may be positively affected by visualising metacognitive awareness information if this information is used to make study decisions (metacognitive regulation; Schnaubert & Bodemer, 2017, 2019), it may even be negatively affected by the presence of partner information if learners are not able to or simply do not discuss and thus potentially resolve differences and uncertainties (Schnaubert & Bodemer, 2016, 2019). These results indicate that providing awareness information may not always be positive, but has to be followed up by adequate learning processes (see Schnaubert & Bodemer, 2019). This lack of adequate processes may be one reason why, despite the substantial effects on study regulation, awareness information did not affect knowledge gain, even though attending to lacks of knowledge and/or conflicts has shown positive effects in the past (e.g., Bodemer, 2011) and the results regarding the data structure suggest that metacognitive awareness information does affect collaborative processes relevant for learning outcomes (Schnaubert & Bodemer, 2018).

While the results additionally suggest that monitoring accuracy may be one factor limiting the effectiveness of metacognitive awareness information (Schnaubert & Bodemer, 2017), which is a known problem within metacognition research and theory (e.g., Dunlosky & Rawson, 2012; Thiede et al., 2003), this cannot explain the lack of effect of cognitive awareness information and conflict-based regulation. There are various possible explanations for this lack of effect ranging from experimental design issues (like the algorithm used to generate partner information in study 2; see section 8.2.2.2) to theoretical assumptions like the lack of benefit of focussing on conflicting issues within collaboration. However, without looking more closely into the cognitive and collaborative processes, this issue cannot be resolved (Schnaubert & Bodemer, 2019).

On a final note, it is interesting that metacognitive judgments seem to be more prone to change than measures on the cognitive level. The cyclic relationship assumed in models of metacognition assumes a bi-directional influence between both levels (e.g., Nelson & Narens, 1990). However, this connection may have been partially blurred by the binary measures (see Schnaubert & Bodemer, 2017, 2019 for more details), but also by the conceptualisation of knowledge. We measured performance as opposed to cognitions and thus used a rigid external standard to validate assumptions. In comparison, measured confidence depended not only on an absolute confidence value based on the perceived magnitude of confidence but additionally on an internal threshold to decide between “certain” and “uncertain” (see Schnaubert & Bodemer, 2019). Thus, measured changes

with regard to confidence may be due to changes in confidence or the decision threshold – adding an extra dynamic and possibly making it more prone to change.

9 Implications

This section brings together the research conducted to derive implications for research and practice in the distinct research areas. It also relates the results to the larger goals of this thesis (see section 5) and points towards further relevant research areas.

9.1 Implications for metacognition research and practice

From a metacognition perspective, the goals of this thesis were (a) to apply awareness mechanisms adopted from group awareness research to individual settings to overcome an implementation deficit of metacognitive regulation and (b) to investigate the impact of socio-cognitive information on individual learning, especially metacognitive regulation (see section 5). Figure 16 illustrates the research conducted with regard to these issues (the right-hand side in red refers to (a) and the left-hand side in green to (b)) and thereby also uncovers open issues like looking more closely into transformation processes or the impact of providing cognitive self-information in an individual context (some, but not all, are discussed below). Additionally, all results reported in this thesis need to be replicated (preferably with larger sample sizes) to consolidate the effects observed.

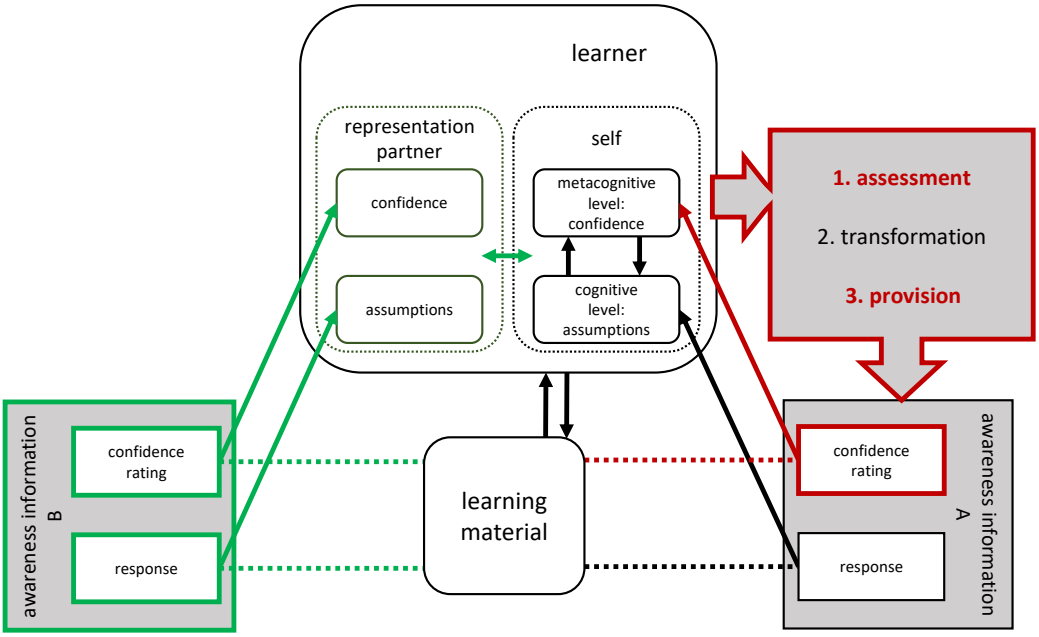

Figure 16. Research conducted in individual settings

9.1.1 Awareness mechanisms and metacognitive regulation

Concerning the first goal (a), the individual-centred studies confirmed the impact of providing metacognitive awareness information to individual learners on metacognitive regulation. This means there are a lot of opportunities for instructional design. Using self-set information to guide learning is an easy to implement way to support self-regulation for example in eBooks or online courses (Schnaubert & Bodemer, 2017) to foster the utilisation of monitoring judgments to regulate learning and thus counter production deficits or a fall-back to habitual strategies (see Ariel & Dunlosky, 2012). Although we did not find effects on learning outcomes, the results of study 1 imply that at least one reason for this lack of effect may be low monitoring accuracy. Low monitoring accuracy and its potentially detrimental effects on learning are issues repeatedly discussed in metacognition research (e.g., Dunlosky & Rawson, 2012; Thiede et al., 2003) and there are multiple attempts to foster accuracy (e.g., Dunlosky & Lipko, 2007; Nietfeld, Cao, & Osborne, 2006). Thus, combining such approaches with the provision of metacognitive awareness information may prove advantageous for learners with inadequate monitoring abilities (Schnaubert & Bodemer, 2017). Additionally, in real-life settings, learners are usually more familiar with a subject and prior knowledge is assumed to have a positive influence on monitoring accuracy especially by reducing overconfidence (e.g., Ehrlinger, Johnson, Banner, Dunning, & Kruger, 2008). Thus, further research should investigate if and how the guidance effects found in our studies can be transferred to real-life learning settings, for example in the context of studying for exams, or to other populations (Schnaubert & Bodemer, 2017). This may also include using the same mechanisms adopted from group awareness research on other relevant metacognitive concepts concerned with relevant study processes such as metacomprehension, which has been connected to metacognitive regulation (e.g., Thiede et al., 2003) as well as text comprehension research (e.g., Wiley, Griffin, & Thiede, 2005), but was also used in group awareness research (Dehler et al., 2009, 2011) although framed differently.

While the positive results of adapting group awareness tools to foster individual learning are encouraging from an instructional design perspective, from a research perspective, they cast doubt on the generalisability of empirical findings from metacognition research (Schnaubert & Bodemer, 2017) and stress the need to explicitly describe research designs and state if and how metacognitive judgements are made available to learners during learning – which is seldom explicitly done in metacognition research. Moreover, while

assessing the information in the first place did only show isolated effects on learning processes in study 1, combined with other research that found prompting effects of assessing metacognitive information (e.g., Mitchum et al., 2016; Soderstrom et al., 2015), we can conclude that metacognition research may reach its limits in studying naturally occurring (= unprompted) metacognitive monitoring and regulation (Schnaubert & Bodemer, 2017) as this line of research greatly relies on potentially reactive self-report data (Dinsmore et al., 2008). Accepting these limits, metacognition research needs to look more deeply into the processes involved in providing metacognitive information and how these affect metacognitive experiences and regulation while simultaneously updating reporting practices.

9.1.2 Socio-cognitive information and metacognitive regulation

With regard to the second goal (b) and thus socio-cognitive information, an important conclusion is that socio-cognitive information has a profound impact on metacognitive regulation (Schnaubert & Bodemer, 2016). While this is acknowledged not only in the field of computer-supported collaborative learning (e.g., Buder, 2017; Järvelä et al., 2016), but also in more generic metacognition research (e.g., Efklides, 2008; Koriat et al., 2018; Salonen et al., 2005), the issue remains understudied, especially with regard to effects on study decisions (guidance effects). This thesis suggests that the impact on learning may be quite substantial and especially information on conflicting assumptions of others affect study decisions. While the effects of cognitive partner information were most pronounced, we found learners to integrate all available information while making study decisions, including the partners' metacognitive evaluation, resulting in uncertainties presumably if conflicts could not be resolved (Schnaubert & Bodemer, 2016). Although we do not know if this effect would be similar in real-life settings, when very different types of group awareness information on other learners may be available, it is important to acknowledge that even information of a complete stranger may impact study decisions. The impact socio-cognitive information has on individual metacognitive regulation is highly relevant for modern forms of learning as information may be obtained from various and at times questionable sources. To understand individual learning processes in such settings, it is thus highly relevant to analyse the role not only content-related information but also their subjective evaluation by the source plays in interaction with the learners' own cognitive and metacognitive status in guiding the search for information. The studies presented here

only provide first indicators about possible interaction mechanisms, but no clear guidelines how to use this information in instructional design as it remains unclear how exactly socio-cognitive information affects metacognitive evaluations and vice versa. From a metacognition perspective, one would argue that information on the object-level (= cognitive) may not be able to trigger regulation processes in itself as they lack an inherent standard (Nelson & Narens, 1990) and thus, cognitive information on conflicts may only trigger learning processes via changes on the meta-level. While this sounds reasonable for individual learning settings, from a collaborative learning perspective, this may not be entirely true. If we perceive a group or dyad of learners as a dyadic system, incongruences within this system may require resolution processes without changing the individual learners' metacognitive evaluations of their knowledge or assumptions (e.g., when there is a need to establish a shared understanding or at an agreement with regard to the content). Thus, for collaborative settings, additional group-level mechanisms need to be taken into account. This warrants further research looking more closely into the mechanisms of how the social information is perceived and processed and how this affects metacognitive self-evaluations but also partner evaluations. Connecting such metacognition research closer to social psychological research, for example on perceived source credibility (e.g., Pornpitakpan, 2004), seems a logical step. Again, it would be also worth looking into these mechanisms in real-life settings, with information on actual learners or peers that have coherent knowledge about relevant content like course material and mock exams.

Another important finding is that resolving uncertainties may be hampered by social information (either by causing uncertainties or by hampering resolution processes) while knowledge itself seems not to be affected. While the results of the studies conducted are not entirely conclusive, they do indicate that the meta-level may be more sensitive to subtle changes than the object-level. Thus, this perspective should be further included in research on social influence (see section 8.2.3) to detect more subtle influences. While this is not entirely new in principle (see for example the research of McGarty et al., 1993), a metacognition perspective may provide benefits, because it includes assumptions about the impact of changes on the meta-level on control processes and thus a feedback loop to object-level assumptions.

The clear impact of socio-cognitive information on regulation, but not on knowledge gain, further indicates that looking at regulatory processes on item selection may not be

enough to understand the dynamics within social learning settings. Rather, while metacognition research assumes that meta-level goal discrepancies affect further learning (e.g., Nelson, 1996; Nelson & Narens, 1990; Thiede & Dunlosky, 1999), such research usually does not differentiate between different sources of discrepancy (e.g., lack of information vs. conflicting information). Although metacognitive self-regulation models like the COPES model (Winne & Hadwin, 1998) explicitly include strategy selection and cognitive operations, a large amount of research (including this thesis) is concerned with studying directly observable learning behaviour like content selection and study time allocation, while ignoring cognitive strategies and modes of engagement (e.g., Chi & Wylie, 2014) that may be better suited to predict not only successful learning but successful regulation distinguishing between different sources of goal discrepancies.

Finally, understanding how self- and social information affects individual learning processes is a necessary, but not sufficient, prerequisite for understanding the effect of group awareness information within collaborative learning. Thus, the next section will look into implications of the conducted research for research on collaborative learning and group awareness.

9.2 Implications for collaborative learning and group awareness research and practice

From a collaborative learning perspective, the goals of this thesis were (a) to investigate the impact of self-, partner, and group information within awareness tools by using individual and collaborative learning settings and (b) to systematically distinguish between different types of group awareness information and analyse how they affect learning processes and outcomes by applying a metacognition framework to knowledge-related group awareness information. The collaborative framework is depicted in Figure 11 (p. 40). As both collaborative studies overlapped with regard to group awareness information provided, the figure is the one depicting the more elaborate study 3 (red and green markings highlight the different types of information as well as information sources). Again, it is important to point out that there is a need for further research (e.g., none of the studies looked into the separate effects of self-, partner and group level information within a collaborative setting) and the studies conducted need to be replicated (preferably with larger sample sizes) to consolidate the effects observed.

9.2.1 Informational levels of awareness information

With regard to the first issue (a), this thesis used individual and collaborative scenarios to analyse the impact of self-, partner and group awareness information on individual and collaborative learning. Although we did not study the effects of different levels of information within a collaborative setting as Figure 11 (p. 40) clearly shows (information was always varied on a group level; Schnaubert & Bodemer, 2018, 2019) and further research should look into this, using individual studies allowed us to eliminate the dynamics from actual interaction processes and study the impact of the information provided on individuals in detail (Schnaubert & Bodemer, 2016). Understanding individual processes in social settings is a key part of understanding the dynamics within collaborative learning, but also to design tools that optimally foster collaborative learning and thus this needs an integration of different perspectives.

The studies conducted on individuals within this thesis show quite clearly the severe impact self-information has on individual learning (Schnaubert & Bodemer, 2017) and that partner information affects this influence (Schnaubert & Bodemer, 2016). Thus, an important take-away from this individual-centred perspective for group awareness research is that the self-information included in most group awareness tools provided for comparison (one notable exception is the tool by Sangin et al., 2011) inevitably provides some form of feedback and even more so if the transformation process of group awareness tools severely interprets and thus alters the information learners provided (Schnaubert & Bodemer, 2019). While in this thesis, the (group) awareness tool minimalised transformation processes by largely mirroring the learners' input (except for the representational features that gave immediate feedback and may have pre-interpreted the confidence information by suggesting the interpretation of less (hatched white-green) and more (full green)) and thus used the self-information rather raw, it still severely impacted learning (Schnaubert & Bodemer, 2017). Additionally, results of study 1 and related research suggest that self-assessment methods may alter metacognitive processes (Mitchum et al., 2016; Schnaubert & Bodemer, 2017; Soderstrom et al., 2015) and may thus be considered an important part of the awareness tool. However, using less reactive forms of data collection by using available educational data like students' essays as, for example, suggested by Erkens and colleagues (M. Erkens, Bodemer, & Hoppe, 2016) often leads to a higher transformation effort. Due to the fact that cognitive processes cannot be directly observed, input data needs to be interpreted either during assessment (by the learner) or

transformation (by the tool or an educator), and thus, there seems to be a trait-off between prompting processes through assessment and providing feedback due to external data transformation (Schnaubert & Bodemer, 2019). While both are not problematic in practice, as it can be argued that employing an awareness tool inherently includes all processing mechanisms and in the end, it does not matter too much "what does the trick" as long as it is done, this is unsatisfactory from a research perspective. It was beyond the scope of this thesis to look into different assessment, transformation or representation processes. However, each processing step may have a severe impact on how the awareness information can be used by the learners (see also Schnaubert & Bodemer, 2017, 2019). Scrutinising the effects of different tool processing steps (Buder & Bodemer, 2008) and their interaction with the learner's perspective (Bodemer & Dehler, 2011; Buder, 2011) is necessary not only to satisfy basic research-related curiosity, but is essential to purposefully design effective and efficient tools by tailoring them to the learners needs (Bodemer et al., 2018; Schnaubert & Bodemer, 2019).

Furthermore, the research conducted suggests that partner information in itself may affect learning processes beyond collaboration. Even though results of research conducted with individuals cannot be directly transferred to collaborative settings, this highlights the role of individual regulation processes involved in group awareness functions. Bodemer and colleagues (Bodemer et al., 2018) state that group awareness tools' central function is to provide information on learning partners in order to facilitate grounding and partner modelling but also to allow for comparisons between learners (see also Schnaubert & Bodemer, 2019). The main function contemplated with regard to these comparison processes, however, is guiding collaboration processes (e.g., Bodemer, 2011; Dehler et al., 2011; Engelmann et al., 2009) rather than triggering intra-individual re-evaluation processes (as would be assumed from a metacognition perspective). Both views are by no means incompatible. For example, research on socio-cognitive conflicts highlights the effects of experiencing conflict on confidence (e.g., Buchs et al., 2004; Butera et al., 2010; McGarty et al., 1993; see also Schnaubert & Bodemer, 2016, 2019) or even subsumes cognitive conflict under metacognitive experiences, because it is the result of monitoring differences between cognitions (e.g., Buder, 2017). However, the role of individual re-formation of content-related (rather than group-related) cognitions in light of group awareness information devoid of inter-personal interaction by triggering re-evaluation processes with regard to own knowledge or assumptions (see section 2.2) or task

characteristics (e.g., Carvalho Filho & Yuzawa, 2001; Karabenick, 1996) or possibly even mere anchoring effects (e.g., Zhao & Linderholm, 2011) is often overlooked (one notable exception is Buder, 2017, who recently related the effects of group awareness information to metacognition in his knowledge exchange framework). This is especially important because metacognitive self-evaluations not only seem to be more sensitive to external influences (effects on confidence in the studies were much more frequent than on performance; see section 8.2.3) but are thought to be the main driver of individual self-regulation (e.g., Nelson & Narens, 1990). Again, taking the learner's perspective is crucial for understanding how learning processes unfold. To study these effects in collaborative settings, further research needs to look closely into the different levels of awareness information. While this is acknowledged elsewhere (especially Dehler et al., 2009, 2011), there is a lack of empirical research systematically comparing the effects of self-, partner- and group-level information within collaborative settings.

Apart from looking into different levels of group awareness information, this thesis took a conceptual lens on dyadic data. We conceptualised statistical interdependence, often viewed as a nuisance due to the strain it puts on statistical analyses, as a result of interaction processes often promoted by interventions designed to support collaborative practices (Schnaubert & Bodemer, 2018). This research argues for a more thorough analysis and description of dyadic data stressing the relationship between collaborative interaction and interdependence. While more details on the specific statistical and conceptual arguments made can be found in the respective paper (Schnaubert & Bodemer, 2018), the results of the empirical research suggest that discounting the structure of dyadic data is not only statistically problematic but a missed opportunity as (statistical) interdependence is part of the dyadic design and a result of the collaborative process as much as individual outcomes are (see section 3.3). Thus, the research presented suggests that integrating different levels of information into collaborative research on group awareness includes not only the self-, partner and group perspective with regard to awareness information but also an individual and dyadic perspective to outcome data (Schnaubert & Bodemer, 2018). While there is current progress in adopting and adapting research methods to the requirements of dyadic data within the field of computer-supported collaborative learning (e.g., Janssen, Erkens, Kirschner, & Kanselaar, 2011), there is still a lack of conceptually acknowledging the relevance and relationship of collaborative processes and resulting data structures (Schnaubert & Bodemer, 2018).

9.2.2 Metacognitive framework for knowledge-related group awareness

Another key, possibly central, aspect of this thesis (b) was to analyse the impact of knowledge-related group awareness tools by systematically separating different kinds of awareness information provided. As described in section 3.5.2, the information provided in group awareness tools differs vastly and there has been few attempts to systematically analyse the impact of different types of knowledge-related information (Bodemer et al., 2018; see also Schnaubert & Bodemer, 2019). By differentiating between object- and meta-level information and tying it to metacognition research, I was able to not only analyse the impact of two different types of group awareness information, but also to connect it to metacognitive concepts and processes (Schnaubert & Bodemer, 2019). Viewing self-report data from a metacognition perspective makes it more than a short-cut way to assess objectifiable knowledge but stresses its role in (self-regulated) learning, allowing to derive hypotheses about its impact on learning (Schnaubert & Bodemer, 2017, 2018, 2019). Taking this learner-centred view, self-information can be perceived as authentic due to its deliberate disclosure (Engelmann et al., 2009) and intentionally providing it can be a way to communicate one's own point of view (e.g., a subjective need for information). Empirically, this thesis found that both kinds of information (cognitive and metacognitive) draw attention to different aspects of the learning material and thus, both can be used strategically depending on the specific goals of the instructor (Schnaubert & Bodemer, 2019). However, none of the interventions fostered knowledge gain. Despite guiding attention to relevant learning material, learners did not gain from the interventions cognitively and thus, further research needs to look more deeply into the actual collaboration and cognitive processes attached to these interactions to shed some light on this apparent mismatch (Schnaubert & Bodemer, 2019). It seems clear that while the awareness information supported metacognitive processes like selecting relevant content and allocating study resources, conducting beneficial object-level operations apparently needs more support. While I argued a similar point in section 9.1.2, within collaborative settings, beneficial cognitive operations may be induced by scaffolding the collaborative process (Kollar, Fischer, & Hesse, 2006). Collaboration scripts (see Kollar et al., 2018) seem to be especially fitting as they may be used to specify beneficial collaboration activities and support their execution (Weinberger, Ertl, Fischer, & Mandl, 2005) and have shown promising results in the past (Vogel, Wecker, Kollar, & Fischer, 2017). Since the type of group awareness information portrayed sets focus on very different aspects (i.e.,

lacks of knowledge and conflicting assumptions), it seems especially promising to match the type of awareness information to the type of script used – both depending on the goals of the instructor (see Schnaubert & Bodemer, 2019).

Apart from using a metacognitive lens while looking into knowledge-related concepts, we used the same lens while studying learning processes. The regulation coefficients used represent meta-level processes of selecting relevant material and allocating study time rather than germane cognitive or collaborative learning processes. While this allowed us to look into joint regulation, it becomes clear that to truly grasp the whole situation, we need to look more closely into inter- and intra-individual dynamics simultaneously including both meta- and object-level processes (see also Schnaubert & Bodemer, 2019). Analysing meta-level activities in individual and collaborative settings adds a new perspective to collaborative learning and gave some indications of why metacognitive awareness information may fail in fostering learning (e.g., due to low monitoring accuracy; Schnaubert & Bodemer, 2017). It also laid bare effects of awareness information on metacognitive confidence that would otherwise have been overlooked (Schnaubert & Bodemer, 2016, 2017, 2019). Thus, metacognitive methodologies and concepts can add valuable information when studying collaborative learning due to the interconnection of meta-level and object-level processes and may thus be adopted by respective research (Schnaubert & Bodemer, 2019).

Finally, looking into metacognitive processes during collaborative learning does not just equal looking more closely at learners, but it means changing perspective (looking out vs. looking in), for example by viewing self-report data not merely as (potentially erroneous) data about learners, but as data from learners describing their point of view and thus the basis of their activities (Schnaubert & Bodemer, 2019). Especially within group awareness research, which particularly stresses the role of self-regulation and agency (e.g., Bodemer, 2011; Hesse, 2007), the learners' perspective needs to receive more attention to fully understand collaborative learning processes.

10 Conclusion

This thesis integrated theoretical assumptions of collaborative learning (e.g., Buder, 2017; Engelmann et al., 2009), group awareness (e.g., Bodemer et al., 2018; Buder & Bodemer, 2008) and metacognition (e.g., Nelson & Narens, 1990; Thiede & Dunlosky, 1999) to build a framework to study the impact of knowledge-related awareness tools in individual and collaborative settings (the framework was introduced in section 4 and can thus be viewed in Figure 8, p. 32). Using this framework to study the impact of different kinds of awareness information, we found that providing metacognitive awareness information can be an asset not only within group awareness tools, but may also support individual learners in utilising their own monitoring judgments during self-regulated learning. These mechanisms can thus be used in instructional design to guide individual as well as collaborative learning processes, although learners may need additional support to profit from the full potential of such a measure. However, this also means that group awareness research should not discount the role of self-information within group awareness tools, but rather embrace its potential in guiding learning processes. Additionally, providing information on other learners may strongly impact individual self-regulation as well as collaborative learning, and learners seems to consider cognitive and metacognitive awareness information on self and partner when making study decisions. The theoretical distinction between object- and meta-level information as done in metacognition research thus seems to be relevant for individual but also collaborative learning and may provide a framework to study the impact of knowledge-related information within group awareness research, as both types of information guide learners' attention towards different aspects of the learning situation. Additionally, considering object- and meta-level learning outcomes as well as individual and dyadic data structures can provide further insights into the effects of awareness information. Thus, integrating research and theory on metacognition and on collaborative learning with a specific focus on group awareness proved beneficial for both fields and stresses the need for more research crossing the boundaries of these research areas. There is some recent progress in merging (metacognitive) self-regulation research and research on group awareness within computer-supported collaborative learning from a self-regulation perspective (e.g., Miller & Hadwin, 2015), a group awareness perspective (e.g., Buder, 2017), and a joint perspective (e.g., Järvelä et al., 2016, 2015). However, theoretically and empirically linking those fields is still in its early stages. Using a framework like presented here provides a basis to systematically research the impact of

awareness information in various settings by drawing on a vast amount of theoretical and empirical research from both fields. This allows for conducting research on individuals and groups to ultimately disentangle self-, partner and group effects and foster our understanding of the dynamics within collaborative and individual learning and will help to design tools that optimally foster learning processes.

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12 Appendix

At the date of submission of this thesis, all included studies have been published in international, peer-reviewed journals (study 1, 3, 4) or conference proceedings (study 2). All manuscripts are attached in this Appendix section.

Study 1: Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments

Schnaubert, L., & Bodemer, D. (2017). Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments. *Learning and Instruction, 49*, 251–262. https://doi.org/10.1016/j.learninstruc.2017.03.004
[Schnaubert, L., & Bodemer, D. (2018). Corrigendum to "Prompting and visualising monitoring outcomes: guiding self-regulatory processes with confidence judgments". *Learning and Instruction, 54,* 47. https://doi.org/10.1016/j.learninstruc.2018.01.010]

Study 2: How socio-cognitive information affects individual study decisions

Schnaubert, L., & Bodemer, D. (2016). How socio-cognitive information affects individual study decisions. In C.-K. Looi, J. Polman, U. Cress, & P. Reimann (Eds.), *Transforming learning, empowering learners: The International Conference of the Learning Sciences (ICLS) 2016* (pp. 274–281). Singapore, SG: International Society of the Learning Sciences.

Study 3: Providing different types of group awareness information to guide collaborative learning

Schnaubert, L., & Bodemer, D. (2019). Providing different types of group awareness information to guide collaborative learning. *International Journal of Computer-Supported Collaborative Learning*. https://doi.org/10.1007/s11412-018-9293-y

Study 4: What interdependence can tell us about collaborative learning: a statistical and psychological perspective

Schnaubert, L., & Bodemer, D. (2018). What interdependence can tell us about collaborative learning: a statistical and psychological perspective. *Research and Practice in Technology Enhanced Learning*, *13*(1), 1–18. https://doi.org/10.1186/s41039-018-0084-x

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Prompting and visualising monitoring outcomes: Guiding self-regulatory processes with confidence judgments

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ABSTRACT

Sensible self-regulated study decisions are largely based on monitoring learning and using this information to control learning processes, but research has found that such processes may not be initiated automatically. To support learners, we adopted prompting and visualisation methods by asking learners to assign confidence ratings to learning tasks and visualising them during re-study, and tested the effects on metacognitive and cognitive measures in an experimental study ($N = 95$). Results show that prompting monitoring increased study efforts while visualising monitoring outcomes during learning focussed these efforts on uncertain answers. Due to low monitoring accuracy, metacognitively sensible regulation did not lead to cognitive learning gains. While the results support the idea of using visualisation techniques to implicitly guide self-regulated learning, more needs to be done to increase monitoring accuracy. Further, our study suggests that researchers should be aware of the effect that assessing confidence judgments has on subsequent learning behaviour.

1. Introduction

1.1. Metacognitive regulation of learning processes

Theories on metacognitive self-regulation of learning assume a cyclic model, in which learners monitor their learning process and use this information to control learning decisions (Efklides, 2008; Nelson & Narens, 1990). According to Nelson and Narens' framework (1990), learners monitor their learning processes and outcomes (i.e., their object level) and use this information to build a dynamic, meta-level model. This model is used as information to control the learning process itself and thus in turn alters the object level. For example, learners may monitor their attempt to retrieve specific information from memory and, due to experiencing difficulties, judge the information as not learned sufficiently. Based on this information, they may decide to re-study the information altering their actual knowledge. There has been extensive research on how and how well learners monitor their learning (e.g., Maki, 1998), how they use this information to control the learning process (regulation of study, e.g., Nelson & Leonesio, 1988; Thiede, Anderson, & Therriault, 2003), and how this affects learning outcomes (e.g., Nelson, Dunlosky, Graf, & Narens, 1994; Thiede, 1999). Researchers widely assume that learners use their monitoring judgments to control studying (cf. Winne & Hadwin, 1998), and research has repeatedly produced strong evidence that learners can do so successfully (e.g., Kornell & Metcalfe, 2006; Metcalfe, 2009; Thiede, 1999). However, metacognitive self-regulation can still be very demanding and overstrain inexperienced learners (Kalyuga, 2009). Thus, in this paper, we introduce a study that investigates ways to support learning processes and outcomes by implicitly guiding self-regulation efforts based on metacognitive monitoring.

When studying, self-regulated learners have to make important decisions about their learning processes, such as what to study when, whether to continue or terminate studying or how long to study material (Nelson & Narens, 1990). According to Metcalfe and Kornell (2005), allocating study time consists of two stages: choice and perseverance. At the choice stage, learners decide which items they need to study and the order in which to study them. Items already mastered are mostly discarded while items not yet mastered are likely candidates for study. Although different views such as the region of proximal learning framework (e.g., Metcalfe & Kornell, 2005) and discrepancy reduction views (e.g., Thiede & Dunlosky, 1999) suggest different approaches, they agree that not-yet mastered items are prioritised. At the perseverance stage, learners decide on how much time to spend on the chosen items

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and thus when to terminate study. All of these decisions may be based on process monitoring (Nelson et al., 1994), but can also be part of overall task goals or agendas (Dunlosky & Ariel, 2011; Dunlosky & Thiede, 2004; Thiede & Dunlosky, 1999). Even if effective agendas vary greatly depending on personal and situational factors, they all involve self-evaluation strategies to adapt study behaviour to subjective needs (Ariel, Dunlosky, & Bailey, 2009). The learner must detect such need and keep it mentally present to make study decisions accordingly. However, this might not be possible in challenging learning scenarios. Thus, there are two obstacles to regulating learning processes: the detection of a need to study and its mental presence in order to make adequate control decisions.

To detect the need to study, learners have to monitor their learning. However, such monitoring processes and the judgments that result from it (monitoring judgments) can only provide a sound basis for controlling the learning process (and thus lead to effective regulation) if they are sufficiently accurate (Dunlosky & Rawson, 2012). There are two possible cases of misjudgement: (1) overconfidence (e.g., a firm belief in the correctness of objectively incorrect information), which could lead to understudying (Dunlosky, Rawson, & Middleton, 2005) or misinformed decisions (Leclercq, 1983); and (2) underconfidence, which might yield positive results due to overlearning given unlimited resources, but might have detrimental effects if it requires that scarce resources be allocated to already mastered learning material (Dunlosky & Rawson, 2012). Regardless of the accuracy of monitoring judgments, low confidence discloses gaps in knowledge that need to be addressed to gain usable knowledge (e.g., Hunt, 2003). Therefore, learners should be likely to address uncertainties if they are aware of them.

Research has shown that actively trying to retrieve an answer from memory positively affects the accuracy of metacognitive judgments (Dunlosky et al., 2005). For example, response confidence judgments (RCJs), which require learners to evaluate their responses to learning tasks, have been shown to be more accurate in predicting actual performance than judgments made prior to retrieval attempts (e.g., Costermans, Lories, & Ansay, 1992; Maki, 1998). As discussed above, accurately monitoring performance is highly important for self-regulated learning processes and outcomes, as it influences the usefulness and the effectiveness of study decisions (Dunlosky & Rawson, 2012), such as deciding when to restudy an item or topic (Thiede, 1999). Consequently, RCJs seem to be a suitable basis for such decisions, as learners can (re-)study if they are not confident about their responses to learning tasks.

As stated, RCJs are subjective post-answer evaluations of the validity of one's own answers (i.e., subjective validity) (Leclercq, 1983) and may thus be used as a guide for further learning. While the formation of such metacognitive evaluations may be an unconscious process (Efklides, 2008), their strategic usage requires an active maintenance of the information in memory in order to compare specific evaluations (Dunlosky & Ariel, 2011) and thus conscious awareness (Efklides, 2008). This active processing consumes cognitive capacities, especially if learners must prioritise and choose between simultaneously presented materials. Item selection within simultaneously presented material activates planning activities, presumably due to automatic engagement of inter-item comparison processes necessary to make well-founded study decisions (Dunlosky & Thiede, 2004). Consequently, metacognitive processes are related to high mental effort. While assigning cognitive resources towards sensible regulation (e.g., sensible item selection) may benefit learning by focussing attention on relevant material, it may still overstrain inexperienced learners (Kalyuga, 2009). The additional effort required by metacognitive processes may be one reason why effective regulation sometimes fails: Learners do not always actively monitor their learning (production deficiency, cf. Veenman, Kerseboom, & Imthorn, 2000; Winne, 1996) or do so only implicitly, which might result in less aware metacognitive information and thus no solid basis for control decisions. Conversely, learners might thoroughly monitor their learning but fail to use this valuable information to control learning processes, resulting in a fall-back to habitual behaviour strategies (Ariel & Dunlosky, 2012; Ariel, Al-Harthy, Was, & Dunlosky, 2011), because the metacognitive information is not readily available and hard to mentally obtain during learning. Thus, effective regulation support should address not only the lack of monitoring, but may also foster the usage of its outcome by enhancing its salience and reducing the effort of utilising this information.

