“Houston, We Have a Problem!” Homogeneous Problem Perception, and Immediacy and Intensity of Strategy Use in Online Collaborative Learning

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Abstract: Under socially distant circumstances, university students frequently self-organize to collectively prepare for exams online through video chat. To learn effectively, emerging challenges need to be regulated successfully. This regulation is supposed to work best when problems are perceived homogeneously in the group, and when regulation strategies which immediately solve the problem are chosen and executed with sufficient intensity. We investigated what problems occur during collaborative online learning and how these are regulated by *N*=222 university students in 106 groups. We found that overall problem prevalence was low. Multilevel-modeling indicated that homogeneous problem perception—contrary to immediate and intensive strategy use—predicted subjective learning success, while objective learning success was not associated. Thus, in well-structured learning contexts, knowing what the problem is seems to be more important than knowing the best possible reaction to the problem. Students might be trained in problem perception in order to increase regulation competency.

Problem statement

Many students deliberately join together in self-organized small groups, e.g. to prepare for exams together. Taking positive effects of collaborative learning on knowledge acquisition found in the literature into account (e.g., Springer et al., 1999), this is a sensible decision. However, collaborative learning unfortunately is not always as effective (Weinberger et al., 2012). In fact, students may be confronted with a variety of problems during collaborative learning that are obstacles to effective learning (Järvenoja et al., 2013). This is also true for online collaborative learning, where learners are often frustrated due to various problems such as an imbalance in commitment, unshared goals or communication difficulties (Capdeferro & Romero, 2012). Only if the group is able to regulate these problems successfully, collaborative learning is effective (Järvelä & Hadwin, 2013).

The ability to regulate occurring problems independently of any instructional support is very important for regulation success especially for students outside formal instructional contexts, who form learning groups on their own initiative. Thus, acquiring necessary regulation skills beforehand is crucial for regulation success during periods of self-organized collaborative learning. To foster these skills, scientific knowledge is needed on how problems are regulated best in such situations. Further, the context how the meeting takes place might be relevant, too: When self-organized study groups cannot meet in person (e.g., at institutions for distance learning, in areas with large physical distances between students, or during times of a pandemic), collaborative learning typically happens online through video conference tools such as Zoom or Skype. Yet, not much is known about how this virtual context influences processes associated with specifically the regulation of problems during self-organized study group meetings. Therefore, this study focuses on how problems are regulated in virtual collaborative learning through video conferencing.

Regulation of problems in collaborative learning

Based on previous research (e.g., Järvenoja et al., 2019), problems in self-organized collaborative learning can be divided into at least the following categories: (a) comprehension problems (e.g., learners may have difficulty understanding the task), (b) coordination problems (e.g., learners may have different objectives for learning together), (c) motivation problems (e.g., the learning material may be perceived as irrelevant) and (d) resource-related problems (e.g., necessary learning material may not be available). For self-organized collaborative learning to be successful, groups must be able to cope with such problems successfully.

To conceptualize the processes involved in this problem regulation, we (Melzner et al., 2020) developed a heuristic process model (see Fig. 1). Following process models of self-regulated learning (e.g., Zimmermann &

Moylan, 2009), metacognitive processes are crucial for the successful regulation of problems in self-organized collaborative learning, with the help of which students (1) perceive and classify these problems. Based on the assessment of a problem, a reaction is initiated to ensure that the goal is achieved despite the problem at hand. For this purpose, students (2) select a strategy to address the problem and (3) execute this strategy with a certain intensity. Once the problem is solved, the learning process can be continued. Along with Melzner et al. (2020), we assume that these three processes (problem perception, choice of regulation strategy, intensity of strategy execution) should predict success in the regulation of problems that occur during collaborative learning.