1.2. Fostering metacognitive self-regulation

Metacognitive self-regulation may fail if learners are not able or not willing to monitor their learning appropriately. There are various methods to overcome availability deficiencies of monitoring, such as strategy training (e.g., Nietfeld, Cao, & Osborne, 2006), which have been successfully used to improve deficient monitoring skills. Production deficiencies, in contrast, happen when available behaviour is not executed, for example due to distraction (cf. Veenman et al., 2000). Here, direct instruction may be used more cautiously to allow for individual regulation (cf. *assistance dilemma*, Koedinger & Aleven, 2007) and instructional methods can be limited to an activation of favourable processes, e.g., by prompting. Prompting has repeatedly been found to be an effective means to support self-regulated learning (Bannert & Reimann, 2012; Wirth, 2009). Metacognitive prompts merely stimulate recall or execution of skills and thus do not teach new information (Bannert, 2009), but they do put emphasis on specific processes or concepts. A mandatory judgment on monitoring outcomes, for example, asks the learner to monitor their cognitive processes explicitly and to externalise the outcome by rating it on a given scale. Following these prompts thus triggers monitoring and additionally makes the outcome more salient. Recent research has shown that monitoring judgments, i.e. judgments of learning, are highly reactive, affecting for example study time allocation (Mitchum, Kelley, & Fox, 2016) or memory (Soderstrom, Clark, Halamish, & Bjork, 2015). While judgments of learning are assumed to foster an active memory search, which may act as rehearsal in case of successful recall, RCJs do not serve this function since they refer to already retrieved answers. Thus, it remains unclear whether assessing RCJs influences self-regulated study processes.

Whilst monitoring processes have been prompted successfully in the past, promoting their usage to guide study decisions seems more difficult. As we discussed earlier, adequate control strategies even though available (e.g., choosing appropriate items to study) might fail if the task exceeds the mental capacities of the learners. Computational systems offer the possibility to permanently take study decisions off the learners' hands (e.g., Kornell & Metcalfe, 2006; Nelson et al., 1994), but this digresses far from the idea of self-regulated and autonomous learners. Thus, support strategies are needed that relieve the cognitive system while tacitly guiding the learners' self-regulation attempts. One strategy, borrowed from group awareness research, is the salient visualisation of knowledge-related information to support learners in structuring their common learning processes (Janssen & Bodemer, 2013); this includes visualisations of metacognitive judgments (Dehler, Bodemer, Buder, & Hesse, 2011). By providing salient, easily comparable visualisations of (lacks of) knowledge, such tools may guide learning while still enabling a self-directed approach (Bodemer, 2011). Previous work conducted in group awareness research

allowed for comparisons of group members' knowledge or knowledge gaps via visualisations, but this approach may also be suitable for individual learning. Making monitoring outcomes like RCJs externally available by saliently visualising them to ease comparison processes between studied items might also foster metacognitive self-regulation. In metacognitive self-regulation the focus is on inter-item rather than inter-individual comparison processes, because the former are necessary for choosing one item over the other (cf. Dunlosky & Thiede, 2004). Such visualisations may act as visual markers, signalling material that needs further attention, without the need of constant mental availability of the information. Similar to group awareness tools, the information provided should be easy to understand and interpret to prevent distraction (Bodemer & Dehler, 2011). Note, however, that such visualisation techniques cannot be addressed entirely separately from prompting, as these visualisations require assessing monitoring outcomes, which in turn requires explicitly asking learners to monitor themselves.

1.3. Research question and hypotheses

Our aim is to investigate ways to support self-regulatory learning processes. More specifically, we want to know: Can we facilitate metacognitive self-regulated learning by prompting monitoring processes and by providing external representations of these mental constructs? We will focus on response confidence judgments (RCJs) attached to responses to specific learning tasks as the target concept. As specified in section 1.1, RCJs serve an important function in monitoring memory and thus learning outcomes and consequently this information is a valuable indicator for the necessity to (re-)study material. We are interested in different dependent measures focussing on learning processes as well as outcomes.

1.3.1. Learning processes

In general, we are interested in the learners' study behaviour and how this relates to their monitoring outcomes. By prompting learners to monitoring their learning outcomes in the form of RCJs, learners may be more aware of their uncertainties and perceived lacks of knowledge. Thus, they may feel the need to increase study efforts by studying more information. However, if they are not supported in using their RCJs to focus their efforts towards specific items (e.g., by visualisation), these efforts may be unfocussed such as searching for information to validate most of their responses. As argued above, visualisation, in contrast, should support learners to utilise their monitoring outcomes and thus conduct a more focussed approach to studying by making it an easily accessible learning strategy to study mainly material that the learners are unsure about (cf. section 1.1). However, since especially the effects of prompting on such quantitative aspects of study behaviour like the amount of material chosen to study are largely unknown, we abstain from formulating a unidirectional hypothesis, but cautiously assume that prompting and visualisation may affect the quantity of study behaviour (hypothesis 1).

Apart from quantitative aspects, we are also interested in qualitative aspects of study decisions. Based on the research mentioned above, we assume that learners in general use their monitoring outcomes (i.e., confidence) to control their learning, since research has shown that learners choose items to re-study based on monitoring outcomes (e.g., Thiede et al., 2003). In accordance with the argumentation in section 1.2, we assume that being asked to provide explicit RCJs to responses to learning tasks prompts monitoring processes. Additionally, the externalisation of the RCJs should increase the salience of the judgments. Both prompting and externalisation processes should thus lead to a better utilisation of these judgments to make study decisions. Having monitoring judgments readily available during learning through visualisations may enhance this effect by making own monitoring outcomes even more salient and facilitating inter-item comparison processes by relieving working memory. Thus, we assume that learners who are prompted to monitor their memory use their RCJs to make study decisions (metacognitive regulation of study). Being particularly supported in utilising the RCJs by external visualisations should enhance this effect (hypothesis 2). Assuming that monitoring outcomes to some extent reflect the actual state of learning (cf. section 1.1), an approach focussing on items solved with low confidence (uncertain items) should also lead primarily to the selection of objectively needed information, i.e., information regarding incorrect responses (hypothesis 3). However, this effect should be smaller than the one specified in hypothesis 2, because monitoring accuracy is a potentially limiting factor.

Additionally, we assume that learners supported by visualisations not only use their ratings to decide what to study, but also when to study it (prioritising, cf. Metcalfe & Kornell, 2005). We assume that they favour information regarding uncertain responses and will not only primarily study such information, but also prioritise it before information regarding certain responses. Again, while learners who are prompted to monitor their memory should attend to uncertain responses first, learners who are additionally supported by visualisations should be more consistent in the usage of their monitoring outcomes to prioritise due to its higher salience (hypothesis 4).

Since learners not only base study decisions on monitoring outcomes, but also allocate more time to items judged as not yet mastered (cf. Metcalfe & Kornell, 2005; Nelson & Leonesio, 1988), we assume that learners allocate more study time to information regarding responses judged as uncertain than to those judged as certain. Again, this effect should be greater if learners have their monitoring outcomes externally available during learning (hypothesis 5). A more focussed approach should also have another effect on study time allocation: if item selection is systematically based on the subjective or objective need to study, quick re-checks (selecting unneeded information) may be avoided and thus study times of selected information should increase as the support that learners receive increases (hypothesis 6).

However, prompting might also have some unwanted side effects. Such additional tasks may interrupt the students' learning processes (Dempsey & Driscoll, 1996) since they require switching between task-related activities (e.g., comprehending the question, retrieving information from memory) and meta-level activities (e.g., actively evaluating the answers during task completion and transforming the experience of one's own confidence to a given scale). Apart from interruption, monitoring and externalising the outcomes are activities that may strain the cognitive system. The visualisations (externalised outcomes) also need resources to be processed, but since they are external representations of metacognitive concepts, they additionally have the potential to relieve the cognitive system by focussing attention and externally providing information relevant for metacognitive regulation (cf. section 1.2). Thus, there are indications to argue for more as well as less strain on the cognitive system and consequently we abstain from formulating a unidirectional hypothesis, but merely assume that prompting monitoring and visualising the outcome affect the mental effort of learners (hypothesis 7).

1.3.2. Learning outcomes

We assume that prompting and, even more so, visualising RCJs enables focussing of study effort. Since research has repeatedly found links between regulation of study and performance (e.g., Nelson et al., 1994; Thiede, 1999; cf. section 1.1), we assume that by

altering learning processes we will foster learning outcomes. We therefore assume knowledge gain during learning to be greater the more a learner is supported (hypothesis 8). Since we assume that prompting and, even more so, visualisation helps learners to focus on and therefore clear up uncertainties, we expect higher post-learning confidence levels for supported learners, especially learners who are able to strategically work through uncertain items due to support by visualisations (hypothesis 9).

Finally, re-studying material might not only help learners to correct faulty or uncertain knowledge, it might also impact monitoring accuracy. Learners aware of their monitoring judgments may use re-study trials to explicitly adjust faulty monitoring decisions. Consequently, we assume that learners who are prompted to externalise their monitoring outcomes will improve their monitoring accuracy and judge their knowledge more accurately. Again, we expect that learners who have their monitoring ratings readily available during learning outperform merely prompted learners (hypothesis 10).

2. Method

2.1. Sample, design and procedure

To test our hypotheses, we conducted an experimental study with $N = 96$ university students. In the course of the study, one participant had to be excluded due to a server error, which left us with $N = 95$ participants in the final sample. They were all university students predominantly enrolled in a Bachelors or Masters course on Applied Cognitive and Media Science (24 males, 71 females) with a mean age of 22.09 ($SD = 2.81$). Topic specific interest regarding the topics addressed in the learning material (blood sugar regulation and diabetes mellitus) measured on a scale from 0 (no interest) to 5 (high interest) was at a medium level throughout the sample (blood sugar regulation: $M = 2.57$, $SD = 0.13$; diabetes mellitus: $M = 2.58$, $SD = 0.14$); Self-assessed prior knowledge measured on a scale from 0 (low knowledge) to 5 (high knowledge) was rather low (blood sugar regulation: $M = 0.87$, $SD = 0.09$; diabetes mellitus: $M = 0.86$, $SD = 0.10$) (cf. section 2.2 for more information on the scales used). All experiments were conducted in our research lab; instructions were given via computer. Participants were rewarded either 12 Euros or course credit for research participation. Before starting the experiment, participants were randomly assigned to one of three experimental conditions. Participants in the prompting + visualisation (referred to as "visualisation" hereafter) condition assigned RCJs to learning tasks and had this information displayed during re-study. Participants in the prompting condition assigned the RCJs, but were not given this information during re-study. Participants in the control condition did not assign RCJs and consequently were not provided with such information during re-study. There were no significant differences in topic-specific interest (blood sugar regulation: $F(2,92) = 0.15$, $p = 0.858$, $\eta^2 < 0.01$; diabetes mellitus: $F(2,92) = 0.10$, $p = 0.909$, $\eta^2 < 0.01$) or self-assessed prior knowledge (blood-sugar regulation: $F(2,92) = 1.17$, $p = 0.315$, $\eta^2 = 0.03$; diabetes mellitus: $F(2,92) = 0.20$, $p = 0.816$, $\eta^2 < 0.01$) between the groups.

After participants were briefed and had given consent to participate in the study, they were provided with the experimental material on a computer screen. They were asked to give demographic information and rated their prior knowledge and interest regarding the topics addressed in the learning material (blood sugar regulation and diabetes mellitus). Then they received textual material about these topics (learning phase one, LP1) and answered learning tasks (with or without RCJs) (t1). Afterwards, they had the opportunity to (re-)study material regarding specific tasks (with or without a visual representation of their RCJs); the tasks were presented in a simultaneous format. During this second learning phase (LP2), they were able to change their answers (and depending on condition their RCJs) (t2). Finally, they answered the learning tasks again from scratch (all with RCJs) (t3) and took a knowledge test on the learned material. After each phase, learners answered an item assessing self-reported mental effort. Fig. 1 represents the overall procedure and highlights the points at which the independent variable was manipulated.

2.2. Material

The demographics questionnaire collected information on age, sex, university course and semester as well as on two variables to control for pre-test differences on blood sugar regulation and diabetes mellitus. These variables were topic-specific interest ("I think the topic diabetes mellitus [blood sugar regulation] is …") assessed on a 6-point scale from "not interesting at all" (0) to "very interesting" (5) and prior knowledge ("My knowledge about diabetes mellitus [blood sugar regulation] is …") assessed on a 6-point scale from "very low" (0) to "very high" (5).

A three-page expository text (1425 words) was used to provide each student with background information on the topics (LP1). 20 learning tasks were designed to capture important aspects of these topics (Note that the term "learning task" is used to stress that – from the learners' perspective – they are used within the learning process. However, they may still be used to assess the learners' knowledge about the material). While some tasks directly referred to information given in the text, others referred to information not previously provided. The learning tasks each consisted of a statement that the learners were asked to verify or falsify (true-false) and were given in an array format. Translated sample items with confidence ratings are depicted in Fig. 2. Depending upon point in time (t1, t2 or t3) and condition, learners were or were not additionally asked to judge their confidence in their answer. The answers were spatially coded (top – true, bottom – false) and confidence judgements were colour coded (filled green – sure, hatched green – unsure), cf. Fig. 2. In t1 and t3, learning tasks were initially blank, in t2 the learners were provided with their own answers from t1 (and depending on condition, with or without respective confidence ratings).

In LP2, learners were able to request additional information on each learning task individually by clicking a button placed next to each task. The provided information was presented by an overlay window and was either taken from the initial text or consisted of

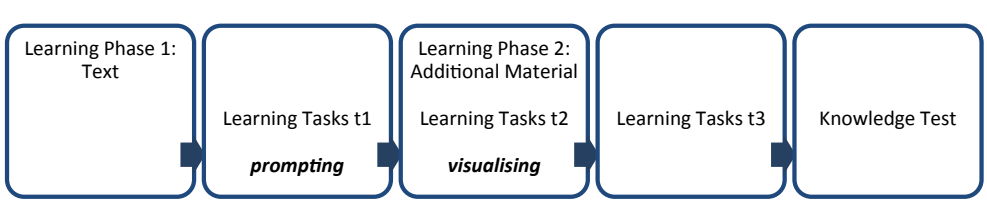

Fig. 1. Overall procedure.

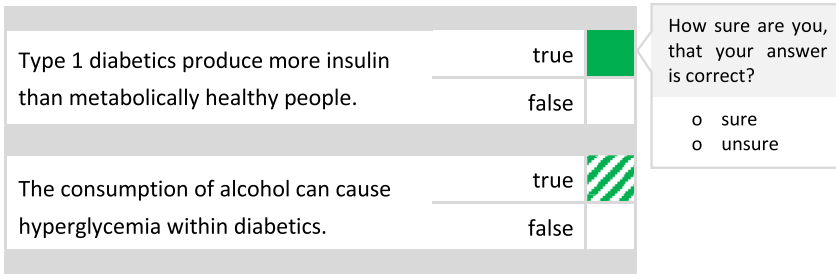

Fig. 2. Learning tasks with confidence ratings.

new information (cf. Fig. 3).

The knowledge test consisted of 25 single choice items with four alternative answers each, designed to test more profound knowledge of the information given. In contrast to the learning tasks, they were not used within the learning process and thus were used to measure if possible learning gains may be transferred to unstudied tasks. To assess individual confidence, 6-point confidence scales ("How sure are you that your answer is correct?"), ranging from "not sure at all" (0) to "absolutely sure" (5) were added. In the current sample, item difficulty was normally distributed ($S\text{-}W = 0.96$, $df = 25$, $p = 0.413$) ranging from 0.08 to 0.98 ($M = 0.51$, $SD = 0.19$) across items.

Learning material and test items were specifically developed for this study in a recursive process, testing the material on small groups of students at a time. The basis for the material was basic literature on blood sugar regulation and diabetes mellitus including common misconceptions. The development was supported by an educationalist on medicine.

Reported mental effort was assessed after LP2 and after answering the first set of learning tasks (t1) to assess differences imposed by the treatment. We used one item asking the learners how demanding the learning phase had been on a 7-point Likert scale, adapted from the mental load scale from Tindall-Ford and colleagues (Tindall-Ford, Chandler, & Sweller, 1997), ranging from "not demanding at all" (0) to "very demanding" (6).

2.3. Independent variables

The main independent variable was the level of metacognitive support the learners received. One group received no such support, whereas two groups were asked to provide a binary confidence rating along with each learning task in t1 in order to prompt metacognitive monitoring processes. One of these groups additionally had these ratings visualised in LP2 to support their usage for the control of study behaviour. This procedure left us with three groups: no support (control), mere prompting of monitoring processes by asking for confidence ratings (prompting), and additional visualisation of said confidence ratings during learning (visualisation). Since the support factor was progressively staggered, Helmert contrasts were used to separate the impact of general support, prompting and visualisation. Additionally, some measures were taken repeatedly, e.g., performance and confidence regarding the learning tasks were measured at two points within the experiment (t1, t3). This left us with a two factorial design with one within- and one between-subjects factor.

2.4. Dependent variables

To measure how metacognitive support affects cognitive learning gain (hypothesis 8), we measured performance in the learning tasks (t1, t3) and the knowledge test (sum of correctly

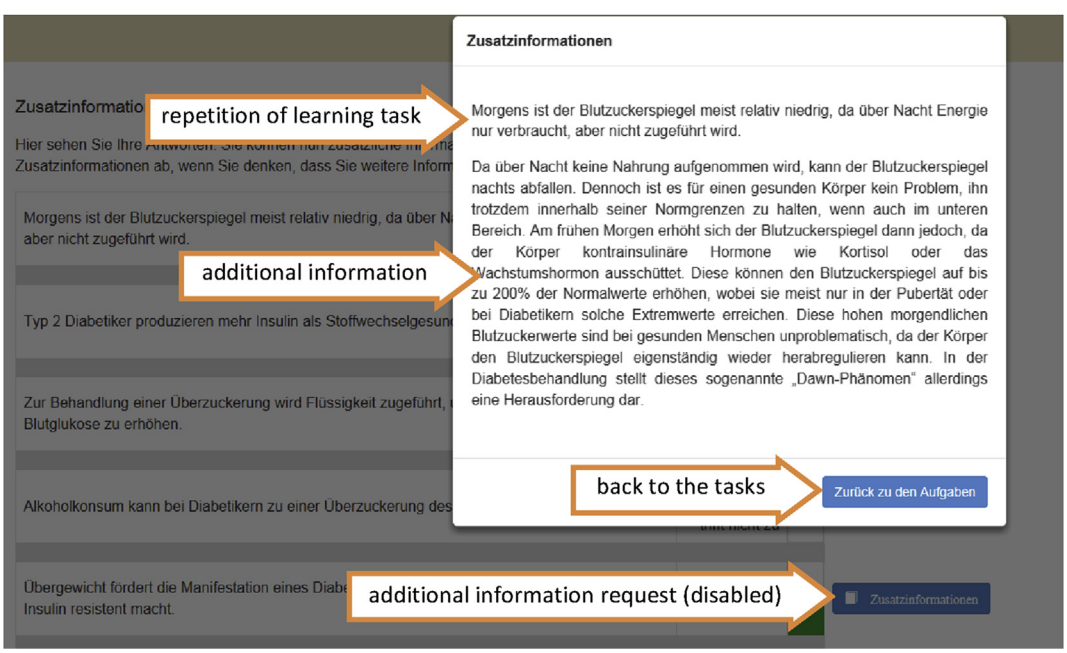

Fig. 3. Additional information.

solved items). Additionally, we were interested in the impact that support had on metacognitive measures. We assessed confidence levels by counting the confidently solved items in the learning tasks (t1 for prompting and visualisation condition, t3) and by computing mean confidence ratings for the knowledge test (independent of correctness of answers) (hypothesis 9). Further, to assess how well learners monitor themselves (hypothesis 10), we computed relative accuracy measures in the form of individual within-subject phi- or Goodman-Kruskal's gamma-coefficients between performance and confidence ratings in the learning tasks (t1 for prompting and visualisation condition, t3) or the knowledge test (cf. Schraw, Kuch, & Gutierrez, 2013). High positive coefficients indicate good monitoring accuracy since learners tend to be confident when they are also correct and not confident when they are incorrect, while negative indices imply the opposite.

Addressing the quantity of study behaviour (hypothesis 1), we assessed how many learning tasks the students requested information for by counting non-recurring information requests. Additionally, we were interested in qualitative aspects of study behaviour, i.e. how learners in the prompting and in the visualisation conditions used their confidence ratings to make study decisions (metacognitive regulation of study, hypothesis 2). Therefore we computed within-subject phi-coefficients between initial confidence (t1) and information requests (LP2), a method frequently used to assess metacognitive regulation of study (e.g., Thiede, 1999). High positive indices indicate that learners mainly assess information about uncertain items (good metacognitive regulation), while negative indices indicate the opposite. Coefficients near zero indicate no differentiation between certain and uncertain items. To see if learners made objectively useful study decisions, we also computed phi-coefficients between performance and information requests to compare between all groups (objective quality, hypothesis 3). We recoded the data to ensure that high coefficients again mean useful study decisions (requesting mainly information on incorrect answers).

To capture the influence of confidence on the order of study requests (hypothesis 4), we used an algorithm designed to measure the time-wise prioritisation of non-confident or confident responses with regard to information requests per learner (Schnaubert & Bodemer, 2016). By computing individual mean-rank differences between confidence levels, we ensured that the number of appearance of each level did not affect the index. The index ranges from +10 (all uncertain items are considered before certain items) to −10 (all certain items are considered first) and has a theoretical mean of 0 (no prioritisation).

With regard to study time allocation, we assessed study durations per requested information (hypothesis 6). We also tested how study time allocation depended on initial confidence for the two conditions that provided confidence ratings prior to learning, by measuring mean study durations per confidence level, including only items for which information was requested (hypothesis 5).

To assess if the support changed the mental effort needed by the learners (hypothesis 7), we compared reported mental effort between the conditions at two points in time: After initial task completion, we compared the prompted conditions with the non-prompted condition, and after LP2 we compared all three conditions.

There were no significant correlations between performance at the beginning of the study (learning tasks t1) and dependent process variables (e.g., number of information requests, metacognitive regulation of study, objective quality of study decisions, etc.) or monitoring accuracy. Thus, we assume this influence on the results to be negligible.

3. Results

To answer our research questions, we conducted several analyses according to distribution assumptions on the dependent variables. If not specified otherwise, results of Shapiro-Wilk tests did not contradict the normality assumption and we therefore used parametric analyses. We also conducted planned contrasts (Helmert) to take into account the staggered arrangement of the metacognitive support. We conducted two-tailed analyses to allow for opposing effects, level of statistical significance was set at $\alpha = 0.05$.

3.1. Learning processes

In the following, we discuss the results concerning learning processes. We focus on the quantity of study behaviour first (3.1.1), followed by two sections on item selection (choice) namely quality of study decisions (3.1.2) and order of processing (3.1.3), and one section on the actual allocation of study time (perseverance, 3.1.4). Finally, we report on the effects on reported mental effort (3.1.5).

3.1.1. Quantity of study behaviour (hypothesis 1)

First, we looked at the quantity of study behaviour (number of information requests). Descriptive statistics are provided in Table 1. A Welch-Test showed no significant difference between the conditions regarding the quantity of study behaviour ($F(2, 58.87) = 2.97$, $p = 0.059$; $\eta^2 = 0.06$). However, Helmert contrasts revealed a significant difference between the non-prompted and both prompted conditions ($t(63.29) = 2.45$, $p = 0.017$, $d = 0.53$), but not between the two prompted conditions ($t(49.44) = -0.60$, $p = 0.549$, $d = 0.15$).

3.1.2. Quality of study decisions (regulation of study; hypotheses 2 & 3)

In a second step, we were interested in how learners used confidence ratings to make their study decisions (hypothesis 2). Descriptive analyses of the phi-coefficients between initial confidence and study requests show a median of 0.17 ($IQR = 0.46$) for the prompting and 0.74 ($IQR = 0.47$) for the visualisation condition (the control condition did not provide confidence ratings at t1 and thus had to be excluded from analyses regarding hypothesis 2). Due to violations of the normality assumption, we conducted a Mann-Whitney-U-test, which revealed a significant difference in study regulation between the two groups ($U = 62.00$, $Z = -0.5739$, $p < 0.001$, $r = 0.07$). A Wilcoxon signed rank test confirmed a significant deviation from zero for the prompting ($Z = -2.443$, $p = 0.015$, $r = 0.43$) as well as for the visualisation condition ($Z = -4.870$, $p < 0.001$, $r = 0.87$), meaning that both groups used their confidence ratings to make study decision, though to a different extent. In contrast, analyses on objective quality of study decisions (hypothesis 3; cf. Table 2) showed no inter-group-differences ($F(2, 89) = 0.41$, $p = 0.667$, $\eta^2 = 0.01$) as well as no significant difference from zero for the whole sample ($N = 92$; $t(91) = -0.50$, $p = 0.616$, $d = 0.05$).

Table 1
Descriptive statistics on number of information requests per condition.

condition	number of information requests		
	N	*M*	*SD*
control	32	8.13	4.63
prompting	32	11.00	6.03
visualisation	31	10.26	3.43
overall	95	9.79	4.93

Table 2
Descriptive statistics on objective quality of study decisions per condition.

condition	objective quality		
	N	*M*	*SD*
control	32	−0.005	0.222
prompting	29	−0.002	0.239
visualisation	31	0.042	0.231
overall	92	0.012	0.229

Table 3
Descriptive statistics on mean study durations per requested information per condition.

condition	study duration per request (sec)		
	N	*M*	*SD*
control	32	23.84	9.59
prompting	32	27.45	14.20
visualisation	31	34.35	13.76
overall	95	28.49	13.28

3.1.3. Order of processing (hypothesis 4)

We then conducted the sequence analyses to assess whether learners attended to uncertain or certain items first – again only with the groups providing confidence ratings prior to learning. Wilcoxon signed rank test showed no significant deviation from zero for the mean rank differences of the prompting condition ($Z = 1.117$, $p = 0.264$, $r = 0.20$), but for the visualisation condition ($Z = 4.880$, $p < 0.001$, $r = 0.88$). A Mann-Whitney-U-Test (conducted due to violations of the normality assumption) revealed a significant difference between the groups ($U = 923.50$, $Z = 5.890$, $p < 0.001$, $r = 0.74$) with the visualisation condition having a significantly higher mean rank difference in favour of uncertain items ($Mdn = 7.50$, $IQR = 4.55$) than the prompting condition ($Mdn = -0.21$, $IQR = 4.37$).

3.1.4. Study time allocation (hypotheses 5 & 6)

While the results described in sections 3.1.2 and 3.1.3 are concerned with item choices, we additionally were interested in how learners allocate study time to those chosen items (hypothesis 6) and if they further differentiate between confidently and not confidently solved items (hypothesis 5). With regard to hypothesis 6, we found that mean study durations per item did differ between the three groups ($F(2, 92) = 5.57$, $p = 0.005$, $\eta^2 = 0.108$). Helmert contrasts revealed that there was a difference between the prompted and not prompted conditions ($t\ (92) = 2.56$, $p = 0.012$, $d = 0.56$) with prompted learners spending more time per additional information, as well as between the prompted conditions ($t\ (92) = 2.16$, $p = 0.033$, $d = 0.54$), again with more support leading to longer study durations (cf. Table 3). Due to the significance of the second contrast, we also contrasted the control and the prompting only condition to extract the prompting effect. A *t*-test for independent samples revealed no significant difference between these conditions ($t\ (62) = 1.19$, $p = 0.239$, $d = 0.30$).

With regard to hypothesis 5, we tested how study-time allocation depended on initial confidence for the two conditions that provided confidence ratings prior to the second learning phase (t1). A two-factorial ANOVA with repeated measures on one factor was administered to test the effects of initial confidence and condition on the mean study duration per selected additional information (cf. Fig. 4). The results show a significant main effect of confidence ($F(1, 46) = 9.05$, $p = 0.004$, $\eta_p^2 = 0.16$), no main effect of condition ($F(1, 46) = 0.10$, $p = 0.753$, $\eta_p^2 < 0.01$), and no significant interaction ($F(1, 46) = 3.62$, $p = 0.063$, $\eta_p^2 = 0.07$). *N* differs from other calculations due to specific study patterns of fourteen participants (who did not select any confidently solved item for re-study) and the elimination of an extreme value in the visualisation group.

3.1.5. Reported mental effort (hypothesis 7)

We assessed reported mental effort with one item. Non-parametrical Mann-Whitney-U-tests revealed no difference in the load imposed by the first set of learning tasks between the prompted and non-prompted conditions ($U = 959.00$, $Z = -0.393$, $p = 0.694$, $r = 0.04$), with both groups reporting a medium load ($Mdn = 3.00$, $IQR = 2.00$; $M_{non\text{-}prompted} = 3.03$, $SD_{non\text{-}prompted} = 1.60$; $M_{prompted} = 2.89$, $SD_{prompted} = 1.43$). Comparing the overall load imposed on the learners by learning phase two also showed no difference among the three conditions (Kruskal-Wallis-test: $H = 0.866$, $df = 2$, $p = 0.649$) and also not between visualisation and non-visualisation conditions ($U = 1097.00$, $Z = 0.852$, $p = 0.394$, $r = 0.09$). The visualisation condition reported a load of $Mdn = 3.00$ ($IQR = 2.00$, $M = 2.42$, $SD = 1.39$), and the others of $Mdn = 2.00$ ($IQR = 2.00$; $M_{prompting} = 2.22$, $SD_{prompting} = 1.48$; $M_{control} = 2.31$, $SD_{control} = 1.47$).

3.2. Learning outcomes

In the following sections, we present the results regarding our research questions on knowledge (3.2.1), confidence levels (3.2.2) and monitoring accuracy (3.2.3).

3.2.1. Task- and test-performance (hypothesis 8)

The mean number of correctly solved items in the knowledge test did not differ among the conditions ($F(2, 92) = 0.03$, $p = 0.972$, $\eta^2 < 0.01$). However, a two-factorial ANOVA on the number of correctly solved items in the learning tasks revealed a significant

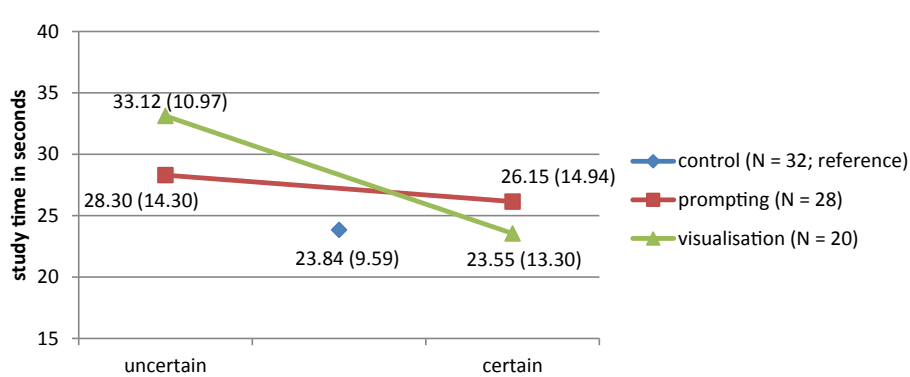

Fig. 4. Means (standard deviations) of study time in seconds per chosen certain or uncertain item.

Table 4
Descriptive statistics on knowledge (test performance) per condition.

condition	N	performance learning tasks pre (max. = 25)		performance knowledge test (max. = 20)		performance learning tasks post (max. = 20)	
		M	*SD*	*M*	*SD*	*M*	*SD*
control	32	12.72	3.14	10.59	1.83	12.38	1.81
prompting	32	12.78	3.51	10.34	2.24	12.41	2.33
visualisation	31	12.90	2.71	11.23	2.06	13.13	1.93
overall	95	12.80	3.11	10.72	2.06	10.72	2.06

main effect of time, with all groups performing significantly better after than before learning phase two ($F(1, 92) = 61.20$, $p < 0.001$, $\eta_p^2 = 0.40$). There was no significant main effect of condition ($F(2, 92) = 2.16$, $p = 0.121$, $\eta_p^2 = 0.05$) or an interaction ($F(2, 92) = 0.11$, $p = 0.894$, $\eta_p^2 < 0.01$). The descriptive statistics are available in Table 4.

3.2.2. Confidence level (hypothesis 9)

Mean confidence levels in the knowledge tests were roughly in the middle of the scale for all three conditions ($M_{control} = 2.79$, $SD_{control} = 0.67$, $M_{prompting} = 2.73$, $SD_{prompting} = 0.71$, $M_{visualisation} = 2.76$, $SD_{visualisation} = 0.68$) and there was no significant difference among the groups ($F(2, 92) = 0.07$, $p = 0.934$, $\eta^2 < 0.01$). However, there was a significant difference among the groups in the learning tasks post learning phase two ($F(2, 92) = 11.43$, $p < 0.001$, $\eta^2 = 0.20$) (cf. t3 in Fig. 5). Helmert contrast revealed a significant effect between both supported conditions and the not supported condition, with learners in the supported conditions being more confident ($t(92) = 4.10$, $p < 0.001$, $d = 0.89$). Additionally, there was a significant difference between the two supported conditions ($t(92) = 2.49$, $p = 0.014$, $d = 0.63$), with learners in the visualisation condition being more confident than those in the prompted only condition. Due to the significance of the second contrast, we contrasted the control and the prompting condition to extract the prompting effect. A *t*-test for independent samples revealed a significant difference between these conditions ($t(62) = 2.19$, $p = 0.032$, $d = 0.58$), with learners in the prompted condition being more confident than those in the control condition. Two-factorial analyses between the two prompted conditions (prompting only and visualisation) revealed a highly significant effect of time ($F(1, 61) = 194.98$, $p < 0.001$, $\eta_p^2 = 0.76$) with the participants becoming more certain from pre to post LP2. Additionally, it showed a significant interaction between time and condition ($F(1, 61) = 9.14$, $p = 0.004$, $\eta_p^2 = 0.13$) with learners in the visualisation condition gaining more confidence than learners in the prompting only condition. There was no main effect of condition ($F(1, 61) = 1.27$, $p = 0.265$, $\eta_p^2 = 0.02$) (cf. Fig. 5).

Table 5
Descriptive statistics on monitoring accuracy (within-subject correlations between certainty and performance) per condition.

condition	N	Gamma knowledge test		Phi learning tasks pre		Phi learning tasks post		
		M	*SD*	*M*	*SD*	*N*[(a)]	*M*	*SD*
control	32	0.37***	0.25	–	–	32	0.18***	0.24
prompting	32	0.39***	0.23	.10°	0.30	28	0.14**	0.22
visualisation	31	0.38***	0.24	.02°	0.25	21	0.11*	0.21
overall	95	0.38***	0.24	–	–	81	0.15***	0.22
all prompt	63	0.39***	0.23	.06°	0.28	49	0.13***	0.21

Significance of the means' deviation from zero: °$p > 0.05$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
[(a)] *N* varies due to stability on the confidence dimension in the learning tasks post (certain in all items).

3.2.3. Monitoring accuracy (hypothesis 10)

Analyses on monitoring accuracy showed that with respect to the learning tasks, phi-coefficients were generally low (cf. Table 5) and did not differ between the three groups post re-study ($F(2, 78) = 0.62$, $p = 0.540$, $\eta^2 = 0.02$). Further, a two-factorial repeated-measures ANOVA for both prompted conditions revealed neither a significant effect of time ($F(1, 47) = 0.85$, $p = 0.360$, $\eta_p^2 = 0.02$) nor of condition ($F(1, 47) = 0.28$, $p = 0.598$, $\eta_p^2 = 0.01$), nor an interaction ($F(1, 47) = 0.02$, $p = 0.898$, $\eta_p^2 < 0.01$). As for the knowledge test, a one-way ANOVA showed no differences in the gamma-coefficients between the three groups ($F(2, 92) = 0.03$, $p = 0.974$, $\eta^2 < 0.01$). Descriptive statistics for the accuracy measures are provided in Table 5.

3.2.4. Interrelation between dependent variables

Since most of our dependent variables are assumed to be interconnected, we modelled these interactions via a moderated mediation (cf. Fig. 6 for the statistical model, coefficients are based on *z*-scores). Results show a significant overall model for explaining objective quality of study regulation through metacognitive regulation moderated by monitoring accuracy ($F(3, 56) = 34.50$, $p < 0.001$, $R^2 = 0.52$) as well as a significant overall model explaining performance gain in the learning tasks from pre- to post-learning ($F(2, 57) = 4.66$, $p = 0.013$, $R^2 = 0.15$) through

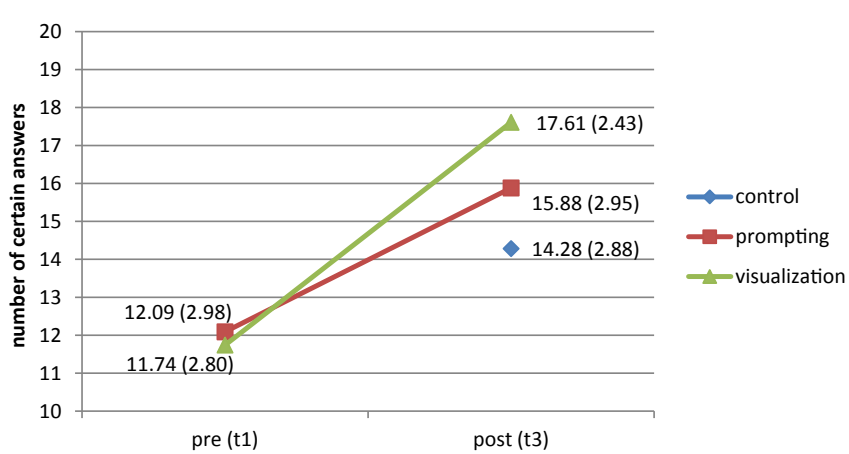

Fig. 5. Means (standard deviations) of number of certain answers to learning tasks pre and post re-study.

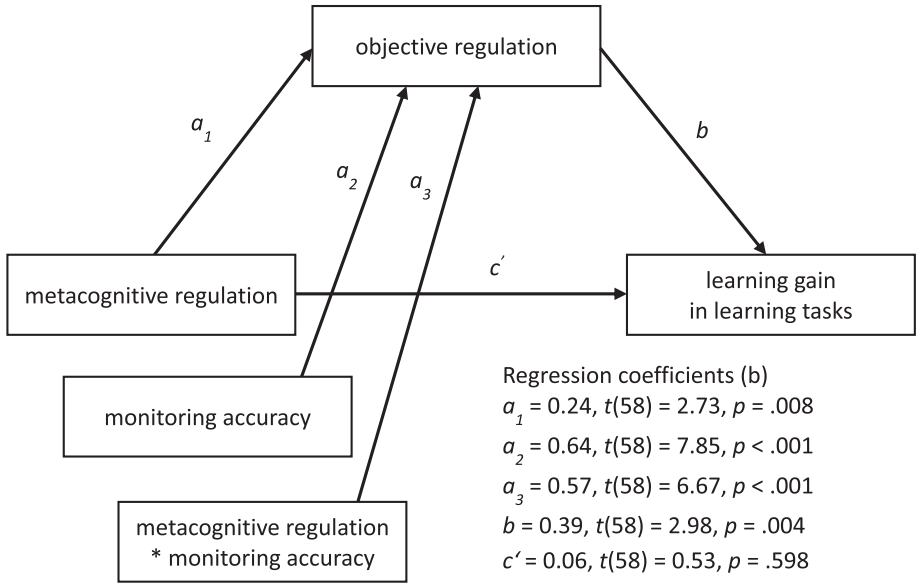

Fig. 6. Statistical model of the moderated mediation: metacognitive regulation explaining learning gain via objective regulation moderated by monitoring accuracy.

objective quality of regulation. Regression coefficients confirm that the effect of metacognitive regulation on learning gain is mediated through objective regulation and thus indirect only. However, monitoring accuracy moderates the relationship between metacognitive and objective regulation (first stage moderated mediation). To describe the mediation effect, we calculated the impact of metacognitive regulation on objective regulation at three different levels of monitoring accuracy. The analyses showed that values one standard deviation below the mean in monitoring accuracy resulted in a slightly negative effect of metacognitive regulation on objective regulation. Mean values in monitoring accuracy resulted in near to no effect, whereas values one standard deviation above the mean resulted in a clearly positive effect of metacognitive regulation on objective quality of regulation.

4. Discussion and conclusion

The aim of our study was to experimentally research two ways of guiding self-regulated learning: by prompting monitoring judgments (asking for binary, item-based confidence ratings) and visualising the resulting ratings during learning. With our experiment, we showed that visualisations, especially, are suitable to foster the utilisation of monitoring judgments and thus may be used to support metacognitive regulation of study.

As expected, prompting primarily affected quantitative aspects of study behaviour and visualisation primarily affected its direction, leading to a more focussed approach. Learners adapted their behaviour to their monitoring outcomes, especially if provided with visualisation, but failed to study objectively sensible items (i.e., items they were unable to solve correctly). Accordingly, learners cleared up more uncertainties if supported by prompting and visualising techniques, but test performance was not affected. This lack of effect on objective values can be explained by a moderated mediation model. The low monitoring accuracy we found in our study hampered the subjectively sensible regulation attempts (studying primarily uncertain items) from leading to objectively sensible decisions (studying incorrectly answered items) and thus to better learning outcomes. Since there is no direct relation between metacognitive study regulation and learning outcomes, changes in study regulation depend on monitoring accuracy to take effect. If monitoring and performance are not related, this detaches the meta-level from the object level, leading —in our case— to completely sensible behaviour and behavioural outcomes from a subject-centred perspective, but not from an outside perspective. Our results suggest that learners were either not able or not willing to precisely monitor their learning, which may have been partly due to the fact that the learning material included common misconceptions on diabetes mellitus, making accurate monitoring even harder. If learners lack the metacognitive skills to effectively use tacit regulatory support, there might be more need to explicitly support the learners' monitoring processes. Apart from the possibility of a lack of skill, prompting may also disrupt the learning processes (Bannert & Reimann, 2012; Dempsey & Driscoll, 1996). If perceived as a distraction, learners might limit the effort put into the monitoring judgments, limiting their usefulness in the long run. The learners' perception of usefulness might be a moderating factor in the usage of support provided and should be considered explicitly in further research.

While monitoring accuracy certainly was a limiting factor in the usefulness of the provided support, the actual extent of the problem cannot be fully captured by the data assessed. Monitoring accuracy measures with regard to the learning tasks might have been tainted by the 50% chance of guessing correctly hampering the validity of monitoring indices. By using binary items to assess and display monitoring judgments, we took an uncommon decision in metacognitive research. Usually, metacognitive ratings are primarily used to assess metacognitive processes or outcomes, while in our study we fed them back to the learners as implicit guidance. Therefore, we used binary ratings (tasks as well as confidence ratings) to support ease of understanding and interpretation by limiting the complexity of the design. However, such measures also limit the conclusiveness of the results. The visualisation does suggest to decide between need and no need for further attention, but also ignores the possibility of more fine-grained usage of metacognitive ratings, for example to plan and prioritise items according to pre-set goals (Ariel et al., 2009). There are various strategies for how to approach learning material based on discrepancy reduction (Thiede & Dunlosky, 1999) or a region of proximal learning approach (Metcalfe & Kornell, 2005), both with different implications for learning. We took the decision to leave sufficient time to

access additional material (up to 20 minutes) with the option to end the process earlier. This procedure is realistic for self-regulated learning scenarios, as there are time constraints yet learners basically decide how long to study. However, narrower time constraints may alter strategic approaches. For example, strategies can shift during learning if time is running out (shift-to-easier-material, Dunlosky & Thiede, 2004). Son and Sethi (2006) argue that the nature of the learning curve as well as time constraints impact optimal learning strategies. Again, due to the binarity of our confidence ratings, we cannot differentiate those strategies to analyse study decisions in more detail, but we need to be aware that visualisations simplify complex concepts and focus attention towards specific aspects of metacognition (in our study, the simplification was maximised for salience and comparability). Thus, depending on how the information is pre-processed and displayed, visualisations may be more suggestive of one strategy than the other. It is possible that this design hampers more advanced processing and it might be useful to scale up the design in a further study, trying to find an optimal level weighing grain-size and complexity. More research is needed to investigate the effects of how gathering and visualising information affects the way the information is perceived and used (Buder, 2011) and how this can be used to best support learning processes. Thus, necessary next steps to take are developing scales that best represent learners' metacognitive status to gather valid, reliable and useful information and combining them with ways to visualise this information for most efficient utilisation that matches the needs of the learners. Additionally, further studies should include measures to analyse the nature of the learning curve as well as the strategic approach in combination with different visualisation methods to guide learners towards effective and meaningful study decision. Simultaneously, it would be an asset to know whether learners actually perceive such metacognitive visualisations as helpful and disencumbering.

The results of our study support findings of studies conducted with judgments of learnings that have shown that judgments might not be explicitly generated automatically, but only be constructed in response to the trigger question (cf. Mitchum et al., 2016; Soderstrom et al., 2015). This prompting function has been shown to alter learning processes for judgments of learning and our study supports this notion for RCJs. This raises the relevant question of the external validity of metacognitive research building on self-report judgments. While literature on metacognition has addressed shortcomings of subjective judgments – for example, Winne (2010) described a variety of self-report shortcomings with regard to self-regulated learning – empirical studies often fail to explicitly acknowledge that asking for monitoring judgments does prompt learners to evaluate their learning. If habitual learning behaviour is targeted by the research conducted, the reactivity of the design is hard to argue with. Thus, understanding the prompting effect of monitoring judgments is essential in order to assess and quantify its impact on metacognitive research.

Self-report is not only problematic because of its possible reactivity. The validity of self-report measures is questionable and our study relied heavily on self-report judgments. Metacognitive judgments for example require learners to assess their metacognitive status and transform it to a given scale. While this process may flaw the outcome to some extent, it still targets the to-be-assessed concept directly (metacognitive judgments aim directly at assessing the learners' subjective view on cognition, not at assessing cognition itself; cf. Nelson & Narens, 1990), making self-report less problematic. This is different for mental effort, as the target concept (mental effort) does not directly equal the assessed variable (subjective perception of effort). More direct measures of mental effort like dual-task methodology are not appropriate for testing instructional methods, since they divert resources away from the primary task (e.g., Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Future studies should explicitly target the effects on mental effort by using physiological measures or dual-task methodology to more accurately assess how the additional monitoring activity and the visualisation of monitoring outcomes affects mental effort. Further, a subjective one-item sensor can only be a rough indicator for actual effort needed. Although one-item sensors for perceived mental effort have been shown to be reliable and sensitive measures (Paas, Merriënboer, & Adam, 1994), we cannot conclude with certainty that our treatments did not affect the mental strain put on learners. Additionally, a one-item measurement prevents distinctions from being made between cognitive resources dedicated to learning and to interfering activities. With more possibilities to differentiate between different sources of mental effort, studies could focus on interventions targeting processes which may be useful for some (e.g., inexperienced) learners, but prove detrimental for others (e.g., experienced learners). Thus, the effort involved increases for very different reasons (cf. Kalyuga, Ayres, Chandler, & Sweller, 2003). For example, for learners who are spontaneously and continuously monitoring their learning, being additionally asked to transform this experience on a given scale might cause detrimental redundancies, while for inexperienced learners it might trigger beneficial monitoring processes. Differential effects are not limited to prompting: On the one hand, visualisations might be helpful for some learners, relieving their cognitive system of efforts to re-construct this information on the fly to use it to direct their learning (resources which might then be freed up for learning processes). On the other hand, visualisations might just add load for learners who do abstain from using this particular information to direct their learning or prefer or even need the information in a different form (different grain-size, more-dimensional, etc.). Thus, effects might differ for learners according to their cognitive abilities. For example, differences in working memory capacity may affect how heavily learners rely on externalisations to relieve their working memory. Some learners supported by externalisations may profit mainly from the working memory relief, while others may profit more from the guiding effects of externalisations. It was beyond the scope of our study to extract the effects of guiding and cognitive relief, but further studies may focus directly on the specific mechanisms involved and take cognitive resources into account.

Another methodological limitation of our study is that the sample consisted of university students only. While we acknowledge that university students may not validly represent the whole population of learners, we have no reason to assume this sample to differ greatly from other university students (with an exception of students of medicine, which were excluded due to the medical topic involved). Thus, our results may not apply to non-university students and should be replicated with other populations, especially a sample with a different educational background. Since our intervention is designed to support learners building on their own competencies, this may be even harder for learners with less metacognitive skills. We can assume that university students may – overall – possess higher metacognitive skills than the general population due to their experience in (successful) self-regulated study, so the support may have greater effects on this sample. On the other hand, it may also interfere with already developed scripts that learners have established and might thus work better with less experienced learners. Our study was not designed to answer these questions and further studies should replicate these findings with other populations and integrate variables to explain possible differences (e.g., metacognitive skills, working memory capacity, intelligence or prior knowledge).

While we investigated self-regulated learning in a very individualistic environment, modern learning is not done in isolation,

but highly affected by others via social learning scenarios (e.g., using social media as a source). Mixing methods from collaborative research with metacognitive research is a step towards merging those fields. Recently, (self-)regulatory processes have been integrated in models of collaborative learning (Järvelä & Hadwin, 2013) and visualisations may be used to support such scenarios (Miller & Hadwin, 2015). Providing information on learners' metacognitive evaluations may not only inform the learner her-/himself, but may also trigger essential co- and shared regulation processes. In turn, other learners may be a valid source of information supporting learners in identifying gaps in knowledge or misconceptions and thus supporting monitoring. Explicitly integrating social context into metacognitive self-regulation research and metacognitive research into collaborative learning is an obvious conclusion and should increasingly be addressed in research.

The overall goal of this study was to find ways to support learners in their own self-regulation efforts. This research is especially relevant when we consider how learning has changed during the last decades. In contrast to very explicit and "enforced" methods to externally structure learning processes, the focus has shifted towards empowering learners and supporting their self-regulated learning processes. Thus, enabling learners to make relevant and sensible decisions during self-regulated learning themselves is vital and our results suggest that prompting and visualising monitoring judgments may at least support some of the required processes. However, prompting monitoring and visualising the outcomes may not only be applied by teachers as a method to train learners to incorporate such strategies into their learning processes. Tools to prompt and visualise monitoring may easily be included in digital textbooks or web-based learning scenarios, enabling students on a larger scale to take control over their learning processes without falling back to habitual, non-reflective behavioural patterns due to limited cognitive capacities or convenience. While much research is done to improve control-based monitoring, research on finding ways to foster the utilisation of monitoring to control learning (monitoring-based control) is still scarce. Thus, the results of our study suggest that assessing and visualising monitoring judgments may be one avenue to explore further and – in combination with interventions to improve monitoring accuracy – may tacitly guide students' self-regulated learning. Such an approach has the potential to enable learners to remain agents of their own learning (cf. Hacker, Dunlosky, & Graesser, 2009) – with adequate support to make informed study decisions.

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Learning and Instruction 54 (2018) 47

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Corrigendum

Corrigendum to "Prompting and visualising monitoring outcomes: Guiding self-regulatory processes with confidence judgments" [Learning and Instruction 59 251–262]

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In section 3.1.2., the inferential data regarding hypothesis 2 contains an error: the data in the paper underestimates the *Z*-score and the effect size *r* by a decimal place. It should read: "Due to violations of the normality assumption, we conducted a Mann-Whitney-U-test, which revealed a significant difference in study regulation between the two groups ($U = 62.00$, $Z = -5.739$, $p < 0.001$, $r = 0.74$)."

Furthermore, in section 3.2.1. Table 4 states descriptive data of task- and test-performance. However, the information designating the variables contains an error: the headings "performance knowledge test" and "performance learning tasks pre" have been interchanged. The corrected version of the table is shown below:

Table 4
Descriptive statistics on knowledge (test performance) per condition.

Condition	*N*	performance knowledge test (max. = 25)		performance learning tasks pre (max. = 20)		performance learning tasks post (max. = 20)	
		M	*SD*	*M*	*SD*	*M*	*SD*
control	32	12.72	3.14	10.59	1.83	12.38	1.81
prompting	32	12.78	3.51	10.34	2.24	12.41	2.33
visualisation	31	12.90	2.71	11.23	2.06	13.13	1.93
overall	95	12.80	3.11	10.72	2.06	10.72	2.06

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Study 2: How socio-cognitive information affects individual study decisions

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How Socio-Cognitive Information Affects Individual Study Decisions

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Abstract: Metacognitive self-regulation theories assume that individual monitoring guides study decisions. However, self-regulated online learning is not done in isolation and inherently social. Group awareness research suggests that socio-cognitive information may be a strong asset to collaborative and individual learning. Integrating individual research traditions into a social setting, our experimental study ($N = 61$) investigates how visualizing socio-cognitive information influences core individual learning processes, especially the search for information, the learners' self-evaluations of knowledge and learning outcomes. While on the surface study behaviour seemed not to be affected by the availability of socio-cognitive information, more profound analyses revealed that learners provided with partner information did rely less heavily on initial self-evaluations, but adapted their evaluations and focused more on the partner information provided. Knowledge gain was not affected. In conclusion, social context can be an important factor in self-regulation emphasizing that individual and collaborative research traditions may complement each other.

Introduction

Open learning environments offer the opportunity for students to choose when and what to learn and how to search for what information, in short: to make important study decisions. Consequently, it is no surprise that research on self-regulated learning in online education increased tremendously in the last years (Tsai, Shen, & Fan, 2013). But online learning is not only self-directed, but also social by nature (Shea & Bidjerano, 2010). With a growing body of web-technology and more and more information available online, self-regulated learning is not done in enclosed spaces and, maybe more importantly, not done in isolation. Further, regulated learning is inherently social, because regulating learning means interacting with an environmental and social context (Järvelä & Hadwin, 2013). Learners may encounter differing opinions challenging the learners' knowledge and creating socio-cognitive conflicts, thus initiating further learning processes. Consequently, we can assume that self-regulated learning is severely influenced by its social context. In collaborative research, social context information is seen as a key prerequisite of meaningful social interaction and thus frequently visualized via (cognitive) group awareness tools which explicitly focus on providing socio-cognitive information, i.e. information on other learners' cognitions, to foster individual as well as collaborative learning processes and outcomes (Janssen & Bodemer, 2013). Integrating individual research traditions in a social setting, our study investigates how visualizing socio-cognitive information influences core individual learning processes, especially the search for information, learners' self-evaluation of knowledge, and learning outcomes.

Background

Metacognitive research suggests that self-regulated learners use their monitoring outcomes to guide their study decisions (Nelson & Narens, 1990). One thoroughly researched metacognitive concept is the individual confidence in one's knowledge or answers, which might act as a sensor for the need to re-study material (Thiede, Anderson, & Therriault, 2003) or influence how much time is spent on it (Dunlosky & Ariel, 2011). It can also support learners in prioritizing and sequencing their learning processes, which is especially important with time constraints (Son & Sethi, 2006). While this usually works well for good self-regulated learners, it relies heavily on the individual skills to monitor the learning progress or outcome (Thiede, 1999). Unfortunately, research also suggests that learners are often overconfident with regard to their knowledge (Pressley, Ghatala, Woloshyn, & Pirie, 1990). This might hamper learning progress due to ineffective study decisions, e.g., learners might feel confident about their knowledge and stop studying early even though they would have needed further study trials to reach their goals (Dunlosky & Rawson, 2012).

There are a number of external sources to inform self-evaluation processes. For example, external evaluations of learning operations or products provided by experts may help to adjust learning strategies and / or monitoring judgments (Butler & Winne, 1995). Conversely, metacognitive judgments also influence the way learners perceive and use externally provided information (Kulhavy & Stock, 1989). Confidence has been shown to influence feedback processing, as well as feedback effects (Butterfield & Metcalfe, 2006). One prevalent theory

is that unexpected feedback (pointing out errors committed with high confidence) motivates deeper elaboration of the feedback message and thus improves learning outcomes (Fazio & Marsh, 2009).

Another source of information informing the individual self-evaluative system is a community or group. Information from large as well as small learning communities may help learners to re-evaluate or even validate (falsify or verify) their knowledge. In collaborative settings, but also in individual online learning, learners may encounter competing and maybe even conflicting opinions of other learners. Comparing one's own knowledge with other learners' externalized knowledge related information can be a strong asset to learning, thus making comparability a key feature of group awareness tools (Bodemer, 2011). Being confronted with opposing points of view constitutes socio-cognitive conflict (Bell, Grossen, & Perret-Clermont, 1985). Within collaborative learning scenarios, socio-cognitive conflicts have been shown to foster learning processes and outcomes (Bodemer, 2011; Johnson & Johnson, 2009; Mugny & Doise, 1978), at least for epistemic conflicts (Darnon, Doll, & Butera, 2007). They are seen as an important motor for collaborative as well as individual learning (Mugny & Doise, 1978). If confronted with conflicting information about the learning subject, the learners own hypotheses are challenged and they are obliged to explain and maybe even defend or backup their position (Johnson & Johnson, 2009) or integrate the differing views (Darnon et al., 2007). Moreover, conceptual conflict has been shown to foster an active search for information due to an increase in epistemic curiosity (Lowry & Johnson, 1981). Within the context of self-regulated learning, cognitive conflicts suggest re-evaluations of one's own cognitions, e.g., they may introduce uncertainty (Buchs, Butera, Mugny, & Darnon, 2004). As a consequence, learners should be prone to initiate search processes to come to a satisfying solution, e.g., to validate one position (Buchs et al., 2004), but this might depend on the interplay of self- and partner-evaluations (Mugny, Butera, Sanchez-Mazas, & Perez, 1995).

While research done in these areas highly suggests that socio-cognitive information alters individual learning processes (e.g., search processes), existing studies only sparsely integrate individual research traditions on metacognitive self-regulation into a social or even collaborative perspective. Contributing in closing this gap, we investigated if and how individual study decisions during self-regulated learning (especially the search for information) are affected by socio-cognitive information about another learner. Thereby we focussed on the interplay of three potentially relevant variables: the individuals' self-evaluation of knowledge (own confidence), the other learners' self-evaluation (partner confidence) and their conflict status (does the partners' knowledge challenge (conflict) or support (consent) own knowledge). The following research questions were addressed:

1. How does the presence of partner information change the selection of additional information?
2. Does the presence of partner information change cognitive or metacognitive learning outcomes?
3. How do learners take their own confidence, the partners' confidence as well as the partners' answers in comparison to own answers (conflict status) into account when selecting additional information?

Methods

The study took place in early summer (May – June) 2014. Data was assessed in the course of a Bachelor's Thesis (Geerdes, 2014). 63 participants took part in the experiment, from which two had to be excluded due to computer failure, which left us with $N = 61$ participants included in our sample. They were all university students, mainly enrolled in a BA or MA course on Applied Cognitive and Media Science (47 female, 14 male). Their age ranged from 18 to 28 years with a mean age of 21.53 ($SD = 2.09$). All experiments were conducted in our research lab; instructions and materials were given via computer. Learners were randomly assigned to one of two research conditions: with and without socio-cognitive partner information available during learning.

Material and procedure

After welcoming and declaration of consent, the participants received some information about the procedure of the experiment and filled out a demographics questionnaire assessing age, sex, and university course. Then they were all presented with a 970-words text on immunology (adapted from material used in a study of Dehler, Bodemer, Buder, and Hesse, 2011, slightly shortened and re-written) and instructed to read the text carefully for up to 20 minutes. When they had finished, they were asked to answer 20 learning tasks, each consisting of a statement they were asked to judge as being true or false (cf. Figure 1). In addition, they were asked to give a confidence rating for each answer by stating on a binary scale if they were sure or unsure that their answer was correct. The answer was spatially coded (true: top, false: bottom), the confidence was color-coded (high confidence: filled-green, low confidence: hatched white-green) (cf. Figure 1). Afterwards, they were again presented with these 20 tasks as well as their answers and confidence ratings and were given up to 15 minutes to request and study additional information on as many tasks as they wanted to by clicking on a respective button provided for each task. They were also able to change their answers and/or confidence ratings. While learners

without partner information (*no partner information* condition) received only their own answers and confidence ratings, learners with partner information (*partner information* condition) additionally received bogus partner information generated by a fixed algorithm, which ensured that partner information was roughly balanced with regard to conflict status and partner confidence for each confidence level (ignoring the validity of the answers). After this second learning phase, participants were all asked to answer the learning tasks again from scratch, including confidence ratings. Finally, they took a knowledge test consisting of 19 questions (four options, single choice format), which assessed the learned concepts more deeply. Again, confidence in each answer was assessed, this time on a six-point Likert scale ranging from "not sure at all" (0) to "absolutely sure" (5).

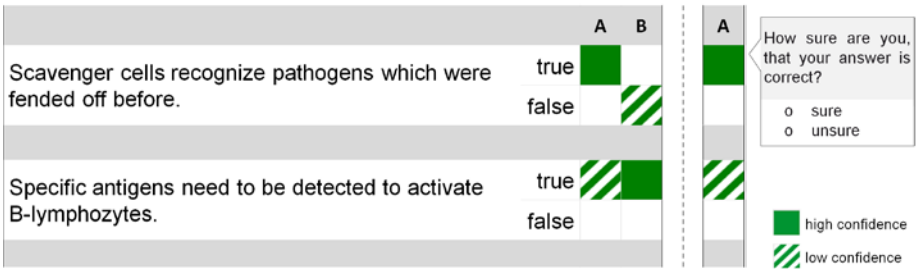

Figure 1. Examples of learning tasks and confidence ratings with (left) and without (right) partner information.

Dependent variables

In order to answer our research questions, we assessed how many and which additional information the learners requested during the second learning phase and in what order and how long they studied the information. To find out if information requests coincided with (low) confidence ratings, we computed within-subject correlations (a method used in metacognition research to describe regulation of study, cf. Thiede, 1999; Thiede et al., 2003). For the *partner information* condition, we also computed a correlation index between conflict status and information requests to capture its influence on learning behaviour. To better understand the interplay between own confidence, partner confidence and conflict status (resulting from a comparison between own and partner answers) on their influence on information requests, we assessed the percentage of information requests for each constellation for the *partner information* condition. Moreover, we assessed performance and confidence levels in the learning tasks and in the knowledge test by counting correctly solved or confident answers and computed a mean confidence for the post test. We assessed relative monitoring accuracy in the form of within-subject phi- or gamma coefficients for each participant (cf. Schraw, Kuch, & Gutierrez, 2013). To analyze the sequence of information requests in conjunction with information on individual confidence (both conditions), partner confidence and conflict status (*partner information* condition only), we ranked the information requests in order of first appearance and computed a mean rank per person for each value (e.g., low) of each variable (e.g., confidence). To eliminate the influence the number of appearances of each value has on its mean rank (mean rank increases automatically with the number of appearances regardless of selection strategy), we computed mean rank differences within each binary variable instead of using the individual values (e.g., [$\text{mean\_rank}_{\text{HighConfidence}} - \text{mean\_rank}_{\text{LowConfidence}}$]). The magnitude of the resulting figure informs about the extent learners give timewise priority to one value before the other, the algebraic sign tells us which one it is.

Findings

How does partner information change the selection of additional information?

To analyse and compare the selection of additional material, we matched the answering patterns of the learners (and their bogus learning partner) with the event of selecting additional information. To compare the selection agendas of the two experimental conditions, we first counted to how many tasks the learners in each group requested additional information and for how long they studied each one (cf. table 1). *t*-tests for independent samples showed no significant differences between the groups for neither the number of information requests ($t(59) = 0.50$, $p = .619$, $d = 0.13$) nor the mean study duration per request ($t(59) = 0.11$, $p = .914$, $d = 0.03$).

In a second step, we analyzed if the availability of partner information changed how learners chose the information to study. Without partner information 79.59% ($SD = 21.05$) of the information requested regarded items answered with low confidence, while with partner information it was only 63.78% ($SD = 23.17$). This difference was statistically significant ($t(59) = 2.78$; $p = .007$, $d = 0.72$). To further evaluate if learners really use their own confidence ratings to choose additional information, but also to see if conflicting opinions might influence these decisions, we computed within-subject correlations between the initial level of individual

confidence (high vs. low) or the conflict status (presence or absence of conflict) and the presence or absence of a request for information to each task, resulting in individual within-learner phi-coefficients (cf. table 1). *t*-tests on one sample confirmed a significant positive mean relation index between (lack of) confidence and information requests for the *no partner information* ($t(27) = 9.45$, $p < .001$, $d = 1.77$) as well as the *partner information* condition ($t(29) = 5.55$, $p < .001$, $d = 1.00$) and a positive relation between conflict and information requests in the *partner information* condition ($t(29) = 5.90$, $p < .001$, $d = 1.09$). *t*-tests for independent samples showed that mean phi-coefficients between confidence and information requests differed significantly between the two conditions, with the *no partner information* condition having significantly higher coefficients than the *partner information* condition ($t(56) = 2.67$, $p = .010$, $d = 0.71$), meaning that confidence ratings were more strongly related to information requests if partner information was not available. A *t*-test for dependent samples comparing the phi-coefficient within the *partner information* condition (own confidence vs. conflicts) showed no difference, meaning neither own confidence nor conflict status was more strongly related to information requests than the other ($t(29) = 0.29$, $p = .774$, $d = 0.05$).

Table 1: Descriptive statistics on dependent variables

	partner information								
	available			**not available**			**overall**		
	n	*M*	*SD*	*n*	*M*	*SD*	*N*	*M*	*SD*
overall study behavior									
…number of information requests	32	11.81	4.48	29	12.38	4.35	61	12.08	4.39
…study duration per information (in seconds)	32	14.58	8.68	29	14.36	7.32	61	14.48	8.00
regulation of study / within-subject phi-coefficient(*)(**)									
…between information requests and own confidence	30	.35	.35	28	.59	.33	58	.47	.36
…between information requests and conflict status	30	.33	.30	--	--	--	--	--	--
performance / number of correctly solved items									
…in knowledge test	32	5.03	2.07	29	5.07	1.60	61	5.05	1.85
…in learning tasks pre	32	13.13	2.06	29	13.38	2.03	61	13.25	2.03
…in learning tasks post	32	15.13	1.91	29	15.45	1.68	61	15.28	1.80
confidence level									
…in knowledge test (mean confidence level)	32	2.02	0.82	29	2.01	0.85	61	2.02	0.82
…in learning tasks pre (number of certain items)	32	9.91	3.60	29	9.62	3.13	61	9.77	3.36
…in learning tasks post (number of certain items)	32	14.50	3.52	29	15.86	2.80	61	15.15	3.25
monitoring accuracy									
…knowledge test (gamma-coefficients)	32	.21	.45	29	.07	.42	61	.14	.44
…learning tasks pre (phi-coefficients)	32	.20	.22	29	.11	.25	61	.15	.24
…learning tasks post (phi-coefficients)(*)	31	.26	.23	26	.22	.30	57	.24	.26
sequencing of study process / mean rank differences(***)									
…own confidence	32	2.20	3.45	29	3.63	4.02	61	2.88	3.77
…conflict status	32	3.96	3.02	--	--	--	--	--	--
…partner confidence	32	0.03	1.45	--	--	--	--	--	--

(*) due to invariability of one factor, no correlation indices could be computed for some participants
(**) positive values indicate that additional information was requested mainly to uncertain answers / conflicts
(***) positive values indicate that uncertain / partner uncertain / conflicting items were considered first

Does partner information change cognitive and metacognitive learning outcomes?