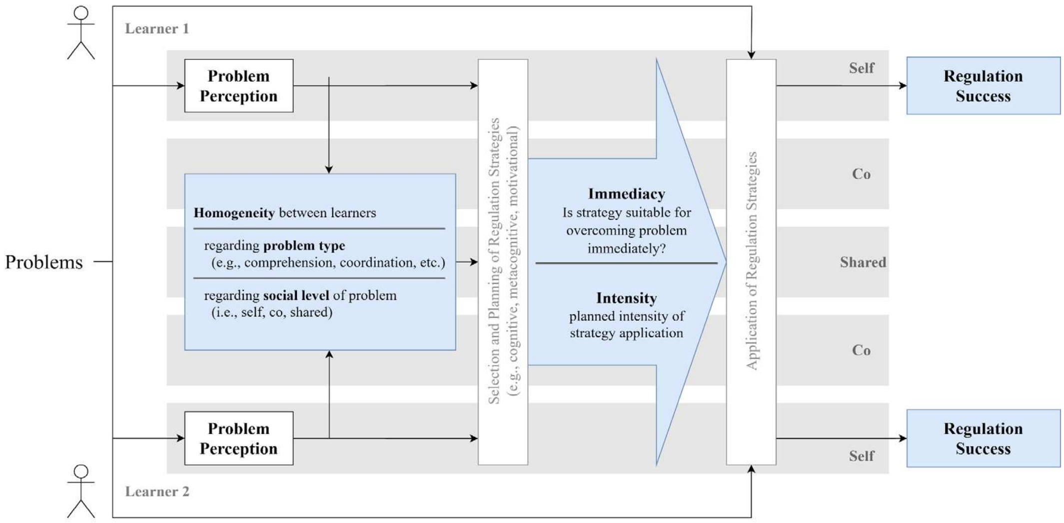

Figure 1. Theoretical model of the regulation of problems during collaborative learning (visualization inspired by Wecker and Fischer, 2014). Concepts in boldface are measured in the present study. Adapted by permission from Springer Nature: IJCSCL. Regulating self-organized collaborative learning: The importance of homogeneous problem perception, immediacy and intensity of strategy use. Melzner, N., Greisel, M., Dresel, M., & Kollar, I. (2020). https://doi.org/10.1007/s11412-020-09323-5

Homogeneity of problem perception

At the beginning of the regulation process, learners perceive and classify a given problem (see Fig. 1). Different group members may arrive at different problem assessments. Divergences can basically be based on two dimensions: First, the type of problem (see e.g., Järvenoja et al., 2013) that is perceived may vary. For example, while one learner may perceive a comprehension problem to be present, another learner may categorize this problem as motivational. On the other hand, there may also be disagreement about the social level at which the problem is located. Using the classification of Järvelä and Hadwin (2013), it can be distinguished whether a learner is affected himself (self-level), whether the problem affects individual other group members (co-level), or whether the whole group is affected (socially shared level). The homogeneity of the problem perception is thus to be understood in terms of (a) the type of problem and (b) the question who is affected by the problem. We suspect that diverging perceptions of the problem within the group make collaborative learning more difficult, since the individual group members are then more likely not to coordinate their regulation efforts. Findings of Melzner et al. (2020) corroborate this.

Immediacy of regulation strategy use

Next, learners select a strategy for the regulation of the previously perceived problem (see Fig. 1). Models of self-regulated learning (e.g., Zimmermann & Moylan, 2009) assume that at this point, the choice of a strategy that fits the learning goal is crucial. Not every strategy is supposed to be equally well suited to achieve a particular goal (e.g., Engelschalk et al., 2016). In our view, a similar assumption may be made regarding the fit between an emerging problem and the chosen strategy for its regulation (e.g., Engelschalk et al., 2016). However, previous research has hardly made statements about what is meant by *fit*. In order to operationalize fit, we have proposed the concept of *immediacy* (Melzner et al., 2020): A strategy can be considered to be appropriate for a problem if it is in principle possible to actually solve the problem when the respective strategy is executed optimally. An example of an immediate strategy would be to switch off cell phones when the group is distracted by incoming messages during learning. An example of a non-immediate strategy, on the other hand, would be if learners make themselves aware of the importance of the exam they are preparing for in order to motivate them to continue learning despite the incoming messages. This strategy would not eliminate the source of distraction and thus would not immediately make the problem disappear, but would only allow learners to continue learning despite the presence of the problem. Thus, for the operationalization of fit, a theoretical assignment of strategies to problems as immediate or non-immediate was proposed by Melzner et al. (2020) and was found to predict satisfaction with the group learning experience in completely self-organized, offline groups.