In order to find out if the presence of partner information influences learning outcomes, we compared how many learning tasks the learners were able to solve correctly pre and post learning and how many items they were able to solve correctly in the knowledge test (cf. table 1). A *t*-Test for independent samples showed no significant group differences in the knowledge test ($t(59) = 0.08$, $p = .937$, $d = 0.02$). Please note that performance in both groups was just beyond chance, indicating high test difficulty. A two-factorial ANOVA with repeated measures on the learners performance in the learning tasks showed a significant main effect of time ($F(1, 59) = 56.32$, $p < .001$, $\eta_p^2 = .49$) with the learners getting better from pre to post, but neither a significant main effect of condition ($F(1, 59) = 0.49$, $p = .488$, $\eta_p^2 = .01$), nor an interaction ($F(1, 59) = 0.02$, $p = .899$, $\eta_p^2 < .001$).

To see if partner information does rattle individual confidence and if being confronted with potentially conflicting information does enhance self-evaluation processes, we compared individual confidence levels as well as monitoring accuracy. We first compared how many learning tasks the learners solved confidently pre and post learning and how mean confidence differed between the groups in the knowledge test (cf. table 1). *t*-tests showed no difference in confidence levels in the knowledge test ($t(59) = 0.06$, $p = .954$, $d = 0.02$). In the learning tasks,

there was a significant effect of time with learners becoming more confident from pre to post ($F(1, 59) = 219.06$, $p < .001$, $\eta_p^2 = .79$) and a significant interaction between time and condition ($F(1, 59) = 5.07$, $p = .028$, $\eta_p^2 = .08$) with the confidence levels of learners with partner information not rising as much as without partner information from pre to post. There was no main effect of condition ($F(1, 59) = 0.50$, $p = .482$, $\eta_p^2 = .01$). Subsequently, we compared monitoring accuracy again with regard to the learning tasks pre and post learning (within-subject phi-coefficients between confidence and performance) and the post-test (within-subject gamma-coefficients between confidence and performance). Descriptive statistics are available in table 1. We conducted a Mann-Whitney-Test (due to violations of the normality assumption) to compare the gamma-coefficients between the groups, but found no significant differences ($U = 558.50$, $Z = 1.37$ $p = .172$, $r = .17$). Accuracy on the learning tasks showed a marginally significant effect of time ($F(1, 55) = 3.49$, $p = .067$, $\eta_p^2 = .06$), but neither an effect of condition ($F(1, 55) = 1.73$, $p = .194$, $\eta_p^2 = .03$), nor an interaction ($F(1, 55) = 0.26$, $p = .611$, $\eta_p^2 = .01$). It is worth mentioning that the correlation-coefficients were quite low in general indicating a weak linkage between self-evaluation and performance (low monitoring accuracy).

How do learners consider own and partner information when requesting information?

To investigate how learners take their own confidence, their partner's answer as well as confidence into account when choosing where and when they need additional information, we first focussed on the *partner information* condition and computed which answer patterns led to requests for additional information. Table 2 visualizes each pattern as well as the mean percentage (and standard deviation) of information requests.

Table 2: Mean information request percentage per answer pattern (*partner information* condition, $n = 28^{(*)}$)

conflict				consensus			
 self uncertain 		 self certain 		 self uncertain 		 self certain 	
partner uncertain	partner certain	partner uncertain	partner certain	partner uncertain	partner certain	partner uncertain	partner certain
$M = 91.96$ $SD = 23.07$	$M = 78.87$ $SD = 36.04$	$M = 51.49$ $SD = 36.43$	$M = 65.77$ $SD = 34.79$	$M = 73.21$ $SD = 36.67$	$M = 65.48$ $SD = 43.49$	$M = 25.00$ $SD = 35.57$	$M = 16.96$ $SD = 33.37$

(*) due to highly unbalanced confidence ratings which did not allow for all constellations, four learners had to be excluded

We computed an ANOVA with our three binary within-subject independent variables describing each pattern (own confidence: high vs. low, partner's confidence: high vs. low, partner's answer: conflicting vs. consenting) and measured the impact on the actual percentage of information requests following each constellation (cf. table 3). Figure 2 illustrates the three-way interaction. Please note that the data was heavily skewed and not normally distributed. We used parametric tests, because methods to model multi-factorial non-parametrical data are scarce. Thus, the results of the inferential analysis should be treated with caution.

Table 3: Results of ANOVA regarding effects of within-subject variables on information request percentage

Effect	**Independent Variable(s)**	***F***	***df1***	***df2***	***p***	η_p^2
main effect	conflict	22.04	1	27	<.001	.45
	confidence	37.38	1	27	<.001	.58
	partner confidence	1.69	1	27	.205	.06
1st order interaction	conflict * confidence	13.30	1	27	.001	.33
	conflict * partner confidence	2.49	1	27	.126	.08
	confidence * partner confidence	5.01	1	27	.034	.16
2nd order interaction	conflict * confidence * partner confidence	6.09	1	27	.020	.18

As also observed while studying the phi-correlations regarding the first research question, these results strengthen the assumption that confidence as well as conflicts are highly responsible for information requests. Further, the results indicate that they interact in doing so. Looking at the plots in Figure 2, it seems that individual confidence matters more, if there is an agreement between learning partners and less, when there are conflicting opinions involved. In contrast, the statistically significant interaction between own and partner confidence on closer inspection seems to be explained by the second order interaction, thus we abstain from interpreting it, but focus on the second order interaction: in case of consenting opinions, partner confidence does not seem to impact information requests – the only information relevant is individual confidence. In the conflict case this is very

different. Here, both confidence variables seem to interact. While conflicts with unsure partner and a sure self triggered the least information request (an unsure partner disagreeing might not be regarded as relevant), a conflict with both partners unsure triggered the most. If the partner is sure of him/herself, the own confidence does not seem to matter too much – information request rate is quite high in both cases.

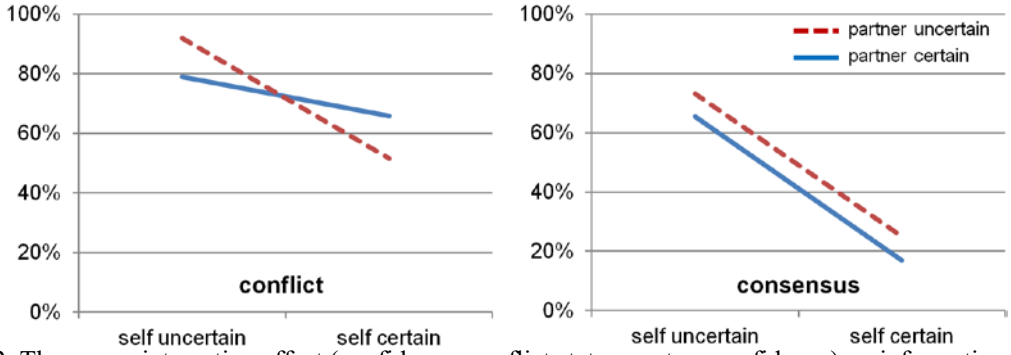

Figure 2. Three-way interaction effect (confidence, conflict status, partner confidence) on information requests.

In a second step we conducted sequential analyses to assess the order of proceeding for the learners in each group. We computed mean rank differences for every variable of interest (procedure described above) to calculate, if learners give precedence to a specific value, e.g., if they consider items with conflicting opinions before considering items with consenting opinions (cf. table 1). *t*-tests on one sample show that own confidence ($t(31) = 3.60$, $p = .001$, $d = 0.64$) as well as conflict status ($t(31) = 7.41$, $p < .001$, $d = 1.31$) influenced the order learners in the *partner information* group requested information –the mean rank differences differed significantly from chance– but partner confidence didn't ($t(31) = 0.10$, $p = .918$, $d = 0.02$). For the *no partner information* group, Wilcoxon signed-rank test (due to violation of the normality assumption) confirmed a similar effect for individual confidence ($Z = 3.67$, $p < .001$, $r = .68$). Taking the direction into account, learners requested information on items they were uncertain about or conflicting items earlier than on items answered with certainty or consenting items. A Mann-Whitney-Test between the conditions showed a marginal effect of condition on the mean rank difference for the (own) confidence dimension ($U = 593.50$, $Z = 1.87$, $p = .061$, $r = .24$), hinting that maybe the *partner information* condition used own confidence slightly less than the *no partner information* condition. Within the *partner information* condition we additionally compared the mean rank differences for the three dimensions own confidence, partner confidence and conflict status with *t*-tests for dependent samples to see which variable showed most influential with regard to order of processing. The results showed that the effect of conflict status was significantly greater than that of own confidence ($t(31) = 2.09$, $p = .045$, $d = 0.34$) or partner confidence ($t(31) = 6.95$, $p < .001$, $d = 1.23$). Mean rank difference for own confidence was significantly greater than for partner confidence ($t(31) = 3.31$, $p = .002$, $d = 0.59$).

Conclusions and implications

Our study aimed at describing how the presence of socio-cognitive information influences individual learning processes – even without the chance to communicate, collaborate or interact with the partner. More precisely, we looked at how partner information (information about knowledge and knowledge evaluations of a potential learning partner) influences the individual search for information and learning outcomes. We expected learners with partner information to access more information and study it longer motivated by the presence of conflicting opinions, but they didn't. Differing opinions might not have the same potentially surprising effect as external feedback, if its origin is unknown (Mugny et al., 1995). Additionally, learning outcomes were not affected by the presence of partner information, but it influenced self-evaluations – although not greatly. As expected, the confidence of learners with partner information available was rattled, presumably by conflicting opinions about the correctness of answers (Buchs et al., 2004), but unfortunately this was independent of performance – if a proper re-evaluation took place, it failed to enhance monitoring accuracy. Even more, this increase in uncertainty did not lead to an increase in study behaviour (e.g., number of information requests or duration of study), but it did change its focus: While in the absence of information on learning partners learners based their study decisions (what to study when) heavily on individual confidence (as frequently reported in self-regulation research, e.g., Thiede, 1999; Thiede et al., 2003), with information on a potential learning partner present, the situation became more complex. Analysing the individual relation between information requests and confidence and conflicts we found that without partner information, own confidence was the main influential factor, with partner information it became less so, with conflicts becoming more important. Timewise, conflicting opinions seemed to capture the

learners' attention resulting in slightly higher mean rank differences for the conflict dimension than for the confidence dimension and it also seemed to lessen the effect own confidence had on the search for information as group comparisons indicated (although this difference was not statistically significant). There exist different models on how learners allocate study time and choose and prioritize information to study, mainly resulting from a discrepancy reduction model (Dunlosky & Hertzog, 1998) or a region of proximal learning approach (Metcalfe, 2009), with task constraints (Son & Sethi, 2006) and personal agendas (Ariel, Dunlosky, & Bailey, 2009) being important influential factors. Further studies should conduct more profound analyses in this area to broaden this existing research on individual self-regulation by integrating social scenarios. In our study, learners were reasonably free to select any information and they not only attended to conflicts or uncertainly answered items first, they did so primarily. Three-way interactions confirmed that –as expected from research on socio-cognitive conflicts (Lowry & Johnson, 1981)– conflicting opinions became a major influence on information search, while partner confidence had a somewhat unexpected effect: it was expected that the lower the partner confidence the lesser the experience of conflict and thus the lesser the search for information, but this was not the case. If the learning partner agreed with the individuals' opinion (consensus), information requests were solely based on individual confidence, disregarding partner confidence. If conflicts occurred, partner confidence interacted with own confidence to influence information requests. We can conclude that learners do take into account how the potential partners evaluate themselves, even though they are completely unknown. If they disagree and are sure of themselves, learners re-check their own information. If partners are uncertain about their answers, learners may still question their own answers, but especially and much more so, if they are unsure anyway. The latter case might indicate that maximum uncertainty (both uncertain) with conflicting opinions (no indication that any one answer is correct) changes our evaluation of the task, which might also lead to increased information search (a discrepancy reduction approach might indicate the farthest group distance from getting the correct answer and thus the most reason to attend to the task).

In conclusion, social context does seem to affect individual learning and we should reinforce our (theoretical and empirical) efforts to describe 21th century self-regulated learning as what it is – a communal process. Study decisions are strongly affected by the presence of socio-cognitive information. Focussing on relevant information might be enhanced by the presence of others, but may also become more complicated as more or unknown actors come into play. While this study was able to shed some light on how learners integrate knowledge of other's opinions as well as their self-evaluations to make study decisions in a highly controlled experimental setting, it was beyond the scope to analyse actual collaborative efforts. While we focussed on socio-cognitive information as a source of information to foster individual study decisions, the next logical step would be to explicitly integrate the notion of a learning partner as a source of further information – to interact, to ask, to explain, to question, in short: into an inherently collaborative learning scenario. Even though research on group awareness tools frequently incorporates socio-cognitive information into collaborative learning settings, combining it with metacognitive research by integrating self-evaluations of both partners as well as cognitive information on content-knowledge and incorporating methods of both research traditions may be a strong asset to research on collaborative as well as individual self-regulated learning.

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Study 3: Providing different types of group awareness information to guide collaborative learning

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Providing different types of group awareness information to guide collaborative learning

Running head: Group Awareness Information

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Abstract Cognitive group awareness tools are a means to guide collaborative learning activities by providing knowledge-related information to the learners. While positive effects of such tools are firmly established, there is no consistency with regard to the awareness information used and a wide range of target concepts exist. However, attempts to compare and integrate the effects of different types of group awareness information are rare. To reduce this gap, our study aims to compare metacognitive and cognitive group awareness information, combining CSCL research and research on metacognition. In our experimental study, 260 university students discussed assumptions on blood-sugar regulation and diabetes mellitus in dyads. We tested the effects of providing cognitive group awareness information on the learners' assumptions (factor 1) and metacognitive group awareness information on their confidence (factor 2) on individual metacognitive and cognitive outcome measures and on the learners' regulation of the collaborative process, i.e., the selection of discussion topics based on confidence in knowledge (confidence-based regulation) and based on agreement regarding assumptions (conflict-based regulation). We found that visualizing information strongly impacts joint regulation and that learners seem to integrate the information provided to steer their learning. However, while the learners gained knowledge and confidence during collaboration, providing group awareness information did not have the expected impact on learning outcomes. Reasons and implications of these results in light of previous research on metacognition and group awareness are discussed.

Keywords Computer-supported collaborative Learning * Group Awareness * Guidance * Metacognition * Self-regulated Learning

Introduction

Collaborative learning has great potential to strengthen learners' content-related and meta-skills. However, learners face many challenges when attempting to learn together, especially concerning communication and coordinating their activities (e.g., G. Erkens, Jaspers, Prangsma, & Kanselaar, 2005; Janssen, Erkens, & Kanselaar, 2007). Thus, guidance is considered to be an important part of (computer-supported) collaborative learning (e.g., Fischer, Kollar, Stegmann, & Wecker, 2013). Research on implicit guidance is focusing on approaches that support learners' self-regulation attempts and foster learners' agency (cf. Hacker, Dunlosky, & Graesser, 2009). Such approaches provide relevant information for learners without giving them explicit structure or instructions, leaving the locus of control with the learners and building directly on individual skills (Hesse, 2007; Janssen & Bodemer, 2013; Miller & Hadwin, 2015).

One prominent way to implicitly guide collaborative learning processes is the provision of knowledge-related group awareness information (cf. Janssen & Bodemer, 2013). Group awareness (GA) is the state of being informed about relevant aspects of group members or the group as a whole (Bodemer & Dehler, 2011; Bodemer, Janssen, & Schnaubert, 2018), for example their knowledge and skills. Collaborating learners need an awareness of such aspects to effectively steer the collaboration process and adjust it to the needs of the group (Bodemer & Dehler, 2011; Fransen, Kirschner, & Erkens, 2011; Soller, Martínez, Jermann, & Muehlenbrock, 2005). If information about the cognitions of other learners is missing, learners may tend to overestimate similarities (Nickerson, 1999) and might thus fail to detect relevant differences in knowledge and/or opinions. Although such information can be provided within the learning situation by using specifically designed tools (GA tools) that support learners' formation of GA (cf. Bodemer et al., 2018), there is a lack of research investigating how different types of knowledge-related GA information within such tools guide learning processes and how this affects learning outcomes.

Group awareness tools

GA tools facilitate GA by providing learners with relevant information about their learning partners. While GA tools used for computer-supported collaborative learning (CSCL) may target various types of learner-related information (including cognitive and/or social variables; cf. Janssen & Bodemer, 2013), they usually process the information in a three step manner: they assess relevant information, transform it and feed it back to the learners, usually by visualizing it in an adequate way (cf. Buder & Bodemer, 2008). All three steps may highly depend on technological support to assess the information (e.g., using computer-based questionnaires or logfile data), transform the information (e.g., by using specific algorithms to condense and thus pre-interpret the information), and visualize it (e.g., by converting the information into a graphical representation within the learning environment).

What sets these tools apart from other tools based on learning analytics is the target audience. While other educational tools relying on learner data often feed information to educators or adaptive systems (e.g., via teacher dashboards, adaptive learning environments, computer-based pedagogical agents), GA tools feed the information back to the learners themselves, meaning that data subjects are identical to data clients (cf. Greller & Drachsler, 2012). This is a vital distinction, because it requires the information to be adapted to characteristics of the learners as target audience as opposed to educators or tool designers. Limitations of the learners as data clients thus put

restrictions on the usage of learning analytics as it is assumed that learners are often not competent enough to learn from learning analytics reports unsupported (Drachsler & Greller, 2012). As a consequence, the provision of GA information has to be tailed to the needs of the learners. Several researchers thus point out, that awareness information has to be perceived as useful (e.g., Janssen, Erkens, & Kirschner, 2011; Nova, Wehrle, Goslin, Bourquin, & Dillenbourg, 2007) and authentic (e.g., Engelmann, Dehler, Bodemer, & Buder, 2009), easy to understand and interpret (e.g., Bodemer, 2011; Dehler, Bodemer, Buder, & Hesse, 2011), and saliently displayed (e.g., Bodemer & Dehler, 2011). This has an impact on all three data processing steps, as it relates to the information itself (i.e., perceived usefulness), the assessment and transformation of the information (i.e., authenticity and interpretability) as well as the presentation (i.e., salience).

GA tools focusing on knowledge-related information (often called "cognitive GA tools", e.g., Bodemer et al., 2018) foster collaborative learning processes by making learners aware of each other's individual or their common cognitive status or processes (Bodemer & Dehler, 2011). These tools may benefit collaborative learning in several ways. By systematically processing knowledge-related information externally (assessing, transforming, presenting), they facilitate the natural formation of GA by adding an external reference (Engelmann et al., 2009) and thus relieve the learners of effortfully extracting relevant information themselves. This can be of vital importance, especially if germane learning processes take up most of the available cognitive resources. Another key function of these tools is to structure learning discourses (cf. Bodemer et al., 2018). By focusing on specific, pre-defined GA information and processing it in a specific way, GA tools offer an interpretation of the collaborative situation and thereby suggest specific courses of action beneficial to learning (via informational and representational guidance; cf. Bodemer, 2011). For example, the information provided may ease the identification of individual (or group) needs or conflicting viewpoints (Engelmann et al., 2009). If the GA information is linked to the learning material, it can focus collaborating learners on aspects of the learning material that need further attention (Bodemer et al., 2018; Bodemer & Scholvien, 2014), helping them to structure and coordinate mutual learning processes (Clark & Brennan, 1991). Further, the availability of such information may trigger beneficial collaboration processes like exchanging and explaining relevant knowledge (Dehler, Bodemer, Buder, & Hesse, 2009; Dehler et al., 2011), argumentation or elaboration (Buder & Bodemer, 2008; Dehler, Bodemer, & Buder, 2007). These processes are beneficial for learning and although they are more likely to occur during collaboration than in individual learning settings, they do not necessarily occur spontaneously (Dillenbourg, Järvelä, & Fischer, 2009; King, 2007).

GA tools may support very different processes relevant for learning. Consequently, there is a multitude of tools that provide very different kinds of information assessed in very different ways (for an overview of different tools see Janssen & Bodemer, 2013). While overall, beneficial effects have been firmly established, one of the challenges of the research field is to systematically explore how these tools foster learning (Buder, 2011) and what tool features are responsible for the effects to ultimately provide efficient and precise support for learners (Bodemer et al., 2018). Thus, our research aims at looking into a distinct feature of GA tools used for CSCL namely the type of learner-related information they portray to learn more about the guidance mechanisms involved to inform researchers, tool designers, and educators alike.

Cognitive and metacognitive information in collaboration

As stated above, GA tools that aim for guidance effects vary greatly in what information they present and thus the learning material they may bring to the learners' attention (and the processes they may trigger). *Cognitive group awareness tools* provide knowledge-related information of the group, e.g., how much learners know (M. Erkens, Bodemer, & Hoppe, 2016; Sangin, Molinari, Nüssli, & Dillenbourg, 2008, 2011), what they think (Bodemer, 2011; Engelmann & Hesse, 2010, 2011; Gijlers, 2005; Gijlers, Saab, van Joolingen, de Jong, & van Hout-Wolters, 2009), or how they judge their knowledge (Dehler et al., 2009, 2011). Research in this area usually adopts an inclusive conception of the term "cognitive" and rarely explicitly differentiates between different types of cognitive information like information about the content of knowledge and information about the learners' metacognitive evaluation of said knowledge. In this line of research, it is often assumed that asking learners to judge their own knowledge is just a short-cut for assessing their actual knowledge. However, in metacognition research, such self-evaluations are seen to have additional benefits and may represent the learner's perspective and thus serve as the basis for their self-regulatory actions. The term "metacognition" originated in the 1970s and has been conceptually described as "thinking about thinking" (e.g., Flavell, 1979). In more recent work, the term comprises of various concepts and processes relating to monitoring, controlling and/or regulating learning processes (e.g., Dinsmore, Alexander, & Loughlin, 2008) including, for example, monitoring knowledge and knowledge acquisition, and planning, controlling and evaluating learning processes.

Within the metamemory framework terminology of Nelson and Narens (1990), information on the content of learners' knowledge is information on the object level (cognitive), while information on learners' self-evaluation of said knowledge constitutes information on the meta-level (metacognitive). Since the term "cognitive" falls short of such a differentiation, we will use the broader term "knowledge-related" for these kinds of information and refer to "cognitive information" when talking about object-level information and the term "metacognitive information" when addressing meta-level information. Using a metacognition framework on GA tools may benefit CSCL research as it allows to differentiate tool effects within collaborative learning by drawing on metacognition theory and research.

Effects of cognitive information: identifying conflict

As stated above, some knowledge-related GA tools provide information on the content of cognitions of group members, such as learners' opinions or assumptions (Bodemer, 2011; Gijlers et al., 2009). If these are presented next to each other and in a similar format, they may foster comparison processes and thus promote the detection of conflicting assumptions on the topic to be learned between learners within a collaborating group (Scholvien & Bodemer, 2013). If learners are not aware of such epistemic conflicts, these conflicts may hamper progress and a shared mental representation of the material to be learned. Additionally, conflicting assumptions are an essential drive to cognitive development (e.g., Levine, Resnick, & Higgins, 1993; Mugny & Doise, 1978; see also Doise & Mugny, 1984). They provide the need to build a consensus and thus, they do not only provide the opportunity to adjust faulty assumptions, but they also provide an opportunity to elaborate on the content while discussing the positions from different perspectives and resolving the conflict in a beneficial way (Dillenbourg & Hong, 2008; Gijlers et al., 2009; D. W. Johnson & Johnson, 2009b). Conflicting assumptions are widely assumed to produce uncertainty about the correctness of assumptions (e.g., Buchs, Butera, Mugny, & Darnon, 2004; Crano & Prislin, 2006; Fraundorf & Benjamin, 2016; Koriat, Adiv, & Schwarz, 2015),

which may also trigger beneficial learning processes. However, uncertainty may prevail if learners do not get the chance to resolve these conflicts sufficiently (Schnaubert & Bodemer, 2016).

Empirically, conflicting assumptions have been found to attract attention in collaborative settings and are discussed more frequently than matching (i.e., congruent) assumptions (Bodemer, 2011). Further, they may trigger beneficial evaluation processes (Buchs et al., 2004; Doise, Mugny, & Perret-Clermont, 1975; D. W. Johnson, Johnson, & Tjosvold, 2000; R. Johnson, Brooker, Stutzman, Hultman, & Johnson, 1985; Mugny, Butera, Sanchez-Mazas, & Perez, 1995; Mugny & Doise, 1978) as well as the search for information (Buchs et al., 2004; Lowry & Johnson, 1981; Schnaubert & Bodemer, 2016) or coordination efforts of the learning process (Mugny & Doise, 1978). In sum, epistemic conflicts can be a driving force during collaborative learning. To benefit from these mechanisms, learners must become aware of the conflicts, and technology (i.e. GA tools) can help to process the necessary information in a beneficial way. Empirically, cognitive GA tools have been found to draw attention towards conflicts (e.g., Bodemer, 2011; Schnaubert & Bodemer, 2016) and have supported conflict resolution (Bodemer, 2011).

Effects of metacognitive information: identifying perceived lacks of knowledge

Other tools do not provide information on the content of learners' cognitions, but on the presence or absence (or degrees) of knowledge. This provides a basis for clearing up lacks of knowledge and has been found to be an effective means to support learning (e.g., Dehler et al., 2009, 2011; Sangin et al., 2011). Assessing knowledge from the learners' perspective allows for authentically capturing the learners' perceived need for information (Engelmann et al., 2009). Such metacognitive information has been used as a target concept for GA tools. For example, Dehler and colleagues (Dehler et al., 2009, 2011) conducted a series of studies providing learners with information on the perceived understanding of content via text comprehension ratings. Such information informs the group about (perceived) lacks of knowledge and knowledge distributions and have been found to guide communication (Dehler et al., 2009, 2011). In this research, comprehension ratings were interpreted as providing information on the presence or absence of knowledge regarding a specific topic, however, from a metacognitive point of view, these ratings provide information about the learners' metacognitions, i.e., metacomprehension.

Within metacognition research, metacognitive monitoring is seen as an essential drive for self-regulation activities (e.g., Nelson & Narens, 1990; Thiede & Dunlosky, 1999; Winne & Hadwin, 1998) as it is thought to provide internal feedback that learners can use to steer their learning processes (Butler & Winne, 1995). Empirical research in this area has repeatedly shown that the result of metacognitive monitoring of learning processes and outcomes is (causally) related to how learners control their learning (e.g., Efklides, Samara, & Petropoulou, 1999; Kornell & Metcalfe, 2006; Metcalfe & Finn, 2008; Nelson, Dunlosky, Graf, & Narens, 1994; Nelson & Leonesio, 1988; Son & Metcalfe, 2000), i.e., what they choose to study and for how long. Such metacognitive regulation can have positive effects on learning outcomes (e.g., Kornell & Metcalfe, 2006; Nelson et al., 1994), especially if monitoring is accurate and thus indicative for performance (Dunlosky & Rawson, 2012; Thiede, 1999; Thiede, Anderson, & Therriault, 2003). Further, monitoring-based (metacognitive) regulation may be fostered by visualizing monitoring outcomes (e.g., response confidence ratings, Schnaubert & Bodemer, 2017). In turn, how learners control their learning also affects monitoring (Koriat, Ma'ayan, & Nussinson, 2006). Thus, monitoring, regulation, and performance are inherently linked (cf. Special Issue Koriat, 2012).

One core metacognitive concept is response confidence (Dunlosky & Metcalfe, 2009; Nelson & Narens, 1990). Drawn from metamemory research, response confidence is an evaluation of preceding performance, i.e., performance monitoring (e.g., Dunlosky & Hertzog, 2000; Hines, Touron, & Hertzog, 2009). Thus, it takes specific test experience into account and is connected to specific assumptions about a topic rather than an overall state of learning. Empirically, it is connected to re-study decisions (e.g., Hines et al., 2009; Schnaubert & Bodemer, 2017), and feedback processing (e.g., Fazio & Marsh, 2009; Kulhavy & Stock, 1989). Moreover, it is diagnostic of performance in some circumstances (Koriat et al., 2006; Maki, 1998b, 1998a). Theoretically, confidence in own assumptions may be viewed as an essential part of knowledge itself (Hunt, 2003) and even objectively correct assumptions require a minimum of confidence to be usable in practice (i.e., to guide decision-making or behavior; cf. Leclercq & Poumay, 2004). Accordingly, confidence in test responses has also been used as additional information in knowledge assessment (confidence marking; Leclercq, 1983, 1993). Since confidence in knowledge may be directly linked to the content of knowledge (i.e., specific assumptions), confidence in responses seem to be particularly suitable to represent learners' metacognitions about their knowledge in a collaborative learning context.

Overall, within metacognition research, metacognitive monitoring and monitoring-based regulation play a crucial role in self-regulating individual learning. However, metacognitive regulation may also be affected by information on other learners' knowledge (Schnaubert & Bodemer, 2016). Within a social scenario, externalizing metacognitive evaluations of knowledge allows learners to intentionally disclose gaps in knowledge (from their perspective) and may thus be used strategically to communicate a need for information. Conversely, learners may detect gaps in their learning partners' knowledge (e.g., by viewing GA information) and use the information to support the partners' learning processes by offering and/or adapting help (Dehler et al., 2007, 2009, 2011). Adapting utterances to the properties of the listener (audience design) is vital for effective communication (Clark & Murphy, 1982) and inherently linked to the common ground of learners interacting (Clark & Brennan, 1991). While there is an increasing interest in regulatory processes within collaborating groups (e.g., socially shared regulation; e.g., Hurme, Palonen, & Järvelä, 2006; Iiskala, Vauras, Lehtinen, & Salonen, 2011; Järvelä & Hadwin, 2013; Järvelä et al., 2016; for an overview see Panadero & Järvelä, 2015), the role of the availability of metacognitive information within CSCL has received only scarce attention so far, although there are notable exceptions (e.g., Järvelä et al., 2015; however, these refer to regulatory activities like planning and task perception rather than metacognitive evaluations of knowledge and memory). Thus, despite research showing that visualizing information on (actual or perceived) lacks of knowledge draws learners' attention and can guide learning and communication processes (e.g., asking questions or providing spontaneous explanations, e.g., Bodemer, 2011; Dehler et al., 2011), there is a lack of research utilizing metacognitive GA information within the context of CSCL and explicitly linking it to metacognition research.

Interaction of cognitive and metacognitive information

While assessing the effects of both cognitive and metacognitive GA information on collaborative learning is firmly based on prior empirical evidence, the two types of information are not independent. There are various ways in which the information of multiple learners may interact and influence each other. In the following, we will briefly describe how other learners' cognitions may affect our own cognitions and metacognitive evaluations, how our own metacognitions may affect how we process

information about other learners, and how others' metacognitive evaluations may affect how much credit we give them as a source of information.

First, information on others' cognitions may be used as feedback on one's own cognitions and thus change not only the cognitions themselves, but also our metacognitive evaluation of them. For example, if a learner's assumption is supported by congruent assumptions of other learners, he/she may be ensured of his/her position. Conversely, firm beliefs may be rattled if learning partners disagree with the individual's assumption, leading to uncertainties (for an overview on social influence affecting individual confidence see Koriat et al., 2015).

However, our metacognitions (such as confidence in our knowledge and assumptions) may also affect how we process incoming information. Within research on cognitive feedback, confidence takes an important role and research indicates that feedback on errors committed with high-confidence is treated differently than feedback on errors committed with low-confidence (Hancock, Stock, & Kulhavy, 1992; Kulhavy & Stock, 1989). For example, feedback messages on high-confidence errors are studied longer (Fazio & Marsh, 2009; Kulhavy & Stock, 1989) and high-confidence errors are corrected more often than low-confidence errors (Butterfield & Metcalfe, 2001, 2006; Metcalfe & Finn, 2011). Similar effects might apply to learning partners disagreeing with low- and high-confidence assumptions, even though a learning partner is not an indisputable source like expert feedback usually is. Thus, how learners evaluate their learning partners' cognitions and competences becomes increasingly relevant and one indicator to use are the partners' own metacognitions.

Consequently, another way cognitive and metacognitive information of collaborating learners interact is that others' metacognitive evaluations may affect how we evaluate their cognitions as well. Metacognitive evaluations of distinct cognitions (like chunks of knowledge or assumptions) may be used to qualify these cognitions (Hunt, 2003; Leclercq & Poumay, 2004) since they may be treated as an indicator for comprehension (Kulhavy, Stock, Hancock, Swindell, & Hammrich, 1990), which may help learners to better understand their peer's position. For example, confidence in assumptions can have a great impact on how these assumptions are perceived. Research on source reliability and credibility has found that confidence is a major factor in estimating whether someone is a reliable source of information (e.g., Tenney, Small, Kondrad, Jaswal, & Spellman, 2011) and thus confidence is used to evaluate knowledge and competence of others as well as accuracy of the information provided (Price & Stone, 2004; Yates, Price, Lee, & Ramirez, 1996).

In sum, confidence in one's own assumptions yields information relevant to individual learning processes that can be used by other learners to judge the learning partners' cognitive status and support the joint regulation of the collaborative learning process. Since the metacognitive and cognitive level are inherently intertwined, the provision of information on both might thus have a distinct effect on learning. While it would seem logical that these two information types might interact in steering learning processes (cf. Schnaubert & Bodemer, 2016), it may also be the case that learners focus on just one aspect because they regard one type of information as more important or because they need to reduce the strain posed on the cognitive system. Thus, while mainly individual-focused research suggests interaction effects between information on the cognitive and metacognitive level, group situations are *per se* much more complex (cf. Dillenbourg & Bétrancourt, 2006) and simplifying courses of action may also be a strategy to handle provided information.

The following study connects individual-focused research on metacognition with research on CSCL, by experimentally pursuing whether metacognitive and cognitive GA information in GA tools interact in guiding collaborative learning processes and fostering learning outcomes or if they are regarded independently. Analyzing the effects

these types of information have on learners when integrated in GA tools will help to improve GA tools and adapt them towards the specific goals of educators and/or tool designers.

Research questions and hypotheses

Ultimately, this study aims at combining two very different types of knowledge-related GA information within GA tools: one providing information on the learners' assumptions capturing learners' cognitions about the topic (cognitive information) and one providing information on the learners' confidence in their assumptions capturing metacognitive evaluations of said knowledge (metacognitive information). Individually they may trigger very different mechanisms: information about specific assumptions may be compared between learners and can evoke socio-cognitive conflicts if assumptions differ and can thus reveal a need for clarification. If assumptions match, learners may see their assumptions validated and abstain from further engagement. Information on learners' metacognitive states may help identify (perceived) lacks of knowledge within the group and thus a need for further engagement with a specific topic. Additionally, recognizing when learners are confident about their knowledge may also help to identify available resources. In combination, both types of information may be used to easily link cognitive and metacognitive information – this may lead to different foci on conflicting assumptions or lacks of knowledge and thus alternative behavioral approaches.

In accordance with research on guidance mechanisms of GA tools, we assume that metacognitive GA information will lead to a focus on needs for information and thus to the primary discussion of aspects learners in the group are unsure about – with low confidence pointing towards a need for clarification within the group. In metacognition research, this type of selection based on metacognitive evaluation of the state of learning is occasionally referred to as "metacognitive regulation" (Thiede, 1999; Thiede et al., 2003). Accordingly, collaborative metacognitive regulation on a group level may be addressed by investigating if metacognitive evaluations on the subjects' knowledge of specific topics guide discussion of said topics. Because research on GA suggests that providing metacognitive information guides learning processes and empirical studies have found that in individual (Schnaubert & Bodemer, 2017) and pseudo-collaborative settings (Schnaubert & Bodemer, 2016) the provision of information on metacognitive confidence ratings may foster metacognitive (i.e., confidence-based) regulation, we hypothesize that providing metacognitive GA information on confidence ratings will foster a structured approach and collaborative metacognitive regulation within groups of learners (H1a) as well. It is further hypothesized that this focus on uncertainties and insufficiently learned topics leads to more accurate knowledge (H2a). Although prior studies using confidence ratings in individual settings have not found this effect on learning outcomes especially if there is low overlap between metacognitive self-evaluations and actual performance (Schnaubert & Bodemer, 2016, 2017), we argue that a learning partner may be able to support individual knowledge construction in the case of uncertainties. Further, uncertainties always indicate a lack of knowledge that needs to be addressed to gain usable knowledge. Explicitly addressing uncertainties should thus give learners the opportunity to clear up uncertainties. Accordingly, we hypothesize higher confidence levels if learners address uncertainties (H3a).

As opposed to metacognitive information, cognitive information has no inherent standard and may thus only be evaluated by measuring it against an external standard. This standard may be a differing opinion of a learning partner. Comparing one's own to a partner's assumption may thus lead to cognitive conflicts and in consequence also a need for clarification on a group level. By providing easily comparable information on

learners' assumptions in a GA tool, we assume to foster the identification of such conflicts. Since research on individual learners (Schnaubert & Bodemer, 2016) as well as on dyads of learners (Bodemer, 2011) has shown that learners focus on conflicting assumptions if such information is provided, we assume this will be the case here as well. We hypothesize that learners regulate their learning more strongly based on conflicts (collaborative conflict-based regulation; comparable to metacognitive regulation with the presence or absence of conflicting assumptions as driving force) if cognitive information is provided than if this information is not provided (H1b). Since socio-cognitive conflicts have repeatedly shown to be beneficial for learning (cf. D. W. Johnson & Johnson, 2009a), we further hypothesize that this focus on conflicting assumptions within a collaborative setting fosters learning (H2b). Discussing and resolving conflicts may thus also lead to firmly established knowledge and thus to high confidence levels regarding this knowledge. Focusing on a lack of consensus apparent in conflicts, however, may also unsettle learners and make them doubt their knowledge (cf. Crano & Prislin, 2006; Koriat et al., 2015). If conflicts cannot be completely resolved, discussing them may thus also foster uncertainties. Consequently, we want to know if and how cognitive information affects confidence levels of the learners interacting, but we abstain from formulating specific hypotheses (RQ1).

Providing cognitive and metacognitive GA information within a GA tool may have different effects on CSCL. Theoretically, learners may use both types of information separately to structure their learning or focus on one type of information at a time, ignoring the other. On the other hand, learners might integrate the two kinds of information by weighing cognitive information with metacognitive information to prioritize and steer their learning process more sophisticatedly. Due to the lack of evidence regarding collaborative learning supported by both cognitive and metacognitive GA information, we abstain from being explicit in our assumptions here, but rather aim at exploring if and how groups of learners deal with the combination of both kinds of information.

Methods

Design and sample

To answer our research questions, we conducted a study with N = 130 dyads of students (260 students in total). They were mainly first semester university students (62.7%) enrolled in a Bachelors' course on Applied Cognitive and Media Science at a German University. 197 students were female (76%), 63 (24%) male. The mean age was 21.00 years (SD = 2.69). 89.2% of the participants judged their knowledge on blood sugar regulation to be low or rather low (values of 0 to 2 on a scale from 0 to 5; M = 1.11, SD = 1.04), 90.8% judged their knowledge on diabetes mellitus to be low or rather low (analogous scale, M = 0.97, SD = 1.02). Their interest in the topic was somewhat higher, with only 41.9% claiming a low or rather low interest in blood sugar regulation (values of 0 to 2 on a scale from 0 to 5; M = 2.72, SD = 1.14) and 40.8% in diabetes mellitus (analogous scale, M = 2.72, SD = 1.16).

The students could sign up together as a dyad or independently. Each dyad was randomly assigned to one of four research conditions in a 2x2 between-dyad design. Additionally, some dependent variables were assessed repeatedly, so the design includes the within-dyad factor "time of assessment" (pre and post intervention).

The learners conducted the first part of the experiment individually. Then they came together on a multi-touch table top computer for the collaborative phase of the experiment. In this phase, we manipulated the independent variables by varying (1) the

display of cognitive GA information on assumptions (displayed: cGAI+ / not displayed: cGAI-) and (2) the display of metacognitive GA information on confidence ratings (displayed: mGAI+ / not displayed: mGAI-). This resulted in four between-dyad experimental conditions: dyads with no GA information provided (mGAI-/cGAI-), dyads with only metacognitive GA information provided (mGAI+/cGAI-), dyads with only cognitive GA information provided (mGAI-/cGAI+) and dyads with both metacognitive and cognitive GA information provided (mGAI+/cGAI+). After collaboration, there was another individual phase where we further assessed dependent variables.

The dependent variables varied not only with respect to number of measurements, but also with respect to level. While individual variables like knowledge or confidence in answers were assessed at an individual level, collaborative process data was assessed on dyadic level. We conducted intra-class-correlations (ICC; cf. Shrout & Fleiss, 1979) based on a single-rating, absolute-agreement, one-way random-effects model to check if data assessed individually was interdependent within dyads and needed to be analyzed on a dyadic level.

Procedure

Learners were invited to take part in the experiments in dyads. After welcoming, introduction and declaration of consent, they conducted the first part of the experiment separately on desktop computers. For the second part, they were asked to collaborate on a multi-touch table top computer. The third part was again conducted separately on the desktop computers (cf. Technical setup section).

An instructor was with the participants throughout the experiment, but did not interfere except to welcome the participants at the beginning and give them a general introduction, to introduce them to the collaboration phase, and to reward them and see them off at the end of the study. Otherwise they interfered only if problems occurred. All instructors acted according to a pre-defined script and were trained by the principle researcher in advance.

First, the instructor started a computer program, which gave all further instructions. The participants first read an introduction, then filled out a demographics questionnaire including questions about their prior knowledge about and interest in the topics blood sugar regulation and diabetes mellitus. Then they each read an assigned learning text on this topic for up to 15 minutes after which they were automatically redirected to the next page. For the last 5 minutes, a countdown was visible to allow the participants to adjust to the available time. They were able to terminate the reading process after a minimum of 10 minutes. Afterwards, they were introduced to learning tasks in the form of true-false questions with three example training items about geography, music and paleontology. They then answered 16 learning tasks including confidence ratings on the topic of blood sugar regulation and diabetes mellitus (t1). When both learners had finished with this task, they were asked by the instructor to come to the multi-touch table top computer. Here, the instructor gave a brief introduction explaining the functions, functionalities and visualizations and handling of the program by using the three training tasks and random text after a fixed script. The instructor gave the participants time to try out the features and answered questions regarding program usage. After they got acquainted with the program, the instructor started the actual collaboration phase, which lasted 16 minutes after which the program shut down automatically. The participants were then led back to their individual computers and resumed the experiment individually. They filled out a questionnaire about their structuring of the collaboration phase, answered the learning tasks again from scratch including confidence ratings (t2) and finished off with a knowledge test. They were

thanked and each either rewarded 12 Euros or course credits. The whole experiment lasted 75 to 90 minutes. The procedure can be viewed in Figure 1. The collaboration was video recorded with the camera pointed at the table top, capturing gestures and voice, but not the faces of the participants. Video data was used to clear up (rare) issues with the log data assessed on the table top computer (cf., Logging of collaboration data section).

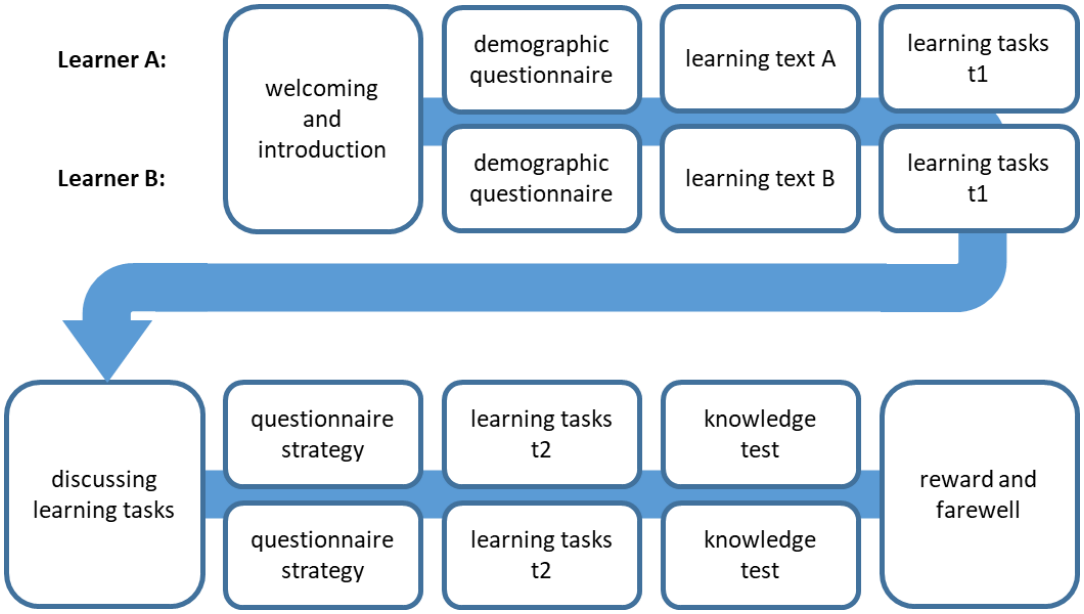

Figure 1: Experimental procedure

Technical setup

During the individual phases, learners worked on individual computers; learners were separated by blinds. Talking between participants was not permitted during this stage. All texts and questionnaires were presented in a pre-defined order using HTML pages and CSS files. The MediaLab v2012 software (Jarvis, 2012) was used to run the experiment and sequence the pages. Client data was saved into an open-source database management system (Apache CouchDB™ v1.5; Apache Software Foundation, 2013) on a central server. The server data was accessible by the multi-touch table top to allow data from the individual phase to be transferred for the collaboration phase.

During the collaborative phase, learning partners worked together on a Samsung SUR40 multi-touch table top computer. The learning environment was programmed using an object-oriented programming language supporting touch events (C#). The client was hooked to the database to access the data from the individual phase and to save data during the collaboration. Before the start of the collaboration, GA information assessed in the individual phase was transferred to the table top. According to experimental condition, data was transformed to allow for the different data visualizations during collaboration (cf. Treatment section).

Material

The material consisted of two texts (one for each learning partner within a dyad), 16 learning tasks and 32 knowledge test items regarding blood sugar regulation and diabetes mellitus, which built on material used in a study on the same topic by Schnaubert and Bodemer (2017). Additionally, we developed a questionnaire asking the learners how they structured their collaborative learning process.

The texts were both 1208 words long and contained ten key paragraphs plus two short introductory paragraphs. The texts had four identical key paragraphs and differed with regard to the six others. For example, one text (A) had a focus on diabetes type 1 and the other (B) on diabetes type 2. Also, text A contained paragraphs explaining the risk and treatment of hyperglycemia, while text B focused on hypoglycemia.

Each of the 16 learning tasks referred to information from exactly one paragraph in any one of the texts and each paragraph was represented by exactly one learning task. Each task consisted of a statement that had to be judged by the participants individually to be true or false (true/false statement; cf. Figure 2). While answering the question by clicking into a respective filed, a pop-up asked learners to state on a binary scale how confident they were, that their answer was correct (confident vs. not confident; cf. Figure 2). A binary scale was chosen to keep the information (and representation) as simple as possible. As argued before, for learners to benefit from GA information, it has to be easily accessible and understandable to guide the learning process without costs with regard to mental load (especially when including multiple types of GA information). Thus, the information needs to be presented in a way that learners understand instantly and fosters comparison processes between learners to detect relevant patterns (cf. Bodemer, 2011), but also between items to support between-items selection processes (cf. Ariel, Dunlosky, & Bailey, 2009).

Texts and tasks were first worked through individually, before learners came together to work on the tasks collaboratively.

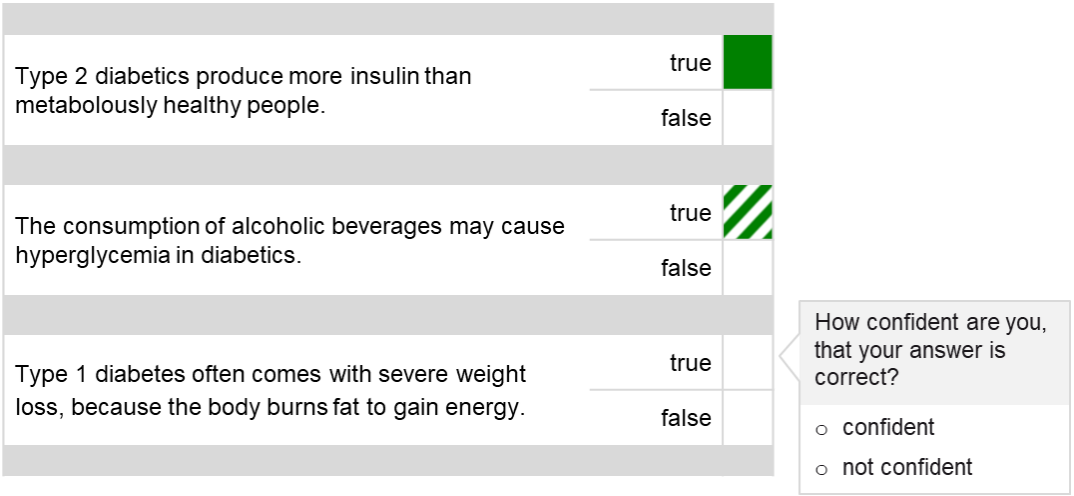

Figure 2: Examples of translated items with answers and confident ratings (confident = full green; not confident = hatched white-green), individual phase

The knowledge test consisted of 32 items – two for each paragraph in the texts and thus learning task. One assessed the knowledge that had also been assessed in the learning tasks more elaborately and one asked for more elaborate information to assess transfer. Again, the tasks had been adapted from the ones used by Schnaubert and Bodemer (2017). Each task was accompanied by a response confidence question (How confident are you, that you solved this task correctly?) on a six-point equidistant ordered response scale ranging from “not confident at all” [0] to “absolutely confident” [5].

We also developed a questionnaire that asked the learners how they structured their learning process. It consisted of two parts. Part one asked the learners to specify how true five statements were with regard to their collaborative learning phase on a six-point equidistant ordered response scales ranging from “not true at all” [0] to “completely true” [5]. Two open-ended questions were included to elaborate on or specify the answers to statements three and five (cf. Table 1). Part two consisted of two questions

asking specifically whether they based their selection of tasks on their (un-)certainties (question 1) and whether they based it on their (dis-)agreement (question 2) with an additional question and an open field to include further selection criteria. The translated items can be viewed in Table 1.

Table 1: Items of the Strategy Questionnaire (translated from German)

no.	item	answer range (0 – 5)
1.1	We went through the tasks in sequence	not true at all – completely true
1.2	We explicitly tried to go through all tasks	not true at all – completely true
1.3	We purposefully selected tasks to work on	not true at all – completely true
1.4	If so: What criteria did you use?	open answer (optional)
1.5	We changed our strategy during learning	not true at all – completely true
1.6	If so: How?	open answer (optional)
1.7	We did not follow a specific strategy	not true at all – completely true
2.1	How much did you consider your and your learning partners' confidence in your answers?	not at all – very much
2.2	How much did you consider your and your learning partners' agreement on the answers?	not at all – very much
2.3	Are there other criteria you used to select tasks?	yes – no (binary: 0 – 1)
2.4	If yes: What were those?	open answer (optional)

Treatment

The treatment variation consisted of two factors: the provision of cognitive GA information in the form of individual assumptions about the correct answers to the learning tasks in t1 (cGAI+: yes vs. cGAI-: no) and the provision of metacognitive GA information in the form of individual confidence ratings with regard to the learning tasks in t1 (mGAI+: yes vs. mGAI-: no) during collaboration. This left us with a 2 x 2 between subjects design. Assumptions and confidence ratings were assessed within all groups during the initial assessment (learning tasks t1) and provided during collaboration to some groups, depending on experimental condition. If provided, the information of both learners was provided in separate columns labelled A and B (consistent with the side of the multi-touch table top they were standing on) next to the task in an easily comparable fashion (cf. Figure 3). By integrating the GA information into the collaborative task presented on a shared workspace, we ensured learners were able to detect relevant information and monitoring the information was associated with low additional costs (cf. Buder, 2011). Cognitive and/or metacognitive GA information provided could be changed during collaboration while an item was discussed (cf. Collaborative learning environment section). The groups provided with cognitive GA information on assumptions received information on the answers the learners had previously given in the learning tasks, and the groups provided with metacognitive GA information on confidence received information on the confidence ratings given with each answer. Cognitive GA information was spatially coded and a colored field either in the top ("true") or bottom ("false") row attached to each statement indicated the answer the learners had previously given in the learning tasks (cf. Figure 3). Metacognitive GA information was color-coded. Confident answers were indicated by a fully green field and non-confident answers were indicated by a hatched white-green field (cf. Figure 3). Figure 3 outlines how information was presented for all four research conditions.

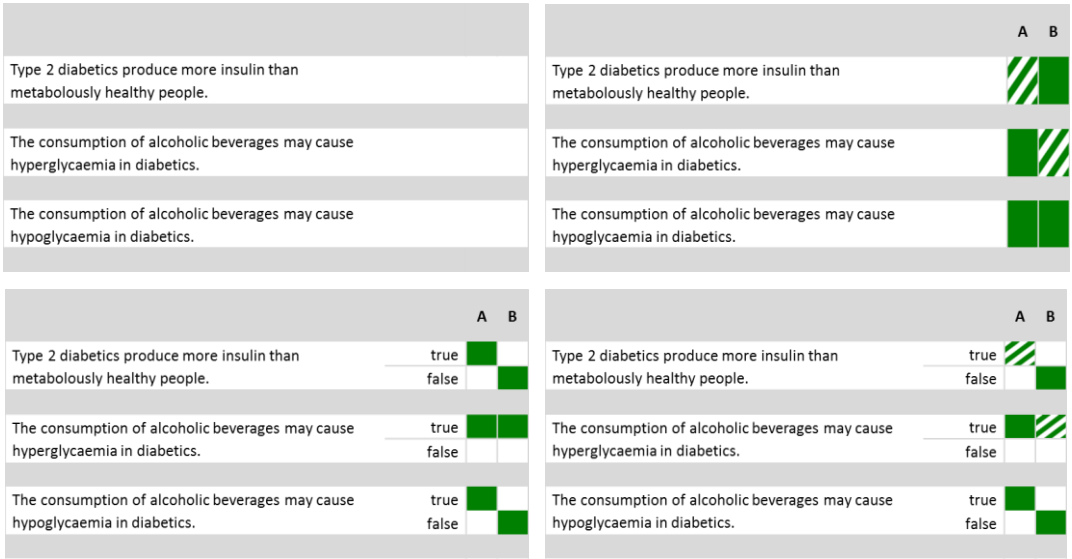

Figure 3: Treatment conditions during collaboration (top left mGAI-/cGAI-; top right mGAI+/cGAI-; bottom left mGAI-/cGAI+; bottom right mGAI+/cGAI+)

Collaborative learning environment

During collaboration, learners interacted face to face on the multi-touch table top computer (cf. Figure 4). Within CSCL, face to face settings are of specific interest as they are common when learners jointly learn together, e.g., in preparation for exams or within schools or university courses, and may combine advantages of unmediated collaboration with the merits of computer support. Multi-touch table tops are designed for co-located learning and have great potential for collaboration (cf. Dillenbourg & Evans, 2011). By supporting face to face learning, table tops allow for multiple modes of communication including talk, gesture or action while still allowing for the benefits of computer-supported learning like interactive learning environments, embedded additional information and a shared interactive workspace. Additionally, such settings support behavioral GA, as the learners can observe each other's activities during collaboration. While the specific design of interactive multi-touch soft- and hardware may vary considerably (cf. Higgins, Mercier, Burd, & Hatch, 2011), the technology usually allows learners to interact intuitively with the system while collaboratively working on a shared screen.

Figure 4: Two learners interacting on the multi-touch table top computer (experimental condition mGAI+/cGAI+; task visible)

During the collaboration in our study, learners were free to use the functions explained below and to discuss the material (Figure 5 shows a statechart depicting the states

within the learning environment). A countdown on the screen showed the remaining time in the collaboration phase starting with 16 minutes. After the time was up, the program shut down automatically. The home screen on the table top computer showed the 16 learning tasks presented in two columns. The answers and/or confidence ratings of the learners were provided to the learners according to experimental condition. The learners had the opportunity to select specific tasks for discussion one at a time. If selected, the respective task was enlarged and shown on the top of the screen and the rest of the tasks were masked by an overlay window (TaskVisible). In this mode, the learners were able to change their previously chosen answers and/or confidence ratings (if provided) on this particular task by tapping on the respective field of the enlarged task (cf. Figure 4). Such changes were saved automatically and applied to the home screen visualization. The learners were also each able to access their original learning texts and scroll through the content, which was presented on their respective side on the table top on request (TextVisible). When doing so, they were each able to select a paragraph and send it to the middle of the screen for their partner's benefit (ParagraphVisible). When they closed the selected task, all open texts and paragraphs disappeared and were inaccessible until another task was selected (HomeScreen).

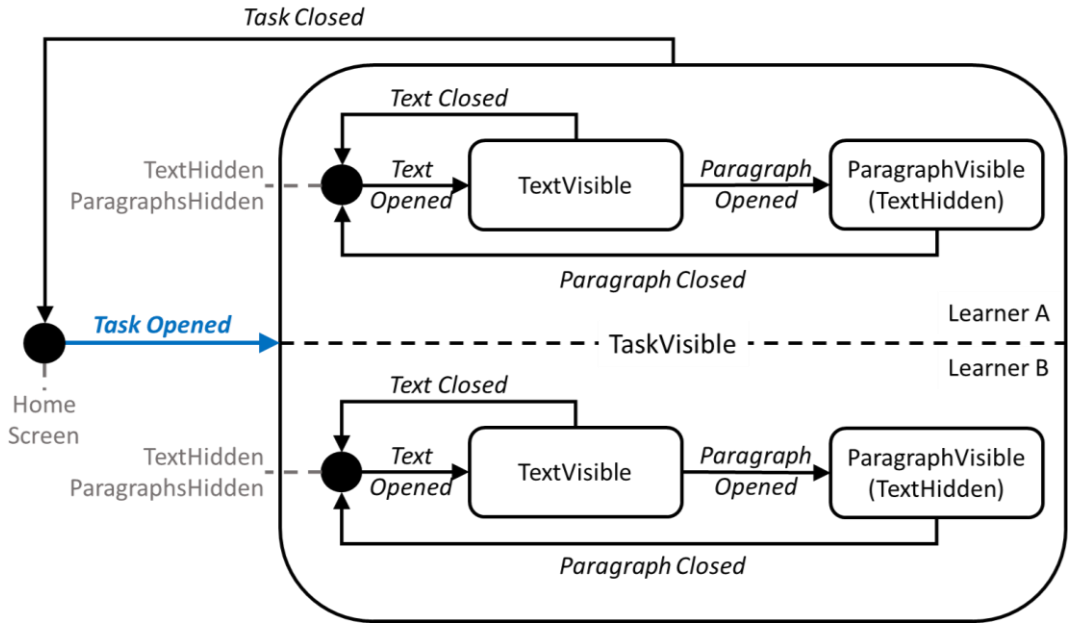

Figure 5: Statechart specifying states (rounded rectangles) and state transitions (arrows) triggered by learner-initiated events (italics) in the collaborative learning environment; central dependent variable bold-faced (blue)

Logging of collaboration data

During the collaboration on the multi-touch table top, we logged changes on the user interface. The user interface comprised multiple states (representing displayed objects), which were connected by transitions initiated by touch events conducted by the learners (cf. Figure 5). Additionally, some touch events were implemented that did not trigger state transitions (i.e., changing answers of tasks). All pre-defined touch events were logged in the form of an event log. Each event log entry consisted of an event-ID (serial number within the session), an event-type (e.g., TaskOpened, AnswerChanged), a timestamp, and a user ID (partnerA, partnerB, or dyad). For events that initiated state transitions, we additionally logged preceding and succeeding states (e.g., event: TaskOpened, preceding state: HomeScreen, succeeding state: TaskVisible; cf. Figure 5) to ease the reconstruction of state transitions and to detect inconsistencies within the

logs (i.e., impossible transitions like opening a task while another is still open). Video data was used to clear up such rare issues and determine the impact on the collaboration. Where applicable, event log entries were accompanied by specifying information like task-ID or paragraph-ID. For changes in answers (assumption or confidence), the log also contained two values representing the answers before and after the change. With this log, it was possible to extract information on the learning process. Of specific interest was the selection of tasks to discuss (TaskOpened, task-ID). These could easily be matched to the previously given answers of the learners, which were saved in a specific start-log that contained information on the answer patterns at the beginning of the collaboration (i.e., the full answers and confidence ratings learners had provided regardless of information visualized).

Dependent variables: learning process

We assessed various information about the learning process and how learners proceeded during collaboration. We were especially interested in what tasks learners selected to discuss and upon what they based their discussion (i.e., conflicts/conflicting assumptions, uncertainties/uncertain assumptions). For this purpose, we used the log data (i.e., TaskOpened) from the collaboration to assess the actual tasks selected as well as questionnaire data to assess the underlying strategy as perceived by the learners.

As a first means of describing the learning process, we assessed how many tasks learners discussed during collaboration. Thus, we counted the unique selections of items to be discussed. A task was selected for discussion when learners marked the item by tapping on it (TaskOpened). It was then enlarged and the learners were able to change answers or access their initial learning texts (cf. Collaborative learning environment section). We only counted unique selections (as specified by the task-ID of each TaskOpened event) meaning that every task was counted maximally once and thus the count ranged from a (hypothetical) zero to sixteen.

We further assessed two types of regulation to assess if learners used their initial confidence and/or conflicting assumptions to regulate their selection of tasks: metacognitive (or confidence-based) regulation and conflict-based regulation. Metacognitive (confidence-based) regulation is a measure often assessed as within-subject correlation between item selection and metacognitive judgement (Thiede, 1999; Thiede et al., 2003) in metacognition research. Thus, we used such a measure to describe confidence-based regulation. We assessed item selection by looking at which items learners tapped on to indicate they would like to discuss them (event: TaskOpened); repeated selections were ignored (unique task-IDs). Tasks were coded as uncertain if at least one learner had been uncertain about their answer in t1 as logged in the start-log (independent of experimental condition). Changes in the certainty ratings during collaboration were not considered, since they always followed item selection and we only included initial selections; thus, at the time learners initially selected items, the data from t1 was the most recent data available. Due to the binarity of the data, we used φ-correlations between certainty and selection as proposed by Schraw and colleagues (Schraw, 2009; Schraw, Kuch, & Gutierrez, 2013) as measures for confidence-based regulation.

As a second measure, we assessed conflict-based regulation. Conflict-based regulation assumes that when there is a conflict, there is a collective need for clarification. Thus, conflict-based regulation was computed in a similar manner to confidence-based regulation: as a within-dyad φ-correlation between conflict-status of items (conflicting assumptions versus congruent assumptions) and item selection.

Since conflict- and confidence-based regulation coefficients both are based on correlations, learners who selected all items (or none) or did not show variation in their

items with regard to confidence or conflict status had to be excluded from these analyses.

To investigate if confidence and conflict within items interact in having an impact on item selection, we assessed at what percentage the conflict-confidence combinations were selected by dividing the number of selections of each category by their occurrence. This left us with four values per dyad (2 (conflict) x 2 (confidence)) describing the percentage the four categories were selected for discussion. For analyses it was imperative that we had information for all four categories per dyad. Thus, dyads with missing categories (no occurrence) had to be excluded from these analyses.

Self-report on processes: self-developed questionnaire

We were also interested in the perspective of the learners and whether they are aware of the strategies they implement during learning and their selection processes. Thus, we used the data obtained in our new questionnaire to assess this. Factor analyses on the first part of the questionnaire (excluding open answer questions 4 and 6) revealed a two-factor solution explaining 60.83% of the variance. The items 1, 2, and 3 (negative) loaded on the first factor (38.43% of variance) and the items 5 (negative) and 7 on the other factor (explaining the remaining 22.40%). Cronbachs Alpha (cf. Cronbach, 1951) showed acceptable reliability for the first factor (unstandardized alpha = .713, whereby alpha is a rather conservative measure of internal consistency, cf. McNeish, 2017) but failed dramatically for the second (alpha = .176). Pearson correlation confirmed the unfortunate fit (r = .10) for this second factor and thus we abstained from interpreting it. The first factor may be interpreted as strategic item selection (vs. habitual behavior) and we used the mean score of the three items (we recoded items 1 and 2 so that a higher score indicated a more strategic selection) for testing purposes. This resulted in a measure for strategic behavior with high values (max = 5) indicating highly selective behavior and low values (min = 0) indicating a very inclusive strategy.

For part two, we were mainly interested in the first two items asking the learners if they based their selection on confidence or conflict to describe the learners' perception of their selection processes and evaluated them separately.

Dependent variables: learning outcomes

As outcome variables we assessed confidence and knowledge resulting from the collaboration. For each of the measures, we used two different tests: the learning tasks measuring changes in confidence and knowledge from pre to post on items directly relevant in the collaboration and thus very close to the treatment, and the knowledge test administered at the end of the study to assess broader and inferential knowledge about the subject as well as the confidence in that knowledge.

To measure confidence, we counted the number of confidently solved learning tasks pre- and post-collaboration. This left us with a measure between zero and sixteen for each point in time. For some analyses, we needed to combine the numbers for two learners within a dyad by computing the mean to obtain dyadic measures. This procedure results in a severe loss in variance, however, it also eliminates the influence of inflating p-values due to adding interdependent data. We additionally computed confidence gain by calculating difference values between pre- and post-test [value_t2 – value_t1]. Theoretically ranging from -16 to 16, positive values indicate a gain in confidence while negative values indicate a loss over time. While confidence gains in the learning tasks are very specific to the collaboration and very close to the learning material used during collaboration, we additionally assessed if learners gain broader knowledge on the subject and confidence in this knowledge. Thus, we used the data

obtained in the knowledge test at the end of the study and computed the mean confidence level for the tasks for each participant. Since confidence was assessed on a six-point equidistant ordered response scale, we coded the data to range from 0 to 100 to receive percentage-like values for each participant.

As a further outcome variable we assessed knowledge resulting from the collaboration. Here, we counted the number of correctly solved learning tasks pre- and post-collaboration. This left us with a measure between zero and sixteen for each point in time. Again, for some analyses, we combined the numbers for two learners within a dyad by computing the mean to obtain dyadic measures, with the abovementioned advantage and disadvantage. Performance gain was also computed analogous to confidence gain by calculating difference values between pre- and post-test [value_t2 – value_t1]. Theoretically ranging from -16 to 16, positive values indicate a gain in performance while negative values indicate a loss over time. Again, while performance gains in the learning tasks are very specific to the collaboration and very close to the learning material, we additionally assessed if learners gain broader knowledge on the subject. For this, we used the data obtained in the knowledge test at the end of the study and computed the percentage of tasks solved correctly in this test for each participant.