Intensity of the execution of the regulation strategy

To be effective, the selected strategy must be applied in the next step (see Fig. 1). Depending on the severity of the problem, however, a single application of the strategy may not be sufficient to achieve the desired effect. For example, if learners bored by the learning materials think only briefly about their goals for the future, this may have little effect on their motivation to devote effort towards understanding the material. However, if they work intensively on how the material will help them to achieve their own goals, this should increase their motivation. We therefore assume that the intensity of strategy use is positively related to regulation success. However, not only the intensity of immediate strategies should be relevant, since non-immediate strategies might also increase regulation success, even if the specific problem is not solved that way. Findings on the effect of regulation intensity are mixed (Eckerlein et al., 2019; Melzner et al., 2020; Schoor & Bannert, 2012). Thus, more research is needed to clarify its influence on regulation success.

Operationalizing regulation success in collaborative learning

Once the regulation process is executed in accordance with Fig. 1, it should be successful. Yet, regulation success may be conceptualized and measured in various ways (e.g., Melzner et al., 2020; Noroozi et al., 2019; Zimmermann & Moylan, 2009). In this paper, we focus on three different conceptualizations: (1) success in applying a regulatory strategy (i.e., the extent to which the problem is overcome after the strategy is applied), (2) satisfaction with the group learning experience, and (3) the subjective and objective learning success resulting from the group learning session. So far, only satisfaction was empirically investigated in this context (e.g., Melzner et al., 2020; Bellhäuser et al., 2019). Yet, not much is known about how problem perception, immediacy and intensity of strategy use contribute to further measures of regulation success.

Research questions and hypotheses

The present study addresses two research gaps: First, it is an open question to what extent the three processes (homogeneity of problem perceptions, immediacy of strategy use, and intensity of strategy use) would be predictive of successful regulation in collaborative online settings. Second, little is known about whether the three processes are differentially predictive of the three conceptualizations of regulation success described above. Therefore, we established the following hypotheses:

1. The more homogeneous learners perceive problems within their groups, the more positive the results on different measures of regulation success are.
2. Learners who use immediate strategies to regulate their problems achieve more positive results on different measures of regulation success than learners who use only non-immediate strategies.
3. The more intensively learners apply regulation strategies, the more positive the results on different measures of regulation success are.

Method

Sample

University students (N = 222) from two basic psychological lectures within the majors educational sciences (29%) and teacher training (70%) answered an online questionnaire. They had an average age of 22 years (M = 21.84, SD = 4.39, 83% female) and were on average in the third semester of their current study subject (M = 2.78, SD = 1.50) and also in their third university semester overall (M = 3.34, SD = 2.57). Participants self-selected into 106 small groups of three persons on average, but not all members of each group participated in the study. Thus, data from 25 groups which were represented in our data by a single person only had to be excluded from regression analysis because a calculation of homogeneity of problem perception only is possible for groups with data of two or more learners.

Procedure

The study was embedded in two large lectures which mainly consisted of weekly uploaded recordings of PowerPoint-presentations provided for individual, asynchronous studying. One session of collaborative learning replaced the regular lecture in the respective week. Learners were instructed to meet online at a time suitable for all group members using a video conference software of their choice to study the lecture content on their own. As learning material, the regular slide deck for this session was provided alongside two excerpts from a textbook, each about one page long. Topics were the ICAP-Model of learning activities (Chi & Wylie, 2014) and the multi-store model of memory (Atkinson & Shiffrin, 1968). We did not structure or scaffold the collaborative learning with additional instructions except the following tasks: "The goal of the group work is to work out the slide contents as well as possible together with your group members. You are welcome to use the additional texts provided." In addition, students were told to record the results of their group work in a shared concept map. Yet, besides this, learners were free to decide in which way, with which activities or tools, they wanted to work on the topic. For learners who were not familiar with an online tool suitable to produce a concept map, we recommended www.mindmeister.com and provided a short tutorial video explaining all functions necessary for accomplishing the task.

After the study meeting, participants were asked to individually answer an online questionnaire. The questionnaire was advertised as containing a knowledge test for which students would receive immediate feedback regarding right and wrong answers. The questions were comparable to the ones in the final exam in the corresponding lectures, so taking the test would be a good chance to practice for the "real" exam.