Results

General remarks

We used different analyses to address different aspects of our research questions. Due to the partially dyadic design (decisions to discuss material were made as a dyad, while tests were taken individually) and specifics of the data (normal distribution, local interdependence, etc.), we did not conduct analyses integrating all process and outcome variables in one design. Thus, we analyzed the impact of experimental conditions on learning outcomes mediated by confidence and conflict-based regulation on a dyadic level (integrating data from both dyad members for the learning outcomes). Additionally, we tested the direct effects of the two factors (metacognitive and cognitive GA) on learning outcomes on individual as well as group level. The direct effects of the treatment on learning processes gained from log data were analyzed exclusively on dyadic level (inherently dyadic data), and data gained from the questionnaire was analyzed on the individual level. To account for distorting effects that the lack of normal distribution may have on the result, we used 10000 percentile bootstrapping in some analyses, e.g., the mediation analyses (cf. Hayes & Preacher, 2014). While other robust methods based on trimming means may be used to account for the lack of normal distribution (cf. Wilcox, 2012), current research has shown that especially in cases with highly skewed distributions (which was the case in some of our data), bootstrapping is the preferred option (Field & Wilcox, 2017). Thus, we used percentile bootstrap confidence intervals (based on 10000 bootstrap samples) as they are less susceptible to type 1 errors with smaller sample sizes than bias-corrected CIs (Fritz, Taylor, & MacKinnon, 2012) and less susceptible to outliers (Creedon & Hayes, 2015). Unless otherwise stated, alpha level was set at 5% and two-tailed tests were conducted to allow for detecting potential detrimental effects as well. Confidence intervals for effect sizes were calculated with the MBESS R-Package (Kelley, 2017).

Overall data on learning behavior

To test if providing GA information affects the raw number of discussed tasks, we counted how many of the 16 tasks were marked as discussed by each dyad and conducted a two-factorial ANOVA. Since normal distribution could not be assumed, we

used 10000 percentile bootstrapping to account for the lack of normality in the data. Results show no significant effect of providing cognitive GA information on assumptions ($F(1, 126) = 0.50$, $p = .479$, $\eta_p^2 < .01$, CI 95% [0, .05]) and no significant interaction between providing cognitive GA information on assumptions and metacognitive GA information on confidence ($F(1, 126) = 0.81$, $p = .370$, $\eta_p^2 < .01$, CI 95% [0, .06]). However, we found a significant main effect of providing metacognitive GA information on confidence ($F(1, 126) = 7.85$, $p = .006$, $\eta_p^2 = .06$, CI 95% [.01, .15]). Descriptive data (Table 2) show that dyads with metacognitive GA information on confidence provided (mGAI+) tended to discuss less tasks than dyads without such information (mGAI-) with a mean difference of 1.20 tasks (CI 95% [0.35, 2.03]).

Table 2: Number of tasks selected by conditions

	number of tasks selected	
	M	*SD*
mGAI+/cGAI+	12.38	2.45
mGAI+/cGAI-	12.29	2.69
mGAI-/cGAI+	13.19	2.16
mGAI-/cGAI-	13.88	2.39

Mediation model: impact of experimental conditions on learning outcomes mediated by regulation

To address our hypotheses with regard to confidence-based regulation (H1a) and conflict-based regulation (H1b) and their effects on learning outcomes (performance gain: H2a, H2b; confidence gain: H3a, RQ1), we first computed two multiple mediation models with multi-categorical predictors predicting performance gain and confidence gain from experimental conditions mediated by confidence-based and conflict-based regulation to assess the influence of the provision of information on learning gain via regulation by using the PROCESS macro for SPSS (cf. Hayes, 2013). We used simple indicator coding for the experimental condition with the control condition (mGAI-/cGAI-: no GA information provided) as the reference. The results are depicted in Figures 6 and 7. We used percentile bootstrap confidence intervals (based on 10000 bootstrap samples) and heteroscedasticity-consistent standard errors (HC3) as described in Hayes and Cai (2007). The two models cannot be considered fully independent, since performance and confidence as outcome measures are theoretically connected, even though the specific measures did not correlate in our study ($r = .018$, $p = .835$, CI_r [-.156, .184]). Thus, we used a Bonferroni adjustment by setting the alpha-level to 2.5 percent (.025).

We first tested the model predicting confidence gain by experimental condition mediated by confidence- and conflict-based regulation (cf. Figure 6). The full model including the mediators (regulation coefficients) for confidence was statistically significant ($F(5, 95) = 4.83$, $p < .001$, $R^2 = .18$, CI 95% [.05, .30]), while the model without the mediators showed only a small and statistically insignificant effect, $F(3, 97) = 0.68$, $p = .567$, $R^2 = .02$, CI 95% [0, .08]. Further analysis revealed that learners receiving metacognitive GA information showed an increase in confidence gain mediated by confidence-based regulation ($a_{11}b_1 = 1.21$, CI 95 % [0.53, 2.07]; $a_{31}b_1 = 0.92$, CI 95% [0.33, 1.70]) (the percentile bootstrap confidence interval for the indirect effect based on 10000 bootstrap samples was entirely above zero). However, this seems to be somewhat outweighed by direct negative effects of the treatment on confidence for learners with metacognitive GA information provided ($c'_1 = -1.18$ (0.64), $p = .069$, CI 95% = [-2.46, 0.09]; $c'_3 = -1.01$ (0.63), $p = .112$, CI 95% [-2.26, 0.24]). Although these effects do not reach statistical significance separately, it is worth mentioning that there

might be adverse effects and the omnibus test confirms general direct effects ($F(3, 95) = 3.74$, $p = .014$, $R^2 = 0.08$, CI 95% [.05, .21]). As expected, providing cognitive GA information led to conflict-based regulation ($a_{22} = .44$ (.09), $p < .001$, CI 95% [.26, .61]; $a_{32} = .46$ (.09), $p < .001$, CI 95% [.29, .64]), however, conflict-based regulation did not affect confidence gain ($b_2 = -1.10$ (0.81), $p = .178$, CI 95% [-2.72, 0.51]). Full data is available in appendix A.

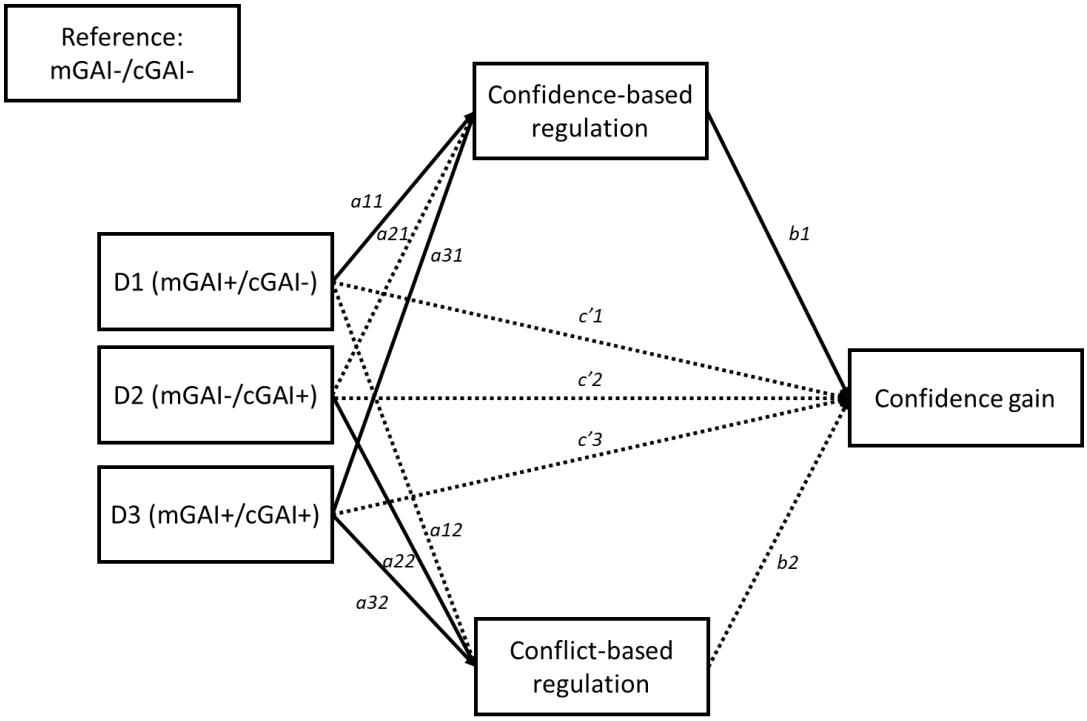

Figure 6: Confidence gain predicted by a multiple mediation model with multi-categorical predictors (significant paths are depicted with solid lines, dotted lines are not statistically significant)

For performance (cf. Figure 7), the full model including the mediators was not statistically significant ($F(5, 95) = 2.00$, $p = .086$, $R^2 = .09$, CI 95% [0, .18]), while the model without just reached statistical significance (even including the quite conservative Bonferroni correction due to two related models being tested); $F(3, 97) = 3.26$, $p = .0247$, $R^2 = .08$, CI 95% [.00, .20]). However, only one condition in the total model (excluding mediators) showed an overall significant effect: the group with only metacognitive GA information performed worse compared to the reference condition ($c_1 = -0.91$, $p = .026$, CI 95% [-1.72, -0.11]), while the other groups did not show a similar effect. Direct effects did not reach statistical significance for any of the conditions; indirect effects were marginal and insignificant (see full data in appendix B).

In the next sections we assess the impact of the treatment on regulation again in more detail – considering the two-factorial design unaccounted for in the mediation analyses.

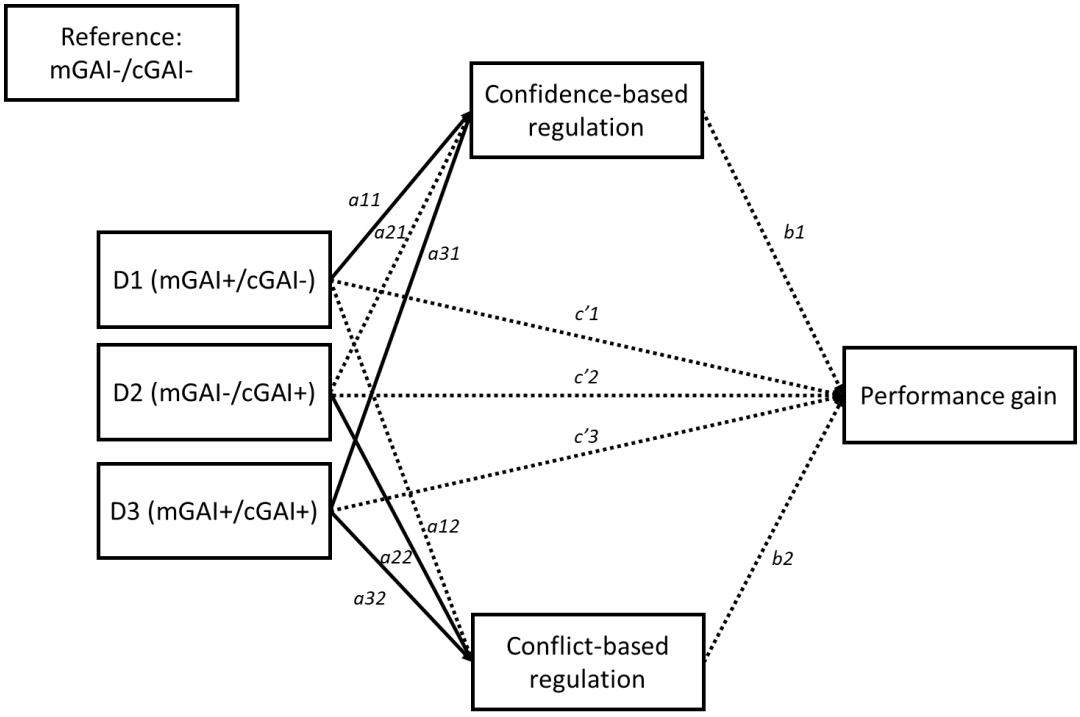

Figure 7: Performance gain predicted by a multiple mediation model with multi-categorical predictors (significant paths are depicted with solid lines, dotted lines are not statistically significant)

Learning processes 1: effects of factors on regulation

Since the mediation model could not account for the two individual factors of the experimental design (provision of metacognitive GA information on confidence and provision of cognitive GA information on assumptions), we assessed the effect of the factors on confidence-based and conflict-based regulation again separately (H1a, H1b) to additionally account for possible interaction effects (exploratory analyses of interaction). To ease the interpretation of the regulation coefficients, they were coded so that high positive coefficients meant primarily selecting uncertain or conflicting items for discussion whereas negative coefficients would mean the primary selection of certain or non-conflicting items. Values close to zero meant that no differentiation in selection was undertaken between certain and uncertain or conflicting and non-conflicting items. We conducted a two-factorial between subject MANOVA to test for the effects of the provision of metacognitive GA information and cognitive GA information on both regulation coefficients and, importantly, to test for possible interactions between the factors. It confirmed an overall effect of metacognitive GA information ($F(2\ ,96) = 17.68$, $p < .001$, $\eta_p^2 = .27$, CI 95% [.12, .39]) and of cognitive GA information ($F(2, 96) = 33.91$, $p < .001$, $\eta_p^2 = .41$, CI 95% [.26, .52]), but no interaction ($F(2, 96) = 1.43$, $p = .245$, $\eta_p^2 = .03$, CI 95% [0, .11]). Metacognitive GA information only had an effect on confidence-based regulation ($F(1, 97) = 35.73$, $p < .001$, $\eta_p^2 = .27$, CI 95% [.13, .40]) but not on conflict-based regulation ($F(1, 97) = 0.31$, $p = .582$, $\eta_p^2 < .01$, CI 95% [0, .06]) and cognitive GA information had an effect solely on conflict-based regulation ($F(1, 97) = 67.67$, $p < .001$, $\eta_p^2 = .41$, CI 95% [.26, .53]), but not on confidence-based regulation ($F(1, 97) = 0.03$, $p = .870$, $\eta_p^2 <.001$, CI 95% [0, .03]). The interaction of the two factors did not have an effect on confidence-based regulation ($F(1, 97) < .01$, $p = .964$, $\eta_p^2 < .001$, CI 95% [.00, .00]) or on conflict-based regulation ($F(1, 97) = 2.87$, $p = .093$, $\eta_p^2 = .03$, CI 95% [0, .12]). Because the data was not normally distributed and thus not fully suited for the analysis used, we confirmed the results using the MANOVA.RM R-Package, bootstrapping the data with a

parametric bootstrapping approach (Friedrich, Konietschke, & Pauly, 2017) and 10000 bootstrapping iterations. The results confirm the multivariate effect of metacognitive GA information ($F_{MATS}(2, 96) = 37.14$, $p < .001$) and cognitive GA information ($F_{MATS}(2, 96) = 63.45$, $p < .001$), as well as the lack of interaction between the two factors ($F_{MATS}(2, 96) = 2.96$, $p = .241$).

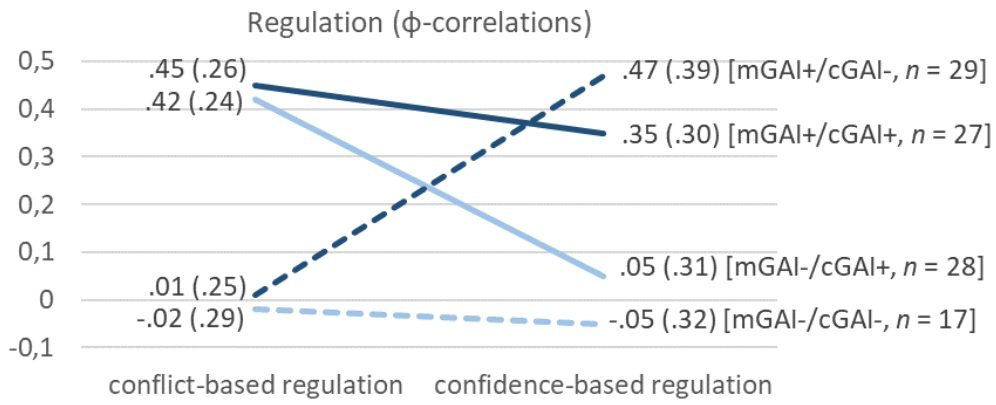

Figure 8: Means (standard deviations) of the regulation coefficients for conflict-based regulation and confidence-based regulation for all groups. Solid lines are for cGAI+ conditions (dotted lines for cGAI-), darker shade lines are for mGAI+ conditions (lighter shade for mGAI-)

Descriptive statistics show that with both types of GA information available (mGAI+/cGAI+), learners use both regulation types and use them fairly equally, while without GA information (mGAI-/cGAI-) there is no correlation between either confidence or conflict with discussion (cf. Figure 8). It is worth mentioning that since the regulation coefficients were based on correlations, dyads who selected all tasks for discussion had to be excluded from the analyses (hypothetically this would have also been true for learners with no variation in terms of certainty or conflict, however, this did not occur). This was the case especially in the group without GA information as support (mGAI-/cGAI-; cf. Figure 8).

Learning processes 2: integration of metacognitive and cognitive information per experimental condition

While we used regulation coefficients to look at how learners base their decisions on confidence levels and conflict status separately, we were further interested in whether they integrated the information (exploratory analyses of interaction). Unfortunately, the full design becomes even more inflated when including these two within-subject factors (confidence level and conflict status) in addition to the two between subject factors (metacognitive GA information on confidence and cognitive GA information on assumptions). Thus, we analyzed the information separately for each experimental condition. To further include the information and especially the interaction of conflict status and confidence on affecting discussion, we mapped the discussion rate (%) for confidence x conflict-status for all groups separately (cf. Figure 9). Since dyads lacking any of the four examined patterns (e.g., conflicting assumptions with both learners being confident) had to be excluded from the analyses, the *n* within the groups may deviate from the data described above.

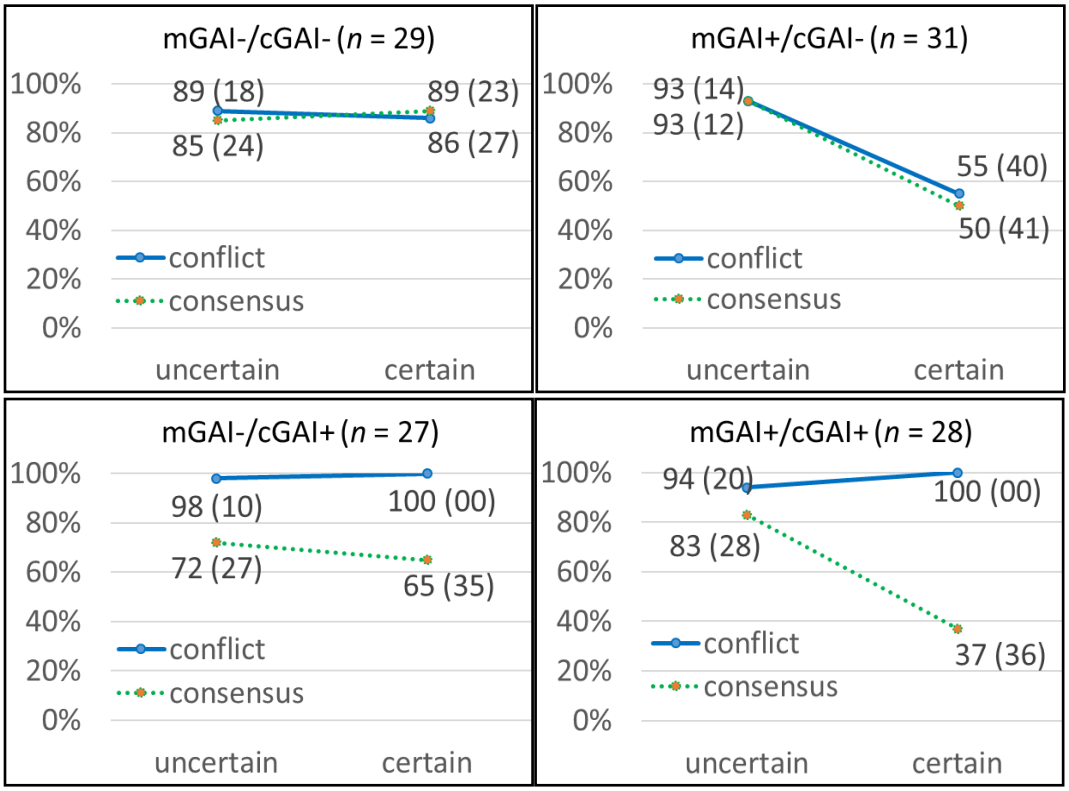

Figure 9: Mean of percentage of tasks discussed (standard deviations) by confidence and conflict status per condition

The results show that for the condition without GA information (mGAI-/cGAI-), neither confidence ($F(1, 28) < .01$, $p = .951$, $\eta_p^2 < .01$, CI 95% [.00, .04]) nor conflict status ($F(1, 28) < .01$, $p = .994$, $\eta_p^2 < .01$, CI 95% [.00, .00]), nor their interaction ($F(1, 28) = 1.24$, $p = .275$, $\eta_p^2 = .04$, CI 95% [0, .24]) had an effect on the rate the items were discussed, which was rather high in general (cf. Figure 9, top left). The condition with only metacognitive GA information on confidence (mGAI+/cGAI-) showed a significant effect of confidence on the discussion rate ($F(1, 30) = 35.43$, $p < .001$, $\eta_p^2 = .54$, CI 95% [.27, .69]), but neither of conflict status ($F(1, 30) = 0.64$, $p = .430$, $\eta_p^2 = .02$, CI 95% [0, .19]) nor an interaction ($F(1, 30) = 0.61$, $p = .443$, $\eta_p^2 = .02$, CI 95% [0, .19]) (cf. Figure 9, top right). The condition with only cognitive GA information on assumptions (mGAI-/cGAI+) showed a significant effect of conflict status on discussion rate ($F(1, 26) = 38.51$, $p < .001$, $\eta_p^2 = .60$, CI 95% [.32, .73]), but not of confidence ($F(1, 26) = 0.36$, $p = .555$, $\eta_p^2 = .01$, CI 95% [0, .19]) nor an interaction effect ($F(1, 26) = 1.21$, $p = .281$, $\eta_p^2 = .05$, CI 95% [0, .25]) (cf. Figure 9, bottom left). For the group with both types of GA information visible (mGAI+/cGAI+), we found significant main effects for both confidence ($F(1, 27) = 26.41$, $p < .001$, $\eta_p^2 = .49$, CI 95% [.20, .66]) and conflict status ($F(1, 27) = 46.69$, $p < .001$, $\eta_p^2 = .63$, CI 95% [.37, .76]) and an interaction effect ($F(1, 27) = 43.65$, $p < .001$, $\eta_p^2 = .62$, CI 95% [.35, .74]) (cf. Figure 9, bottom right). Viewing the descriptive data in Figure 9, we can see that while conflict might have a universal effect on discussion percentage (albeit marginalized if accounting for/extracting the interaction), the main effect of confidence level can well be explained by the interaction. Since the data was heavily skewed for some cells (mainly ceiling effects), the results need to be interpreted with caution and merely provide an indicator for the effect the patterns have on topic discussions within each experimental condition.

Learning processes 3: strategic procedure from questionnaire data

We further inquired if learners perceived their own behavior as being strategic and selective (H1a, H1b, self-report). The data showed relatively low scores on the scale ranging from more habitual learning behavior on the low end (e.g., working through tasks in sequential order, not choosing specific tasks, but working through all of them) to more selective behavior on the high end (cf. Table 3). However, statistical analyses revealed differences between the groups. A two-factorial ANOVA showed no effect for metacognitive GA information on confidence ($F(1, 256) = 1.30$, $p = .255$, $\eta_p^2 < .01$, CI 95% [0, .04]) or the interaction of the two types of GA information ($F(1, 256) = 1.52$, $p = .219$, $\eta_p^2 < .01$, CI 95% [0, .04]), but a statistically significant effect of cognitive GA information on assumption ($F(1, 256) = 16.23$, $p < .001$, $\eta_p^2 = .06$, CI 95% [.02, .12]). For the latter effect, mean distances were roughly 0.70 (CI 95% [0.36, 1.04]) with the conditions with cognitive GA information on assumptions (cGAI+) reporting higher levels of selective behavior. We used 10000 percentile bootstrapping samples for estimation to account for the lack of normal distribution in the data. Descriptive statistics can be found in Table 3.

Table 3: Descriptive statistics on questionnaire data

	selective behavior scale	selection due to confidence	selection due to conflict
	M (SD)	*M (SD)*	*M (SD)*
mGAI+/cGAI+	2.04 (1.56)	3.03 (1.31)	3.89 (1.24)
mGAI+/cGAI-	1.55 (1.45)	2.94 (1.41)	3.66 (1.28)
mGAI-/cGAI+	2.05 (1.31)	2.95 (0.98)	4.03 (0.93)
mGAI-/cGAI-	1.14 (1.31)	3.19 (0.92)	3.75 (1.20)

To assess if learners perceived their procedure to be based on confidence, we conducted a 2-way ANOVA (10000 percentile bootstrapping). It showed no differences between the factor levels for either the provision of metacognitive GA information on confidence ($F(1, 256) = 0.33$, $p = .566$, $\eta_p^2 < .01$, CI 95% [0, .02]), the provision of cognitive GA information on assumptions ($F(1, 256 = 0.23$, $p = .623$, $\eta_p^2 < .01$, CI 95% [0, .02]) or the interaction of both ($F(1, 256) = 1.23$, $p = .269$, $\eta_p^2 < .01$, CI 95% [0, .04]). We used the same procedure to assess whether learners perceived their procedure to be based on conflict. Again, we found no significant effects of providing metacognitive GA information on confidence ($F(1, 256) = 0.62$, $p = .431$, $\eta_p^2 < .01$, CI 95% [0, .03]), cognitive GA information on assumptions ($F(1, 256) = 3.10$, $p = .080$, $\eta_p^2 = .01$, CI 95% [0, .05]), or their interaction ($F(1, 256) = 0.03$, $p = .857$, $\eta_p^2 < .01$, CI 95% [0, .01]). Descriptive statistics for both items are shown in Table 3.

Learning outcomes: effects of factors on cognitive and metacognitive learning outcomes

Due to the complexity of the design, we used dyadic performance gain and confidence gain in the learning tasks in the mediation model, thereby losing variance between measurements (post – pre) and dyad members (Mean[learner A, learner B]). Since the mediation models could not provide full details on the variance of direct effects, we additionally analyzed the data again without mediators (testing H2a, H2b, H3a, and RQ1), thereby including measurement points (within-subject factor time: pre, post) and learners separately in a 2x2x2 MANOVA with repeated measures on one factor (cf. Table 4). Since normal distribution could not be assumed for some of the cells in the design, the results need to be interpreted with caution.

Results showed a highly significant multivariate effect of time ($F(2, 255) = 204.70$, $p < .001$, $\eta_p^2 = .62$, CI95% [.54, .67]), which can be seen in univariate analyses to be due to both gains in confidence ($F(1, 255) = 112.81$, $p < .001$, $\eta_p^2 = .31$, CI 95% [.22, .39]) and performance ($F(1, 255) = 321.08$, $p < .001$, $\eta_p^2 = .56$, CI 95% [.48, .62]). However, as shown in Table 4, no other main or interaction effects were statistically significant.

Table 4: Multivariate effects of time and the two types of GA information on learning outcomes (performance and confidence) [2x2x2 MANOVA]

factors (type)	$F(2, 255)$	p	η_p^2	CI 95%
main effects				
time (within)	204.70	< .001	.62	.54, .67
metacognitive GA information (between)	2.00	.138	.02	.00, .05
cognitive GA information (between)	0.03	.967	< .01	.00, .001
first order interactions				
metacognitive * cognitive GA information	0.46	.632	< .01	.00, .03
time * metacognitive GA information	1.95	.144	.02	.00, .05
time * cognitive GA information	1.30	.273	.01	.00, .04
second order interaction				
time * metacognitive * cognitive GA information	2.40	.093	.02	.00, .06

Due to partial interdependence of the dyad members (cf. Table 5) as measured with the intra-class correlation (ICC; Shrout & Fleiss, 1979), we confirmed the results on the dyad level (discarding inner-dyadic variance). The data can be viewed in Appendix C. The results are consistent with the individual level analyses with only an effect of time of measurement (pre or post collaboration) being statistically significant.

Interestingly, intra-class correlation coefficients differed between conditions: While as expected, performance and confidence level prior to the collaboration were not interdependent within dyads (ICC values ranged from -.15 to .19 for performance and .04 to .24 for confidence and were statistically non-significant), and overall showed statistically significant interdependences post-collaboration, the post-collaboration values differed between the conditions (cf. Table 5). While there is no straightforward interpretation, it seems that learners with metacognitive GA information (mGAI+) are more strongly interdependent when it comes to metacognitive outcomes (confidence level post), than learners without such information (mGAI-). However, with regard to cognitive outcomes, the opposite seems to be the case: Learners without metacognitive GA information (mGAI-) seem to be more interdependent than learners with metacognitive GA information (mGAI+). However, this seems to depend on cognitive information as well. Further, it is interesting, that in one condition only (mGAI+/cGAI+), partners' performance scores seem not to be interrelated. With regard to confidence, cognitive GA information does not seem to play a major role as the ICC values are quite similar between groups with (cGAI+) and without (cGAI-).

Table 5: ICC values (and *p*-values) [*n*] for the learning tasks post collaboration

	performance post			confidence post		
	cGAI+ ICC (*p*)	cGAI- ICC (*p*)	overall ICC (*p*)	cGAI+ ICC (*p*)	cGAI- ICC (*p*)	overall ICC (*p*)
mGAI+	-.205 (.875) [*n* = 32]	.358 (.017) [*n* = 34]	.126 (.154) [*n* = 66]	.458 (.003) [*n* = 32]	.610 (<.001) [*n* = 34]	.537 (<.001) [*n* = 66]
mGAI-	.580 (<.001) [*n* = 32]	.499 (.001) [*n* = 32]	.534 (<.001) [*n* = 64]	.365 (.017) [*n* = 32]	.241 (.086) [*n* = 32]	.307 (.006) [*n* = 64]
overall	.246 (.023) [*n* = 64]	.444 (<.001) [*n* = 66]	.352 (<.001) [*n* = 130]	.392 (.001) [*n* = 64]	.417 (<.001) [*n* = 66]	.400 (<.001) [*n* = 130]

We conducted another two-factorial MANOVA testing the impact of GA information on post-learning confidence (H3a, RQ1) and performance levels (H2a, H2b) assessed in the knowledge test at the end of the study. We conducted the analysis with individual data since intra-class-correlation measures showed no indication of interdependence between learners (values were entirely below .20 and non-significant). The test for normality showed no significant deviation from normality, after one outlier was excluded from the calculation. Results showed that neither the provision of metacognitive GA information on confidence ($F(2, 254) = 0.23$, $p = .796$, $\eta_p^2 < .01$, CI 95% [0, .02]), nor the provision of cognitive GA information on assumptions ($F(2, 254) = 1.91$, $p = .150$, $\eta_p^2 = .02$, CI 95% [0, .04]), nor their interaction ($F(2, 254) = 1.61$, $p = .203$, $\eta_p^2 = .01$, CI 95% [0, .04]) had an impact on the results in the post test. Descriptive data can be viewed in Table 6.

Table 6: descriptive data on confidence and performance in knowledge test (percentage)

		mean performance knowledge test (0 - 100)		mean confidence knowledge test (0 - 100)	
experimental condition	*n*	*M*	*SD*	*M*	*SD*
mGAI+/cGAI+	64	45.23	5.43	63.05	14.69
mGAI+/cGAI-	67	47.00	6.30	63.93	14.04
mGAI-/cGAI+	64	46.28	6.64	59.86	13.33
mGAI-/cGAI-	64	46.22	5.21	64.95	14.26

Discussion

Results of the study

In our study we compared two types of knowledge-related group awareness (GA) information within a CSCL scenario regarding their impact on learning processes and outcomes: cognitive content information enabling conflict identification and metacognitive confidence information enabling identification of perceived lacks of knowledge. Overall, we found that the type of information provided guided the selection of material to discuss. Learners used the information provided to make study decisions (confirming H1a & H1b) and even somewhat seemed to integrate the information if both were provided. This ties in with GA research and shows the power of GA information to guide learning decisions. Interestingly, the interaction effect between conflict and confidence on the discussion rates if both types of information are provided hints at a universal effect of conflict, but confidence guiding learning decisions primarily when there is consensus amongst learners (or when there is no information on conflict provided). Because the data base for these results is quite scarce, follow-up

studies should revisit these effects and look more closely at how both types of information are perceived and processed by the learners.

While selection processes were adapted as expected, this did not have the expected impact on learning. Overall, learners gained knowledge while working collaboratively within the learning environment, but that seemed to not depend on the GA information provided or regulation processes (rejecting H2a & H2b). While previous studies showed a similar lack of effect of GA tools on learning outcomes (e.g., Buder & Bodemer, 2008; Engelmann & Hesse, 2011; Schnaubert & Bodemer, 2016), it is still surprising that even regarding the precise items they worked with, discussing conflicts and uncertainties did not have beneficial effects on performance, even if research on metacognition and socio-cognitive conflicts would suggest differently (cf. Cognitive and metacognitive information in collaboration section).

However, looking into the discussion rates, we can see that even if unsupported learners do not focus on conflicts and uncertainties, they still look into almost all the items. Thus, the benefit in providing GA information may be an issue of efficiency rather than effectiveness (especially the provision of metacognitive information seems to reduce the number of items discussed). In our study, all learners had the same amount of time and were not allowed to terminate the process prematurely. Because we kept the learning time stable to avoid time as an influential factor, there might have been no urgent need to structure and decide on a strategy and some learners may have thought that using a strategy like looking at all items would suffice. Tighter time constraints should force learners to make strategic decisions. Without it, one potentially beneficial effect may have been lost, because learners were able to attend to all material. More realistically, learners could have been given the opportunity to terminate the session prematurely. This would be more realistic, since in practice, there are usually some time constraints students face when working collaboratively on a task, but they usually still have some control over the time and effort they put into learning. While effects could then not be attributed to the quality of collaboration, but maybe merely the quantity, this procedure would be in line with research on self-regulated learning, which assumes that deciding when to terminate study is an important learning decision (e.g., Metcalfe & Kornell, 2005).

Another explanation for the lack of effect on learning gain would be that learners may have tried to resolve conflicts by quick consensus building activities (Weinberger & Fischer, 2006) and may have wanted to complete the task rather than gaining knowledge. Such an approach is less beneficial and may have been supported by the experimental setup (participation was rewarded, but there may have been no internal value in gaining knowledge). Additionally, providing information on differences of assumptions has been shown to foster this approach under some circumstances (Gijlers et al., 2009) and this might have hampered the potentially beneficial effects of attending to conflicts in the conditions with cognitive GA information available.

Providing cognitive GA information on assumptions did not affect post-learning confidence levels (RQ1), but we did find that metacognitive GA information had an indirect impact on confidence mediated by confidence-based regulation, however, this was partially masked by a negative (albeit not statistically significant) direct effect on this measure for both groups with metacognitive GA information available (thus only partially confirming H3a). Consequently, it seems possible that if learners do not strategically use the information on own uncertainties to steer their learning process, having it saliently visible throughout learning may foster the preservation of these uncertainties. While such effects would have to be backed up by further research (especially in light of the still scarce evidence), we have to consider the possibility of detrimental effects of GA information if it is not used strategically.

Such detrimental effects of providing additional information may also be explained by limitations of the working memory (e.g., Sweller, 1994), especially with novice learners as was the case in our study (cf. Kalyuga, 2013). If information is provided that does not serve the learning process, this may put an additional strain on the cognitive system and thus hamper germane learning processes (Sweller, van Merrienboer, & Paas, 1998). This may even be more relevant within CSCL scenarios, where the collaboration may add to the complexity of the situation and transactive activities produce additional costs (cf. Dillenbourg & Bétrancourt, 2006; Kirschner, Sweller, Kirschner, & Zambrano R., 2018). In addition, a shared workspace forces learners to negotiate not only their understanding of a task, but also negotiate and coordinate their interaction with the learning environment (cf. Dourish & Bellotti, 1992). However, mental overload may only partially explain the found effects, since knowledge gain was not affected, but rather the metacognitive evaluation. Thus, it may well be that providing GA information on uncertainties may lead to further uncertainties because learners become aware of their gaps in knowledge and if they do not use this (meta-level) knowledge to clear up uncertainties, they may be unsettled. To avoid such effects, providing metacognitive GA information on confidence may be accompanied by more direct instructions to ensure their usage to benefit learning (e.g., by prompting or scripting, cf. Kollar, Wecker, & Fischer, 2018).

Interestingly, while we found clear patterns about how learners used GA information to structure their learning process in the log files, their self-reports did not differ in terms of usage of one type of information or the other. There are various possible explanations for this. The easiest would be to assume that learners are just not aware of the strategies they use or are not able to reproduce them after learning (flaws on self-report, e.g., Nisbett & Wilson, 1977). However, it is equally possible that if not provided, learners reconstruct the information on certainty and assumptions during collaboration and that this repetition of the process results in different assumptions and certainties than before. We do know that metacognitive judgments may change over time and with attention to material (e.g., Koriat & Levy-Sadot, 2001; Vernon & Usher, 2003), and especially assumptions made under high levels of uncertainty (like guessing) seem likely to change merely due to chance.

Additionally, information gathered during the collaboration may affect the learners' certainties and assumptions, e.g., conflicting cognitive information from the learning partners may make learners uncertain. The learners may then use the adjusted information as a basis for regulatory processes. If such changes are only initiated during collaboration, they will be unaccounted for in the experimental log data initially assessed and may lead us to false assumptions about the regulatory processes taking place. Especially if learners do not reproduce but newly construct the information, it seems logical that they take information gathered during collaboration into account (e.g., provided answers of their learning partner may affect confidence; information gathered during collaboration may affect assumptions). Thus, the learners in our study may well have been using this newly constructed information very precisely, but without a chance for us to account for these cognitive and metacognitive changes when relying on pre-collaboration data. That said, reconstructing the information on the fly may well produce a more accurate picture of the learners' knowledge than using information produced prior to collaboration (although merely reproducing it could also be essentially flawed, e.g., due to constrains in memory). However, reconstructing information takes up valuable resources. Metacognitive monitoring processes and the need to keep the information mentally present while performing other cognitive activities essentially for learning may overstrain learners (Valcke, 2002). Although prior studies with similar material did not show an overall rise in mental effort if metacognitive information was not visualized (Schnaubert & Bodemer, 2017), it is

possible that in a collaborative scenario the additional effort of maintaining metacognitive and cognitive information of both partners may tip the balance and produce a load on the cognitive system that was too high to handle properly.

While the log data paints a different picture than the self-reports, there is another aspect which may have had a potential impact on these results. While providing GA information set focus on conflicting issues and uncertainties, the assessment of the GA information alone may have had similar effects. Individual research has shown repeatedly that merely assessing metacognitive ratings (like confidence ratings or judgments of learning) affects memory (Soderstrom, Clark, Halamish, & Bjork, 2015) and study choices (Mitchum, Kelley, & Fox, 2016; Schnaubert & Bodemer, 2017) by prompting the assessed monitoring processes in the first place. While this somewhat hampers the external validity of the study results with regard to the effects of providing GA information, assessing and transforming relevant information is a crucial part of GA tools (Bodemer et al., 2018; Buder & Bodemer, 2008). Using potentially reactive direct assessment methods of the target concepts as opposed to non-obtrusively attained data (like analyzing available products of student work, e.g., essays: M. Erkens et al., 2016) may also yield benefits as transformation processes may be kept to a minimum. Transformation processes inevitably integrate external information or algorithms and thus are a source of external feedback for the learners, especially if they are complex like common in the field of learning analytics. This has several implications: First, such processes require external information of high quality like expert models or computational algorithms adjusted to the content domain. This makes such tools inflexible and somewhat impractical for various settings (including school settings) as it hampers transferability to different learning materials and domains. Second, forgoing transformation makes the whole process of obtaining and providing GA information instantly transparent and easily acceptable for learners as they are in control of the information provided. Thus, providing untampered information about the learners' take on their knowledge can easily be interpreted by target learners, as they provided the information in the first place (we acknowledge that this may differ between learners and may thus sometimes be less straightforward when learners interpret their learning partner's information). This focus on information provided by the learners themselves rather than on externally provided information further strengthens the notion of guiding without governing, which is focal for self-regulation and agency and sets GA apart from other instructional methods like feedback and more explicit guidance.

Limitations of the study

There are some limitations to the study that need to be addressed. Possibly the most obvious one concerns the regulation measure. Although the effects on regulation seem strong and stable, it is worth mentioning that the individual regulation coefficients might be somewhat error prone. The correlation coefficients were based on 16 observations each – some of them unevenly distributed on either of the variables, which is a rather low number of observations; to get more stable measures, more data points would be needed. However, 16 items was already a large set and we wanted to avoid overloading learners, which could pressure them into using the provided information as guidance due to the sheer amount of information. Interestingly, most of the dyads we had to exclude from the calculations because they discussed all tasks (and no correlation could be computed) were in the group without GA information support. We excluded them from the calculation, but it is fair to point out that, technically, they did not differentiate between conflicting and non-conflicting items or certain and uncertain items, since they did look at all tasks without fault. This further supports the notion that guidance occurred when GA information support was provided.

We have some further limitations to the data that are worth mentioning. Some of the dependent variables assessed showed highly skewed distributions (e.g., ceiling effects) and although bootstrapping was used whenever possible, this does not account for all problems associated with this.

Due to the dyadic and complex design, we also abstained from using multilevel analyses, even though our subjects worked together in dyads and thus have shown interdependences in some instances. The learning processes we investigated are not affected, since they are dyadic by nature, but learning gains and confidence levels in the learning tasks were affected. ICC values showed that learners aligned their confidence levels especially when information on confidence was provided and less so if it wasn't. However, the opposite seemed to be the case for performance. This is in line with previous findings, where metacognitive information led to higher interdependencies with regard to confidence levels and lower interdependencies with regard to performance (Schnaubert & Bodemer, 2018). However, in our study, one condition especially seemed to break ranks with regard to performance: learners provided with both types of information were not more similar within than between dyads. One interpretation is that while learners may align their assumptions especially if cognitive information is provided, information on confidence might allow learners to maintain differing assumptions by reducing socio-cognitive conflict due to salience of low confidence (confidence in assumptions is believed to be a factor in perceiving socio-cognitive conflict and thus the need to align opinions; cf. Lee & Kwon, 2001; Lee et al., 2003). However, descriptively looking into ICC values may help with interpreting the results but cannot provide definitive conclusions without inspecting collaboration processes. To account for the fact that we violated the independency assumption of the statistical tests used, we additionally performed the analyses on a dyadic level. While this does come with other problems (cf. Janssen, Erkens, Kirschner, & Kanselaar, 2011), it does account for underestimated *p*-values due to interrelated data. Overall, while we might have overestimated effects on learning outcomes by ignoring the hierarchical structure and using individual data, we found no effects to speak of on learning outcomes anyway, rendering the critique merely academic.

Another decision that needs to be discussed is the usage of binary information with regard to the information portrayed in our GA tool. Within metacognition research, it is common to assess metacognitive information on a more fine-grained scale and binary confident scales are assumed to be inferior for research purposes (cf. Dinsmore & Parkinson, 2013). However, in this kind of research, the aim usually is to assess metacognitive information to study it, not to guide learning processes. As argued above, within GA tools, the information has to be presented in an easy to understand way and aligned to the intended guidance mechanisms (cf. Bodemer, 2011). Theoretically, it would have been possible to assess the information on a more fine-grained scale (for research purposes) but present it in a binary fashion (for the learners' benefit). However, any transformation chosen may not align with what learners individually perceive as relevant differences between certainty and uncertainty. Confronted with a binary choice, learners are able to define a threshold of what is "certain enough", which aligns with the binary decision of what needs no further attention. While this seems fitting for supporting task selection, it may hamper more fine-grained decision making like prioritizing (cf. Schnaubert & Bodemer, 2017).

Ultimately, tool design needs to strike a balance between portraying rich information and keeping processing costs low. In terms of guidance, such design decisions are crucial and need to be scrutinized in detail, because how data is assessed, transformed and visualized may have a huge impact on guidance mechanisms (for an example see the work on representational guidance mechanisms, e.g., Suthers, 2001; Suthers & Hundhausen, 2003). While our research focused on the information portrayed, this

cannot be fully detached from design decisions made that may suggest certain learning behaviors more than others. Further research should explicitly target such decisions to find the best possible balance between richness and usability.

Implications for practitioners and CSCL design

The results of this research suggest that different types of GA information lead to very different approaches to learning material. Co-located learners working in learning groups may profit from information about each other by being supported by GA tools to detect conflicting information or perceived uncertainties. Integrating the GA information into the collaborative task at hand proved useful as this ensured that the information did not divert attention from the task (cf. Buder, 2011) and our results showed that learners used the information for content selection. Further, learners were able to integrate both types of information when provided. This suggests that educators wanting learners to focus on different types of information simultaneously may use tools providing different types of information without overburdening the learners – at least in cases where the information is of low complexity, easy to understand and integrated in the learning environment. Scaling up the information by including richer data still needs to be done with caution, as more complex data may exponentially increase the mental effort needed to integrate various kinds of information and thus warrants further research to explicitly test the boundaries for specific learning arrangements.

Looking at the interaction effect between conflict status and confidence with regard to the discussion rates, the data cautiously suggests that especially confident learners may be engaged in collaborative learning processes by including information about conflicts and it may even be worth deliberately pairing them with partners disagreeing to encourage engagement with the learning content (an example of a script containing such a paring algorithm with relation to opinions is the argue graph script, cf. Jermann & Dillenbourg, 2003).

While the guidance effects were clearly visible in the study, our results did not suggest benefits of GA information with regard to learning outcomes. One of the strengths of GA support to guide learning is that it builds on self-regulatory skills and gives learners the freedom to adapt the learning process to their needs. However, this may just also be its greatest weakness: learners with low self-regulatory skills or learners struggling with other cognitive or collaborative processes involved (like argumentation) may not be able to profit from such support in terms of learning gains. There is ongoing debate about how much and directive support to grant learners (e.g., Kirschner & van Merriënboer, 2013). In our study, learners had support in regulating their study choices, but no support in conducting the studying itself. While the setup and tool provided opportunities for collaborative activities such as joining attention towards aspects by pointing or referring to a shared external representation or sharing information from each individual text, no explicit structure for discussing the content was provided. Although more explicit guidance is often seen in stark contrast to implicit guidance mechanisms such as awareness tools, this view is not unchallenged (see the debate in Wise & Schwarz, 2017). By carefully looking into guidance effects as well as learning outcomes, our research points towards an integrative approach: while the GA information portrayed by the GA tool in our study managed to draw the learners' attention towards relevant aspects of the learning material and thus supported the metacognitive activity of selecting relevant content and allocating study resources, the process of collaboratively dealing with the material may need more support. Scaffolding beneficial collaborative activities (e.g., by scripting, Kollar et al., 2018) to complement GA support seems to be especially fitting, as scripts may be used to specify activities

and support their execution (cf. Weinberger, Ertl, Fischer, & Mandl, 2005), while the GA information helped learners to identify relevant conditions within the collaborative situation and focused their attention on specific content. If collaborative learning is supported by implicit and explicit guidance mechanisms in unison, both types of support not only need to match the goals of the educator and the cognitive processes involved, but also need to be aligned to each other. For instance, cognitive information on assumptions may warrant support in argumentation and conflict resolution processes (e.g., Stegmann, Wecker, Weinberger, & Fischer, 2012; Stegmann, Weinberger, & Fischer, 2007), while metacognitive information on confidence may be accompanied by support in explaining content or asking questions (e.g., King, 1992; Rosenshine, Meister, & Chapman, 1996).

The use of these guidance mechanisms requires educators to be aware of their learners' individual characteristics as these may determine if and how learners benefit from the support provided. Unfortunately, research on individual characteristics and their relation to implicit guidance approaches are rare (for a notable exception see Heimbuch & Bodemer, 2018). Looking more thoroughly into learners' skill sets and other potentially relevant characteristics may be needed to better adapt the support towards the learners' needs.

Closing remark

Our study focused on guidance effects of GA information within a shared learning environment and thus on how learners structure their learning with the aid of GA information by interacting with the learning material within the learning environment rather than what cognitive and collaborative processes happen during collaboration. We are aware that this perspective does not directly target cognitive and metacognitive processes relevant to learning, but merely their behavioral outputs. From a self-regulation perspective, guiding study behavior and choosing what aspects of learning material are worth allocating study time to are crucial aspects of knowledge acquisition and have thus received a lot of attention in metacognition research. Within research on collaborative learning, the focus often lies in communication and interaction processes between learners as they are the core of collaboration and additionally allow us to study cognitive processes in more detail as they are often externalized for the learning partners' benefit. While this was beyond the scope of the research presented in this study, looking more deeply into the processes of sharing and building knowledge may help explain the lack of effect on knowledge and help us to better understand how learners use cognitive and metacognitive GA information for learning. Finally, our study provided relevant insight into the effects of different types of GA information portrayed within knowledge-related GA tools. However, more studies are needed that systematically vary specific aspects of these tools in different settings to advance our knowledge on mechanisms and boundary conditions of GA tools to improve their effectiveness in supporting CSCL.

Acknowledgements We would like to thank Christian Schlusche, M.Sc., for the extensive technical support he provided.

Appendices

Appendix A

```
Run MATRIX procedure:
************* PROCESS Procedure for SPSS Release 2.16.1 ***********
          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3
**************************************************************************
Model = 4
    Y = Confiden [annot.: confidence gain learning tasks]
    X = GA_condi [annot.: group awareness condition]
   M1 = reg_conf [annot.: conflict-based regulation]
   M2 = reg_rc_u [annot.: confidence-based regulation]
Sample size: 101
Coding of categorical X variable for analysis:
 GA_condi       D1       D2       D3
     1.00      .00      .00      .00 [annot.: no visual.]
     2.00     1.00      .00      .00 [annot.: confidence visual.]
     3.00      .00     1.00      .00 [annot.: assumption visual.]
     4.00      .00      .00     1.00 [annot.: both visualizations]
**************************************************************************
Outcome: reg_conf
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6455      .4166      .0672    21.9210     3.0000    97.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
Constant     -.0180      .0736     -.2443      .8075     -.1641      .1281
D1            .0316      .0875      .3610      .7189     -.1422      .2054
D2            .4370      .0869     5.0272      .0000      .2645      .6096
D3            .4639      .0900     5.1544      .0000      .2853      .6425
**************************************************************************
Outcome: reg_rc_u
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5314      .2824      .1118    11.8293     3.0000    97.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
Constant     -.0495      .0795     -.6229      .5348     -.2072      .1082
D1            .5227      .1086     4.8130      .0000      .3071      .7382
D2            .1043      .0990     1.0533      .2948     -.0922      .3008
D3            .3960      .0992     3.9911      .0001      .1991      .5930
**************************************************************************
Outcome: Confiden
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4190      .1756     3.4924     4.8263     5.0000    95.0000      .0006
Model
```

```
            coeff         se          t          p       LLCI       ULCI
Constant     3.0357      .4631     6.5547      .0000     2.1163     3.9552
reg_conf    -1.1034      .8127    -1.3578      .1777    -2.7168      .5099
reg_rc_u     2.3108      .6090     3.7947      .0003     1.1019     3.5198
D1          -1.1831      .6437    -1.8378      .0692    -2.4610      .0949
D2           .3715      .6236      .5957      .5528     -.8665     1.6096
D3          -1.0112      .6296    -1.6061      .1116    -2.2610      .2387
************************** TOTAL EFFECT MODEL ******************
Outcome: Confiden
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1476      .0218     4.0584      .6783     3.0000    97.0000      .5674
Model
            coeff         se          t          p       LLCI       ULCI
Constant     2.9412      .4305     6.8322      .0000     2.0868     3.7956
D1          -.0101      .5788     -.0175      .9861    -1.1589     1.1386
D2           .1303      .5937      .2194      .8268    -1.0481     1.3086
D3          -.6078      .5862    -1.0370      .3023    -1.7712      .5556
***************** TOTAL, DIRECT, AND INDIRECT EFFECTS **********
Relative total effects of X of Y
        coeff         se          t          p       LLCI       ULCI
D1     -.0101      .5788     -.0175      .9861    -1.1589     1.1386
D2      .1303      .5937      .2194      .8268    -1.0481     1.3086
D3     -.6078      .5862    -1.0370      .3023    -1.7712      .5556
Omnibus test of total effect of X on Y
       R-sq          F        df1        df2          p
      .0218      .6783     3.0000    97.0000      .5674
=====
Relative direct effects of X on Y
        coeff         se          t          p       LLCI       ULCI
D1    -1.1831      .6437    -1.8378      .0692    -2.4610      .0949
D2      .3715      .6236      .5957      .5528     -.8665     1.6096
D3    -1.0112      .6296    -1.6061      .1116    -2.2610      .2387
Omnibus test of direct effect of X on Y
       R-sq          F        df1        df2          p
      .0829     3.7386     3.0000    95.0000      .0137
=====
Relative indirect effect(s) of X on Y through:  reg_conf
           Effect   SE(boot)       LLCI       ULCI
D1         -.0349      .1210     -.3022      .2076
D2         -.4822      .3609    -1.1770      .2520
D3         -.5118      .3994    -1.3219      .2619
Omnibus    -.4398      .3530    -1.1730      .2576
----------
Relative indirect effect(s) of X on Y through:  reg_rc_u
           Effect   SE(boot)       LLCI       ULCI
D1         1.2078      .3968      .5276     2.0702
D2          .2410      .2394     -.2098      .7508
D3          .9152      .3496      .3341     1.6971
Omnibus     .6012      .2533      .2386     1.2128
----------
******************* ANALYSIS NOTES AND WARNINGS *************
```

Number of bootstrap samples for percentile bootstrap confidence intervals: 10000
Level of confidence for all confidence intervals in output: 95.00
NOTE: Some cases were deleted due to missing data. The number of such cases was: 29
NOTE: All standard errors for continuous outcome models are based on the HC3 estimator
------ END MATRIX -----

Appendix B

Run MATRIX procedure:
********** PROCESS Procedure for SPSS Release 2.16.1 **********
Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2013). www.guilford.com/p/hayes3
****
Model = 4
Y = Performa [annot.: performance gain learning tasks]
X = GA_condi [annot.: group awareness condition]
M1 = reg_conf [annot.: conflict-based regulation]
M2 = reg_rc_u [annot.: confidence-based regulation]
Sample size: 101
Coding of categorical X variable for analysis:

GA_condi	D1	D2	D3	
1.00	.00	.00	.00	[annot.: no visual.]
2.00	1.00	.00	.00	[annot.: confidence visual.]
3.00	.00	1.00	.00	[annot.: assumption visual.]
4.00	.00	.00	1.00	[annot.: both visualizations]

****
Outcome: reg_conf
Model Summary

R	R-sq	MSE	F	df1	df2	p
.6455	.4166	.0672	21.9210	3.0000	97.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
Constant	-.0180	.0736	-.2443	.8075	-.1641	.1281
D1	.0316	.0875	.3610	.7189	-.1422	.2054
D2	.4370	.0869	5.0272	.0000	.2645	.6096
D3	.4639	.0900	5.1544	.0000	.2853	.6425

****
Outcome: reg_rc_u
Model Summary

R	R-sq	MSE	F	df1	df2	p
.5314	.2824	.1118	11.8293	3.0000	97.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
Constant	-.0495	.0795	-.6229	.5348	-.2072	.1082
D1	.5227	.1086	4.8130	.0000	.3071	.7382
D2	.1043	.0990	1.0533	.2948	-.0922	.3008
D3	.3960	.0992	3.9911	.0001	.1991	.5930

****
Outcome: Performa

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2929      .0858     1.9170     2.0006     5.0000    95.0000      .0855
Model
              coeff         se          t          p       LLCI       ULCI
Constant     1.4880      .3323     4.4774      .0000      .8283     2.1478
reg_conf     -.2775      .4309     -.6439      .5212    -1.1330      .5780
reg_rc_u     -.1408      .3846     -.3661      .7151     -.9043      .6227
D1           -.8314      .4326    -1.9219      .0576    -1.6903      .0274
D2            .0645      .4649      .1388      .8899     -.8584      .9875
D3            .1845      .4101      .4498      .6539     -.6297      .9987
************************** TOTAL EFFECT MODEL ******************
Outcome: Performa
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2862      .0819     1.8855     3.2637     3.0000    97.0000      .0247
Model
              coeff         se          t          p       LLCI       ULCI
Constant     1.5000      .3337     4.4956      .0000      .8378     2.1622
D1           -.9138      .4053    -2.2544      .0264    -1.7183     -.1093
D2           -.0714      .4536     -.1575      .8752     -.9718      .8289
D3            .0000      .4200      .0000     1.0000     -.8336      .8336
***************** TOTAL, DIRECT, AND INDIRECT EFFECTS **********
Relative total effects of X of Y
        coeff         se          t          p       LLCI       ULCI
D1     -.9138      .4053    -2.2544      .0264    -1.7183     -.1093
D2     -.0714      .4536     -.1575      .8752     -.9718      .8289
D3      .0000      .4200      .0000     1.0000     -.8336      .8336
Omnibus test of total effect of X on Y
       R-sq          F        df1        df2          p
      .0819     3.2637     3.0000    97.0000      .0247
=====
Relative direct effects of X on Y
        coeff         se          t          p       LLCI       ULCI
D1     -.8314      .4326    -1.9219      .0576    -1.6903      .0274
D2      .0645      .4649      .1388      .8899     -.8584      .9875
D3      .1845      .4101      .4498      .6539     -.6297      .9987
Omnibus test of direct effect of X on Y
       R-sq          F        df1        df2          p
      .0600     2.5732     3.0000    95.0000      .0586
=====
Relative indirect effect(s) of X on Y through: reg_conf
           Effect   SE(boot)       LLCI       ULCI
D1         -.0088      .0466     -.1346      .0609
D2         -.1213      .1981     -.5348      .2491
D3         -.1287      .2116     -.5691      .2606
Omnibus    -.1106      .1920     -.5087      .2550
----------
Relative indirect effect(s) of X on Y through: reg_rc_u
           Effect   SE(boot)       LLCI       ULCI
D1         -.0736      .2066     -.4875      .3385
D2         -.0147      .0552     -.1387      .0998
```

D3 -.0558 .1556 -.3731 .2495
Omnibus -.0366 .1148 -.2841 .1832

********** ANALYSIS NOTES AND WARNINGS **********
Number of bootstrap samples for percentile bootstrap confidence intervals: 10000
Level of confidence for all confidence intervals in output: 95.00
NOTE: Some cases were deleted due to missing data. The number of such cases was: 29
NOTE: All standard errors for continuous outcome models are based on the HC3 estimator
------ END MATRIX -----

Appendix C

factors (type)	$F(2, 125)$	p	η_p^2
main effects			
time (within)	179.70	< .001	.74
metacognitive GA information (between)	1.57	.211	.03
cognitive GA information (between)	0.03	.974	< .01
first order interactions			
metacognitive * cognitive GA information	0.36	.700	< .01
time * metacognitive GA information	1.75	.177	.03
time * cognitive GA information	1.15	.320	.02
second order interaction			
time * metacognitive * cognitive GA information	1.95	.147	.03

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Study 4: What interdependence can tell us about collaborative learning: a statistical and psychological perspective

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What interdependence can tell us about collaborative learning: a statistical and psychological perspective

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Abstract

When learning collaboratively, learners interact and communicate transactively. Interventions to foster collaborative learning frequently target such interactive processes and thus may drastically change how learners engage with and thus influence each other. One statistical phenomenon related to collaborative learning is the interdependence of data gained from learners collaborating. Often viewed as a mere statistical phenomenon, on a conceptual level, statistical interdependence is a similarity between learners mainly resulting from the mutual influence learners have on each other while collaborating and is thus closely related to collaborative practices. In this paper, we report data of an exemplary study ($N = 82$) to illustrate how information on interdependence and within- and between-dyad variance may add to data interpretation. The study examined how providing metacognitive group awareness information during collaboration affects individual learning outcomes. We found indications that the information fosters knowledge gain, but not confidence. Surprisingly, the data revealed different levels of interdependence between conditions, which led us to assume interdependence to be part of the treatment effect resulting from differential collaboration processes. We discuss reasons and implications of varying levels of statistical interdependence and their impact on inferential and descriptive statistics.

Keywords: Interdependence, Intra-class correlation, Collaborative learning, Experimental study, Group awareness, Metacognition

Introduction

Collaborative learning (CL) yields a lot of potential to foster knowledge construction. When learning collaboratively, learners interact and communicate transactively. They exchange and commonly build knowledge and/or skills. Interventions to foster collaborative learning frequently target such interactive processes and thus may drastically change how the learners engage with and thus influence each other. However, research on collaborative learning comes with a number of additional challenges. One important issue is that collaboration is an interactive activity of learners that is thought to foster not only group performance but also individual learning (Hesse 2007). Thus, the data collected is frequently on different levels (individual and group) and/or heavily intertwined (like in turn-taking during discussion) (cf. Strijbos and Fischer 2007). This poses a great challenge for quantitative research, because traditional analyses (like

ANOVAS) require independent data and are not designed to handle statistical interdependence (cf. Janssen et al. 2011).

While there have been promising developments like multi-level approaches to deal with hierarchical data, these approaches are often limited especially when working with dyadic data and/or require high standards like large sample sizes (Janssen et al. 2011; Nezlek et al. 2006). Thus, dealing with hierarchical data usually comprises of testing for interdependence using for example the intra-class correlation (ICC) before deciding on an appropriate strategy. If the ICC indicates practically relevant levels of interdependence, the data is analyzed accordingly by accounting for the non-independence (Cress 2008). There are different ways to handle interdependence (cf. Janssen et al. 2011). For example, data is sometimes analyzed on group level loosing information about individual data; however, this approach may have downsides (e.g., increasing the risk of type 2 errors by losing statistical power due to reduced sample size). Recently, more and more researchers use multi-level approaches to account for interdependence. However, dyadic data provides a special challenge for the later, since the usual regression-based approaches are not appropriate (Kenny and Kashy 2011). If the data shows no signs of interdependence, statistically, the dyads do not have to be taken into consideration and independence may be assumed. While this often solves analytical problems, theoretically, this may be a short-sighted perspective. To get to the bottom of this, we first need to take a closer look at what statistical interdependence means statistically, but also conceptually.

Statistically, interdependence means that data (for example of specific subjects within a sample) is correlated; in CL research, this is usually measured with the intra-class correlation coefficient (ICC) (Griffin and Gonzalez 1995; Kenny et al. 2006; Shrout and Fleiss 1979). The ICC measures the percentage of variance due to belonging to the same group or dyad. One interpretation is thus, how much of the variance between subjects may be explained by the (random) dyad factor (Gonzalez and Griffin 2012; Griffin and Gonzalez 1995; Kenny et al. 2006). Thus, the more similar members of a dyad are (in comparison to members of the whole sample), the higher the value. Conceptually, positive statistical interdependence resulting from collaboration describes a similarity between learners that had been in the same group or dyad during collaboration.

To grasp the theoretical/psychological meaning of statistical interdependence within CL research, it is important to take a look at how interdependence occurs within collaborative learning scenarios. Statistical interdependence of learners after collaboration may have various causes. According to Cress (2008), assuming random assignments to a group or dyad (no compositional effects), these causes are common fate and reciprocal influence. Common fate refers to unique experiences learners in a group share during collaboration by being confronted with the same influences within the learning environment, e.g., when following the same discussion thread or listening to the same arguments. Taking this further, within CL, learners are supposed to actively interact and thus influence each other; this is known as reciprocal influence. Thus, learners influence each other's cognitions, motivation, and behavior, which may lead to both greater differences between groups and convergence within the groups. Within CL research, reciprocal influence is important not only because it is the main cause of interdependence (Bonito 2002; Cress 2008), but because it is the core of collaboration.

However, interdependence is not only a phenomenon observed within collaborative learning processes but also within individual learning outcomes that rely on collaboration processes. Depending on the outcomes measured, results of collaborative efforts may be heavily interdependent between learners in a group or dyad due to mutual influence caused by interactive processes. While these processes do not have to cause statistical interdependence that is visible in the data a researcher is interested in, conceptually, interrelations should be expected for variables directly related to collaborative practices. Especially learning outcomes like knowledge are expected to be highly impacted by knowledge exchange and mutual knowledge building processes as they highly depend on interactive processes.

For example, imagine a scenario with all learners having unique prior knowledge on a subject and being brought together in dyads in an environment designed to share their knowledge and build a common knowledge base. The learning partners then start exchanging their knowledge by externalizing internal cognitive information for the group's benefit and by perceiving observable group level activities. Ideally, they each share (i.e., externalize) all relevant content information they possess on the subject, while processing, comprehending, and elaborating on the information (Buder 2017). Further, they might detect misconceptions and correct them together. In this scenario, the content of their knowledge after collaboration would be rather similar due to convergence (Weinberger et al. 2007). Additionally, their levels of knowledge would be interdependent since the amount of shared information contributes to the amount of knowledge they have on the subject. Moreover, if we assume reciprocal processes, collaboration should benefit both learners similarly, albeit not identically. For example, high-quality collaboration should benefit both learners, while poor strategic decisions should hamper learning for both. Of course, going beyond knowledge exchange and toward collaborative knowledge building activities, the relation between the collaborative activities and interdependence of outcomes are even more pronounced, since these processes rely on transactivity (cf. Teasley 1997). Obviously, there are other scenarios in which learning processes are not balanced, but for example complementary or unilateral. In these scenarios where the collaborative processes lack reciprocity, learners may profit very differently. However, even within less reciprocal settings, learners may influence each other in a unique way that fosters interdependence: a weak learner might for example profit from a more knowledgeable partner not only by internalizing the information given by the partner but also by adopting the other one's thought processes. In such a scenario, learning outcomes may be highly interdependent even though learner partners profit from collaboration very differently.

Even though the mechanisms behind interdependent data may highly depend on the concept measured and on the processes expected within collaboration, whenever inter- or even transactive learning activities occur, a certain degree of interdependence can be expected in outcomes directly related to collaborative practices. Thus, although not definitive, a lack of interdependence may indicate an undesirable lack of such collaborative processes. A lack of interdependence may indicate problems with the theoretical assumptions about collaborative practices and/or with the actual collaboration processes happening within the experimental design and should be critically addressed. Although some researchers point out that interdependence should be studied and not merely eliminated (e.g., Gonzalez and Griffin 2012) and reciprocal influence—a major

cause of statistical interdependence—is desired within CL (Cress 2008), a lack of statistical interdependence in the data after collaboration is seldom commented on within CL research, let alone discussed in detail.

Altogether, this means that interdependence is indicative for collaborative processes (which does not mean that the absence likewise is inevitably and indicator of the lack of such) and should thus be celebrated rather than bemoaned. It also means that the collaborative processes taking place strongly influence the level of interdependence between learners within a dyad or group. This is important, since interventions targeting these processes may not only have an impact on these collaborative learning processes and individual learning outcomes but also on the relatedness/interdependence of these outcomes. Every time interventions targeting collaboration processes are believed to affect individual learning outcomes, they may affect the level of interdependence of these outcomes as well, especially if they are specifically designed to foster individual knowledge construction via such mechanisms. Thus, statistical interdependence of data of learners within dyads may not always be similar between experimental conditions within an experimental setup.

If we connect information about the nature of psychological research and treatment effects on interdependence with statistical practices, it is surprising that while statistically straightforward, in practice, interdependence is usually measured on the whole sample. Apart from ignoring possible differences in interdependencies between experimental conditions, this additionally conflates treatment variance with variance due to dyad (interdependence of learners within a dyad will be inflated in cases of between-dyad variations of treatments, especially when effects are large, and deflated for within-dyad variations). While one can correct for this effect by factoring out treatment variance (and only use dyad and residual variance to estimate interdependence), this is seldom explicitly reported. And even if the treatment effect is adjusted for, such a procedure still assumes that the variance due to belonging to the same dyad is comparable between experimental conditions. Conceptually, this is a bold and even flawed assumption considering that interventions varied within an experiment often target interactive processes within the collaborative situation.

To sum it up, in this paper, we argue that (1) statistical interdependence after collaboration is something to be expected and even hoped for in CL; (2) assessing the ICC on a sample level is flawed on principle, because variance caused by the treatment will taint the results and lead to overestimations of interdependence within dyads; (3) interdependence can be highly influenced by interventions targeting collaborative learning processes and may thus differ dramatically between experimental conditions; and (4) information on interdependence is valuable and indicative of collaborative processes, and thus should be explicitly and critically reviewed. To illustrate this, we will describe data of an exemplary study to show how a treatment designed to foster interactive processes between individuals learning in a dyadic setting may affect interdependence, which in turn affects the data assessed. While we are aware that multi-level approaches may account for such differences, we argue that statistical interdependence is not primarily a statistical nuisance to be eliminated from our data, but a valid diagnostic outcome to be explicitly discussed in research on collaborative learning, as it is the core of collaboration. The dataset we present is drawn from a study designed to investigate how metacognitive information in group awareness tools affects collaborative learning

outcomes in a dyadic setting. Due to the methodological focus of this paper, we will only briefly sketch the theoretical background, research questions, and methods of this exemplary study. We will then describe the results of statistical analyses by comparing individual and dyadic data in detail and discuss the results with a specific focus on the value of information on interdependence.

Interdependence in CSCL: an example from group awareness research

In many studies within computer-supported collaborative learning research (CSCL), interventions are thought to foster collaboration processes that—in turn—foster individual processes (often cognitive in nature) leading to better knowledge acquisition or skill development. Progress in ICT makes it possible to support these collaborative learning processes in various ways. One typical example is group awareness tools. Group awareness tools are specifically designed to inform learners about cognitive, social, and/or behavioral aspects of group members or the group as a whole in order to implicitly guide their learning processes to ultimately benefit individual learning (Bodemer et al. 2018). By providing relevant information without giving an explicit structure or instructions, this approach builds heavily on individual skills and therefore enables diverse approaches to learning. While tools providing (cognitive) group awareness information can support relevant learning processes (cf. Janssen and Bodemer 2013), empirical research uses a great variety of target concepts, some of which may well be framed within a metacognitive context (e.g., Dehler et al. 2011). However, the field lacks a thorough investigation of the role of metacognitive awareness information in collaborative learning. Thus, in our experimental study, we aim to investigate whether metacognitive information has an added bonus to mere cognitive content information for both cognitive and metacognitive learning outcomes, drawing on group awareness research on collaborative learning and metacognitive research on individual self-regulation. While analyzing the data, we will look in detail at interdependencies between learners and compare individual and dyadic approaches to data analyzes.

Metacognitive group awareness information: research questions and hypotheses

Group awareness tools foster collaborative learning processes by providing learners with relevant information about other learners within their group or the whole group in order to make them aware of their individual or common status (Bodemer and Dehler 2011). For example, they may visualize individual needs or conflicting opinions or assumptions (Engelmann et al. 2009), helping learners to identify what aspects of the learning material need further attention. Thus, learners may use the information to structure their common learning processes. Additionally, providing social context information may foster grounding processes and partner modeling. These processes are vital for effective collaboration (Dillenbourg 1999), because they may help learners to coordinate their common learning processes (Clark and Brennan 1991) and to tail their conversation to the specific needs of the individuals (Clark and Murphy 1982) to foster effective communication. Ultimately, this is assumed to foster knowledge exchange processes and constructing shared knowledge. Empirically, such tools have shown to foster individual knowledge gains as well (e.g., Bodemer 2011; Sangin et al. 2011).

However, there is a multitude of tools providing very different kinds of information assessed in very different ways (for an overview on social and cognitive group awareness tools, see Janssen and Bodemer 2013). For example, some tools provide information about the content of other learners' cognitions, fostering awareness about conflicting assumptions within the group (e.g., Bodemer 2011), while others provide more contextual information (cf. Engelmann et al. 2009). From a metacognitive perspective, the latter tools may provide information on learners' metacognitive self-evaluations rather than cognitions (e.g., Dehler et al. 2011). Subjective evaluations of knowledge have an inherent stand-alone value (Efklides 2008) exploited by group awareness research: they indicate subjective needs by pointing out uncertainties or lacks of knowledge (Engelmann et al. 2009). Utilizing such metacognitive information is part of the causal chain for successfully self-regulating learning (Nelson et al. 1994). Additionally, metacognitions may validate cognitive information by giving a subjective value to objectively evaluable assumptions. For example, confidence in response ratings (usually seen as basic metacognitive judgments, cf. Dunlosky and Metcalfe 2009) may be seen as giving value to otherwise meaningless responses or assumptions: without a high degree of subjective certainty attached to assumptions, these may not be viewed as knowledge and may not guide real-life decisions and behavior (cf. Hunt 2003). While information on contents of knowledge can foster awareness about socio-cognitive conflicts and thus coordination efforts of the learning process, additional confidence information might change how such conflicts are handled (Schnaubert and Bodemer 2016). Ultimately, metacognitive confidence information may provide social context information that may help learners interpret their partners' knowledge and their communication efforts.

Through the above described mechanisms, confidence information may lead to better aligned communication and help learners to better ascertain knowledge distributions and control/adapt knowledge exchange processes. While this should foster knowledge gain, knowledge about learning partners' confidence in assumptions may also enable to interpret the assumptions themselves in terms of conflict perception and may thus help resolve these conflicts more efficiently. We already established that fostering knowledge exchange processes through intervention may also impact knowledge interdependence. It follows, then, that higher knowledge interdependence with metacognitive confidence information could be expected.

Confidence information may also impact the interdependence of confidence levels within groups. For example, confidence might be an indicator for successfully resolving uncertainties or epistemic conflicts. Since these resolution processes are at least similar for learners within a dyad (cognitive processes may differ, but the arguments and interactive processes the learners are exposed to are the same), the outcomes are also expected to be somewhat aligned. But even without active interaction, confidence within dyads may be aligned. Metacognition research within the area of social influence and social consensus has found that being confronted with social information may make learners start doubting their own estimations if there is a mismatch between the social information (e.g., performance) and their own estimation of item difficulty (Fraundorf and Benjamin 2016). Similarly, consensus in a group fosters certainty and being aware of controversies may be detrimental to individual confidence levels (e.g., Luus and Wells 1994; Yaniv et al. 2009). Since these concepts (consensus and controversy) both

emerge on group level, they should apply similarly to members of the same dyad, but not members of different dyads, thus fostering interdependence.

In sum, metacognitive information may support learners in identifying aspects of the learning material that need further attention. Additionally, they may foster grounding processes enabling learners to tail their conversation and learning process better to the needs of the individuals and thus should foster knowledge gain. Consequently, we assume that learners provided with metacognitive group awareness information in the form of confidence regarding specific assumptions gain more knowledge during collaboration than learners without this information (hypothesis 1) due to improved collaboration processes. However, we acknowledge the possibility that additional information might also put an extra strain on the learners' cognitive system, already charged by the collaborative situation (Dillenbourg and Bétrancourt 2006). On the other hand, metacognitive confidence information may also directly affect learners' confidence levels, since insecurities signaling an individual need for clarification can easily be identified and thus addressed during collaboration—leading to a higher clear-up rate. For example, Dehler et al. (2011) found that providing information on self-assessed levels of understanding led learners to tailor their communication to these aspects. Thus, we further hypothesize that learners receiving information on metacognitive confidence regarding specific assumptions gain more confidence during collaboration than learners without this information (hypothesis 2). In terms of interdependence, we expect enhanced knowledge exchange and conflict resolution processes to increase interdependence between learners within the same dyad.

Methods

To answer our research questions concerning the influence of metacognitive awareness information on collaborative learning and to study the impact of such an intervention on the structure (i.e., interdependence) of the data assessed, we evaluated data of an experimental study with 41 dyads of learners (82 subjects), randomly assigned to the (between-dyad) research conditions. They were all university students (55 female, 27 male) with ages ranging from 18 to 31 years ($M = 22.01$, $SD = 3.13$). Dyads were uni- and mixed sex. The study was conducted in accordance to the ethics guidelines of the German Psychological Society and approved by the ethics committee of the university. All participants gave their explicit and informed consent. We focus our analyses on one between-dyad factor varying the availability of metacognitive confidence information (MC) during collaboration. Consequently, we will compare two research conditions: one only receiving information on the learners' assumptions during learning (MC−) and one additionally receiving information on the learners' metacognitive confidence with regard to the assumptions (MC+). We then measure how collaboration affects learning outcomes by measuring the data pre and post collaboration (within-subject factor time). However, the complete design included another between-dyad factor (availability of information on overall pre-test performance), making it originally a $2 \times 2 \times 2$ design with repeated measures on one factor, counterbalanced regarding factor levels. Since it is not the focus of the current paper and the factors did not interact in influencing any of the dependent variables (multivariate interaction for both between dyad factors and the within-dyad factor time: $F(2, 77) = 0.07$, $p = .935$, $\eta_p^2 < .01$), we limit our analyses to the first factor (metacognitive confidence information). Thus, the

data set provides a typical example of research on collaborative learning in which a treatment is implemented on dyad level to foster beneficial collaboration of learning partners interacting in a dyadic setting, and individual outcome measures are measured pre and post collaboration.

Procedure

All experiments were conducted in our research lab with learners working individually on a computer and in dyads on a multi-touch tabletop. Again, this is quite common in CSCL studies, where typically individual and collaborative parts of the experiment alternate. After welcoming the participants, two learners were simultaneously placed in front of a computer screen each and started the experiment individually. After filling out questionnaires, e.g., about demographics, each learner received a text on diabetes mellitus and blood-sugar regulation and had up to 15 min to study the text. In order to foster within-dyad knowledge interdependence and support interactive engagement in the task (cf. Deiglmayr and Schalk 2015), each learner in a dyad received different text versions, that shared basic information on blood-sugar regulation available to both learners, but had a different focus especially on diabetes mellitus. They then each individually answered 18 binary true-false questions about the content of both texts and provided binary confidence ratings on each item. Answers given with confidence were visualized green, unconfident answers were visualized hatched white-green (cf. Fig. 1).

When both learners had finished this part, the experimenter asked them to the multi-touch tabletop and loaded the experimental setting. This consisted of a visualization of the binary questions and the answers provided by both participants (A and B, cf. Fig. 2) and the instruction to discuss the items for up to 20 min. They had the opportunity to access additional information on each item selected from the texts by pressing a blue button next to each item and were able to change the answers to the items. Additionally, in one experimental condition, dyads had information on the confidence ratings available during learning (MC+), the other one did not (MC−). After collaboration, learners were placed again in front of individual computers and individually answered the learning tasks again from scratch, including confidence ratings.

Independent and dependent variables

Dyads were randomly assigned to one of two conditions at the beginning of the experiment: dyads receiving metacognitive confidence information during collaboration and dyads not receiving this information (between-dyad factor: MC+ vs. MC−). Additionally, we assessed our dependent variables twice within the experiment: before and after collaboration

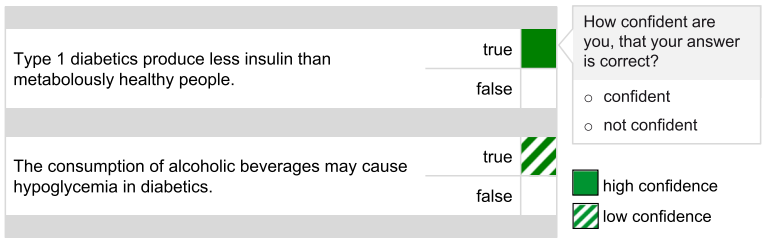
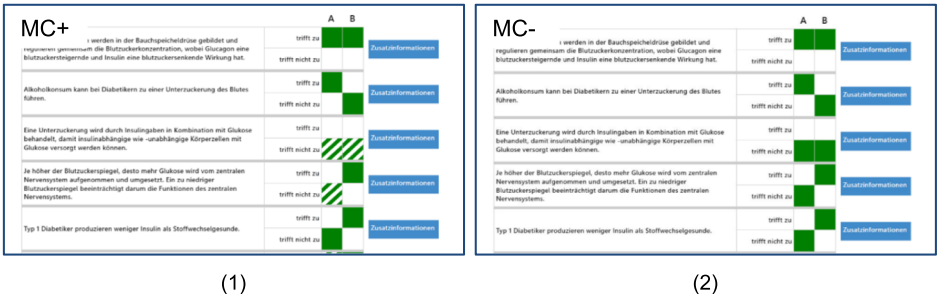


Fig. 1 Examples of translated tasks with answers and confidence rating



(1) (2)

Fig. 2 Arrangement of collaborative learning scenario on the multi-touch tabletop; (1) with metacognitive information available (MC+); (2) without metacognitive information available (MC–)

(within-subject factor: pre vs. post). Consequently, our design was a 2 × 2 factorial design with repeated measures on one factor—a common design in research on collaborative learning. Our dependent variables were the number of learning tasks correctly solved by each individual pre and post collaboration to assess knowledge gain (performance) and the number of learning tasks confidently solved by each individual pre and post collaboration to assess changes in confidence levels (confidence). Thus, while the treatment was implemented on dyad level, outcome measures were assessed for each individual separately.

Methodological approach

Since we worked with potentially dependent data (individuals were nested within dyads), we assessed statistical interdependence between subjects within dyads with regard to our learning outcomes by computing intra-class correlation coefficients (ICC; Shrout and Fleiss 1979) for each experimental condition and each dependent variable. ICC estimates and their 95% confident intervals were calculated using SPSS statistical package version 24 based on a single-rating, absolute-agreement, one-way random-effects model (the ICC estimates are thus based on ANOVA models). While it is a common practice to calculate the ICC over the whole sample, this practice falls short for different reasons: because we assigned whole dyads to experimental conditions (between-dyad independent variable), we expect within-group variances within each condition to be lower than between-group variances (cf. hypotheses 1–2) and thus ICCs over the whole sample may partially reflect treatment effects rather than within-dyad dependencies. However, while we could partial out the treatment effect (Kenny et al. 2006), this procedure ignores possible differences in dependencies between research conditions. For example, some treatments may foster collaboration and thus interdependence between learners while others might not (cf. introduction). Since the dependencies differed between the experimental groups in our study (cf. Table 3), we decided to calculate effects based on data for each individual and repeat the analyses using dyads as units of measurement (dyad values = means over individuals within a dyad). By comparing these analyses, we get a closer look into the relationship between local dependencies and inferential as well as descriptive data, which we will describe in the results section. We added multi-level analyses for reference (cf. Table 1). We also conducted variance decompositions for the dependent variables pre and post collaboration using ANOVA models (cf. Table 4).

Table 1 Inferential statistics of the MANOVA for dyads and individuals and multilevel analyses

				Time			Group			Time × Group		
	N	df_1	df_2	*F*	*p*	η_p^2	*F*	*p*	η_p^2	*F*	*p*	η_p^2
Multivariate												
Dyad level	41	2	38	81.92	< .001	.81	2.04	.144	.10	3.38	.045	.15
Individual level	82	2	79	100.68	< .001	.72	2.40	.097	.06	3.55	.033	.08
Performance												
Dyad level	41	1	39	62.98	< .001	.62	0.58	.450	.01	4.63	.038	.11
Individual level	82	1	80	62.45	< .001	.44	0.64	.428	.01	4.59	.035	.05
Multilevel	82	1	39/121	52.81	< .001	.30	0.58	.450	.01	3.88	.051	.03
Confidence												
Dyad level	41	1	39	115.39	< .001	.75	2.21	.145	.05	1.90	.176	.05
Individual level	82	1	80	146.50	< .001	.65	2.78	.099	.03	2.41	.125	.03
Multilevel	82	1	39/121	109.25	< .001	.47	2.21	.145	.05	1.80	.183	.01

Results

To test our hypotheses on learning outcomes (hypotheses 1 and 2), we conducted a two-factorial MANOVA with repeated measures on one factor. Our independent variables were experimental condition (MC+ vs. MC−) and time (pre vs. post collaboration). Our dependent variables were performance and confidence level in the learning tasks. The MANOVA was conducted once with the individual and once with the dyad as the unit of measurement. Apart from some violations of the normality assumptions for the individual data and the interdependence of the data we focus on in this paper, prerequisites were met. Since two-factorial analyses were pertinent for this design and there are no fully satisfying non-parametric alternatives, we decided to use the parametric test despite the violations. Thus, the results of the inferential statistics should be treated with caution. Level of significance was set at $\alpha = .05$.

The results of the MANOVA can be viewed in Table 1. As we can see, there is a multivariate main effect of time (but not of group) and an interaction effect visible for both units of measurement. Univariate ANOVAs confirm main effects of time on both variables with performance and confidence levels rising significantly from pre to post. They also show a significant interaction effect on performance with learners in MC+ showing a steeper increase from pre to post than learners in MC− (cf. Table 2). To account for the dyadic structure, we additionally analyzed the data via a dyadic multi-level model using linear mixed modeling with restricted maximum likelihood estimation (REML) taking into account the dependencies between learners within dyads (analogous to Kenny et al. 2006), that has been used in similar studies before (e.g., Lam and Muldner 2017). While the results were similar to the other analyses, effect sizes were overall somewhat smaller and the interaction effect between time and group just missed statistical significance.

Relationship between local dependencies and inferential and descriptive statistics

We used two different units of measurement and contrasted the results due to the non-independence of the individual subjects within our sample. By violating the independency assumption due to the local dependencies within dyads, we overestimate statistical significance for individual units of measurement (by underestimating *p* values),

Table 2 Descriptive statistics of the results for dyad and individual data (including ICC)

	N		*M*	*SD*		% Decrease in *SD*	ICC
	Individual	Dyad		Individual	Dyad		
Without MC							
Performance pre	42	21	10.10	1.86	1.01	45.70	– .41
Performance post	42	21	11.50	1.76	1.62	7.95	.67
Confidence pre	42	21	11.52	2.73	2.03	25.64	.11
Confidence post	42	21	15.31	2.24	1.78	20.54	.26
With MC							
Performance pre	40	20	9.83	2.09	1.34	35.89	– .17
Performance post	40	20	12.28	1.49	1.21	18.79	.31
Confidence pre	40	20	11.20	2.13	1.57	26.29	.08
Confidence post	40	20	14.13	2.46	2.19	10.98	.56
Overall							
Performance pre	82	41	9.96	2.00	1.17	41.50	– .28
Performance post	82	41	11.88	1.67	1.47	11.98	.55
Confidence pre	82	41	11.37	2.44	1.81	25.82	.09
Confidence post	82	41	14.73	2.41	2.05	14.94	.44

since we assume learners within a dyad to be more similar rather than more different from random pairs. When we look at the inferential statistics for both units of measurement, we can see that *p* values increase from individual to dyad level analyses (as to be expected, since *N* is halved and is directly related to *p*). However, our effect size also increases from individual to dyad level. This is due to the elimination of within-dyad variance (by computing within-dyad means) and thus a deduction of residual variance: for individual data, we *under*estimate the within-group variance in comparison to between-group variance because of local dependence within the dyads, thereby *over*estimating the effect of the between group treatment (cf. Bliese and Hanges 2004). Replacing within-dyad variance by calculation mean scores further adds to this effect, completely evening out individual differences within dyads in the process. Thus, this procedure comes at a price: by eliminating the within-dyad variance to get rid of overestimation effects of statistical significance, we keep information about mean scores, but lose information on residual variance (cf. Table 2). Accounting for this effect by conducting a multi-level approach confirms the mostly lower effect sizes and higher *p* values.

The changes in the standard deviation due to the elimination of within-dyad variance from individual to group are presented in the %-decrease column. We also added information on ICC values and *p* (cf. Table 3). While these measures may be somewhat unstable (confidence intervals are quite large) due to the small *N* especially when looking at each experimental condition individually (Kenny et al. 1998 recommend at least 36 dyads for 80% power in detecting consequential non-independence), they still give a rough indication on within-dyad dependence. As we can see, higher ICC values are associated with a decrease in the variance lost from individual to group level. This is because learners that are more closely related do vary less between them (within dyad) than unrelated learners. Table 4 shows the decomposition of variance for each condition and outcome variable. As expected, ICC values are low for the pre-test scores,

Table 3 Intra-class correlation coefficients per group and outcome variable

	Intra-class correlation coefficient (ICC)	95% Confidence interval		*p*
		Lower bound	Upper bound	
Without MC				
Performance pre	– .41	– .70	.02	.971
Performance post	.67	.36	.85	< .001
Confidence pre	.11	– .32	.51	.308
Confidence post	.26	– .18	.61	.120
With MC				
Performance pre	– .17	– .56	.28	.772
Performance post	.31	– .13	.66	.079
Confidence pre	.08	– .35	.50	.355
Confidence post	.56	.17	.80	.004
Overall				
Performance pre	– .28	– .54	.02	.966
Performance post	.55	.29	.73	< .001
Confidence pre	.09	– .22	.39	.277
Confidence post	.44	.16	.66	.001

which is to be expected since the learners within each dyad did not collaborate yet in any way (please note that learners within a dyad received different versions of the learning text, leading to negative ICC values for performance pre collaboration—since negative values violate the ICCs model assumption, associated *p* values may not be interpreted). Variance decomposition shows that dyads do not account for much of the variance pre collaboration and error variance is quite high. Thus, computing a mean dyad score of largely unrelated learners eliminates large amounts of variance in pre-test. However, as dependencies (and thereby ICC values) increase in post-test due to collaboration and a large amount of the variance can be explained by dyads, the loss in variance decreases. Meanwhile, the means stay identical since the dyad value was computed as a mean between dyad members. It is interesting to notice that within the MC– condition, learners' performance scores are more closely related to each other than in the MC+ condition (cf. ICC in Table 3), and thus, losses in variance (and information) are greater for the latter condition, if we combine the data to get dyad level data (cf. Table 2).

If we look more closely at the actual variance, we can see that in the MC– condition, variance for individual performance data is more or less equal in pre and post (slight decrease), whereas on dyad level, variance noticeably increases (cf. Table 2). Factoring

Table 4 Variance decomposition (ANOVA) for performance and confidence pre and post collaboration

	Var(dyad)	Var(error)	Var(overall)	Var(dyad)	Var(error)	Var(overall)
	Performance pre			Performance post		
Without MC	– 1.39	4.81	3.45	2.11	1.02	3.09
With MC	– 0.74	5.08	4.35	0.70	1.53	2.20
	Confidence pre			Confidence post		
Without MC	0.83	6.62	7.43	1.29	3.74	5.00
With MC	0.38	4.15	4.52	3.42	2.73	6.06

in the high interdependence in post-test for this group, the data suggests that while learners within dyads may be more similar post collaboration, the dyads themselves seem to grow apart. This is especially interesting since we do not see the same effect for MC+: here, the variance on the individual level decreases visibly from pre to post, while the decrease on dyad level is negligible. Table 4 shows that while error variance is roughly similar between the conditions for performance post, the variance explained by the dyad is three times higher for learners without metacognitive information (MC–). For confidence, we get a different picture: although there are no overall effects of the treatment (cf. Table 1), the ICC after collaboration is much higher for learners within MC+ (cf. Table 3). Thus, while the loss in variance from individual to dyad level is rather similar pre collaboration, the losses are visibly smaller post collaboration within MC+ (cf. Table 2). Table 4 supports this notion: we can see that while unexplained variance for confidence post collaboration is smaller in MC+, the variance explained by the dyad is more than twice the size as in the MC– condition. From pre to post however, overall variance decreases in the MC– condition and increases in the MC+ condition (both units of measurement). With a larger percentage of variance in post being due to between dyad variance for MC+ than for MC–, on a dyad level, the difference between the groups is more obvious than on an individual level.

Discussion

Our experimental study aimed at investigating whether metacognitive confidence information may be a valuable contribution to information on specific assumptions in group awareness tools. As argued before, adding metacognitive information (i.e., subjective evaluations on one's knowledge) may be used to validate assumptions and thus foster grounding processes (Clark and Brennan 1991), enabling learners to better tail their learning processes to each other (Clark and Murphy 1982), leading to better learning (Dehler et al. 2011). Our inferential analyses with regard to our hypotheses coherently indicate that learners gain knowledge and confidence during collaboration, but the treatment does not affect confidence gain (hypothesis 2). For performance gain (hypothesis 1), the effects are also similar for all analyses, and—taken together—the evidence gently points toward a possible treatment effect, although multi-level analyses just missed the level of statistical significance. Without more specific analyses of the interdependencies, we might thus have cautiously concluded that adding metacognitive information may foster collaboration processes relevant for learning. However, looking at the interdependencies, it is startling that learners without the metacognitive information are higher interdependent regarding their performance, while still performing somewhat worse. Thus, interpreting that the treatment does foster collaboration processes seems to fall short. One more suitable explanation might be that learners without metacognitive information more explicitly target differences between them rather than discussing the underlying concepts needed to gain knowledge. Such an approach might tail in with quick consensus building (cf. Weinberger and Fischer 2006) and may account for both the high interdependence as well as the somewhat lower knowledge gain for this condition. While it seems that learners with metacognitive information available collaborated differently, we would have expected improved collaborative learning processes to lead to more aligned performances within dyads as well. However, we did not observe such an alignment. This might be explained by the value learners

assign to low confidence assumptions. Confidence cues are used to judge the knowledge of others, but also the validity of assumptions (e.g., Price and Stone 2004), and confidence in assumptions is also seen as a prerequisite for experiencing cognitive conflict (Lee et al. 2003). If confidence information is visualized and thus more salient, in cases of low confidence this might reduce the learners' need to align their understanding and reach consensus about the content. As discussed before, while aligned performance levels do not necessarily come with conversion of assumptions, differences in basic assumptions could explain some of the differences and may explain why dyads do not explain a lot of the variance within the condition with metacognitive information. Alternatively, providing metacognitive confidence information may also have made learners assume different roles within the process according to their respective confidence levels (e.g., more confident student mainly explaining and providing information), which may have led to less reciprocal yet still effective learning processes. In such a scenario, the dyad itself might still explain some variance, but less, and the variance within dyads (error variance) should be comparably high. While confirming any of these interpretations would of course require further research, the different levels of local dependencies cast doubt about the assumption that metacognitive information simply enhanced and guided reciprocal knowledge exchange processes. On a descriptive level, the variances for dyad level data on performance show that dyads without metacognitive information become more diverse from pre to post while dyads with the information rather become more similar, so that most of the variance is due to individual error. One plausible explanation would be that dyads with metacognitive information use the provided information in a similar fashion resulting in similar mean performance, while dyads without such information apply slightly more diverse approaches. While this may explain the differences in variance due to dyad, it does not explain what strategies may lead to higher within-dyad variance (error variance) and lower between-dyad variance, except for more individualistic approaches and less collaboration.

As for confidence, overall results did not show any differences between the conditions neither on dyad, on individual, nor on multi-level. Interestingly, although performance scores seem to be more related for learners without metacognitive information, confidence scores are more interdependent for learners with metacognitive information available. This may be due to the fact that learners with metacognitive information actively align their confidence levels, but ultimately without gaining more or less confidence in the process. On the dyadic level, we see slightly lower variance for the condition without metacognitive information and thus, the dyads rather than the individuals seem to be more alike. Thus, dyads may have different approaches to learning that affect confidence levels differently if metacognitive information is provided, leading to greater variance between dyads, but interrelated approaches within. Further research should look into those approaches as they may not only account for interindividual differences but also explain why there was no overall effect on confidence levels while the differing ICC values indicate that the treatment had some effect on the collaboration process relevant to confidence levels. An alternative explanation may be re-interpretations of own knowledge in light of social information as has been found for example with regard to information on performance of others (Fraundorf and Benjamin 2016) or on co-learners having questions about the material (Karabenick 1996).

In our study, learners may have established an agreement on how overly confident they were about the learning material, especially when confidence information was provided. While negotiating agreement is a collaborative act, this explanation focuses more on the common exposure aspect of interdependence, because such alignment processes may well happen without the learners interacting or explicitly discussing confidence if metacognitive information is provided. Finally, it is important to point out that unexplained (error) variances in confidence levels were quite different between the conditions pre collaboration and thus, some effects might be due to random differences between the learners rather than experimental treatment.

Of course, our descriptive analyses of changes and differences in variances are not suitable to draw definite conclusions. Rather, they provide clues into possible mechanisms of collaboration that may be used to generate hypotheses to be tested in further studies. Similarly, while the ICC values post collaboration seem very different descriptively, confidence intervals are quite large due to the small samples and considerably overlap, so jumping to conclusions may be premature. However, they still provide however-fragile evidence that suggests that collaboration processes might have been affected by the treatment in an unexpected way and should thus be further examined.

Overall, comparing dyadic and individual level data showed that both approaches produced similar outcomes for our data. Multi-level analyses reached similar conclusions, although the effect sizes were smaller and the interaction effect on performance was not statistically significant. Since the advantages of multi-level approaches to analyze data within collaborative learning settings have been repeatedly illustrated elsewhere (for detailed examples contrasting results drawn from individual, dyadic, and multi-level analyses, see, e.g., Janssen et al. 2011), we did not compare multi-level results with dyadic and individual data in detail. Rather, we argue that looking into the ICCs and variances allowed us to gain some insight into the collaboration processes. Using this additional information, we conclude that providing confidence information may have led learners to focus on different aspects of the collaboration—aligning confidence rather than performance levels. While this may lead to higher performance gains, the mechanisms need to be further investigated. To achieve this, methodological one-track approaches are insufficient. Causal models require a sound description of generative mechanisms able to explain variations within the data and quantitative methods are limited to testing for differences and co-variations. Thus, analyses of variance have limited capacity to help us understand the underlying processes of the observed phenomena as they reduce social reality to a fixed set of linear relationships largely disregarding social-contextual complexity and dynamics (cf. Abbott 1988). A meaningful integration of theoretical and statistical models thus requires a combination of in-depth analyses of collaborative and transactive processes to explain observed variances within the data by providing a rationale of causal relationships (e.g., via qualitative analyses of the interaction and communication processes) and inferential statistics to secure these findings on a larger scale.

Conclusion

Local dependencies in collaborative research are often unwelcome in light of constrains they put on statistical analyses. However, it is important to keep in mind that such dependencies may result from favorable interaction processes. Collaborative learning

scenarios often explicitly target such processes of learners exchanging information, co-constructing knowledge, or in other ways interacting while influencing the learning partners' cognitive processes (Dillenbourg 1999). Hence, the focus of our study was to exemplarily show how interdependencies (i.e., ICCs) may be used to gain more insight into the mechanisms of collaboration. Comparing results of statistical analyses between different units of measurement (individual vs. dyad) and decomposing variance may further provide valuable information easily lost when compensating for these effects rather than interpreting them. While none of the statistical aspects of local dependence discussed in this paper are genuinely new, the results described demonstrate the effect this has on specific dyadic data drawn from a study typical for quantitatively assessing the effect of a treatment to foster collaboration on individual learning outcomes. We argue that this valid information should not be viewed as hampering our statistical design, but as enriching our analyses by providing valuable information. As stated before, interdependence is not a mere statistical phenomenon, but needs to be interpreted psychologically as the result of collaborative processes or shared experiences (Cress 2008). Thus, it has theoretical value and should be critically analyzed, especially if the research conducted targets the aforementioned collaboration processes as frequently done in CL research. Interventions designed to support collaborative learning processes affect the interaction processes between learners. These processes are pivotal to collaborative learning, where peers interact while pursuing a learning goal (Dillenbourg et al. 2009; Suthers 2012) and thus, it is reasonable to assume that such interventions affect the interdependence between learners. While in cooperative settings this might be somewhat different (when learners split their work and focus on very different aspects of a task), we argue that when considering collaboration within CL, our underlying theoretical assumptions about collaborative processes should often lead us to expect interdependencies and their absence might be a reason to rethink these assumptions. Apart from adjusting statistical models to the characteristics of our specific data, using quantitative and qualitative methods to take a closer look at the fit between our model assumptions about collaborative processes taking place in a specific educational scenario and the outcome data retrieved is a great opportunity to adjust our assumptions about educational practices and ultimately build better models.

Abbreviations

CL: Collaborative learning; CSCL: Computer-supported collaborative learning; ICC: Intra-class correlation coefficient; MC: Metacognitive confidence information; MC−: Research condition without information on the learners' metacognitive confidence; MC+ : Research condition with information on the learners' metacognitive confidence

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Availability of data and materials

The dataset supporting the conclusions of this article is available in the Open Science Framework (OSF) repository under https://osf.io/a972m/. Further data including raw data and materials used in the experiment are available on request. To access this or additional information, please contact the corresponding author.

Authors' contributions

Both authors read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

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