Measures

To measure the *prevalence of problems during collaborative learning*, we developed a questionnaire with 32 different problems represented by three items each. Each item had to be rated on a Likert-scale (from 0 = *did not occur/no problem* to 4 = *big problem*). Based on problem typologies or theoretical classifications in the literature (e.g., Järvenoja et al. 2013; Koivuniemi et al., 2017), our questionnaire covered four broad categories of problems: comprehension, coordination, motivation, and resources (see Fig. 2 for a complete list of individual problems). For example, for the problem of "low value of learning method", a sample item was "Single/multiple group members did not find group work as a learning method useful in the given situation." An extensive series of confirmatory factor analyses comparing the theoretical factor structure to other theoretical plausible clusterings of items indicated that the theoretical factors with three items per factor were distinguishable from each other, and that the theoretical solution has the best fit to the data. Cronbach's alpha was .79 on average. After rating each problem, participants selected one of them as the biggest problem they encountered during the learning session.

To determine the *homogeneity regarding the type of problem within each group*, we calculated the variance within each group for each rated problem separately, and then determined the average variance per group over all problems. To transform the variance into a measure of homogeneity, we multiplied it by −1 and centered it. To determine the *homogeneity regarding the social level*, we used three items measuring the extent to which the biggest problem affected the self-, co-, or shared-level on a five-point Likert-scale (from *not at all true* to *completely true*). A sample item representing the self-level was: "The mentioned problem had effects on my personal learning process." The ratings for each item were dichotomized by median split, resulting in a zero-one-coding. Then, groups were coded as being homogeneous regarding the social level of problem perception when the social level at which they located the biggest problem matched the respective ratings of each other group member. For example, a group was considered to be homogeneous when one person located the problem only at the self-level, while the two other group members located the problem only at the co-level.

To measure *immediacy and intensity of strategy use*, we asked participants to name the strategies they used to regulate the problem they marked as the biggest one at the self-, co- and shared level in an open answer format (e.g., at the self-level: "What did you personally think, do, or say to ensure high quality of your own learning in this situation?"; at the shared level: "What did you as a group think, do, or say to ensure high quality of the learning of the whole group in this situation"). These answers were segmented into single regulation strategies (interrater-agreement 90-91%). Then, each strategy was classified as one out of 27 possible types of strategies (for a list, see Melzner et al., 2020). Interrater-reliability was sufficient (Gwet's AC1 = .73). Next, each strategy was automatically coded as being either immediate for the selected biggest problem or not, using a theoretical determined mapping of strategies to problems (previous version published in Melzner et al., 2020). In the end, a person was dichotomously classified as reporting an immediate strategy when at least one strategy could be considered as immediately solving their biggest problem. To determine the intensity of strategy use, we added up the number of valid regulation strategies reported at all social levels.

To measure *successful problem regulation*, we adapted three items from Engelschalk et al. (2016) (e.g., "During group learning, we got the biggest problem under control."). Each item had to be rated on a Likert-scale (from 1 = *not at all true* to 5 = *completely true*). Cronbach's alpha was .96.

Satisfaction with the group learning experience was measured by five items from the German version of the Satisfaction with Life Scale (SWLS; Glaesmer et al., 2011) adapted to the group learning context (e.g., "Our group work was excellent."). Each item employed a 5-point Likert scale ranging from 1 (*not at all true*) to 5 (*completely true*). Cronbach's alpha was .92.

We assessed *subjective learning success* by using six adapted items from the Training Evaluation Inventory (TEI; Ritzmann et al., 2014). Learning success with regard to the ICAP-Model (Chi & Wylie, 2014) and learning success with regard to the multi-store model of memory (Atkinson & Shiffrin, 1968) were measured separately by three items each (e.g., "I have the impression that my knowledge on the ICAP-Model/the multi-store model of memory has expanded on a long-term basis") on a 5-point Likert-scale (from 1 = *not at all true* to 5 = *completely true*). Cronbach's alpha was .92.

As an *objective measure of learning success*, we mimicked a typical standardized psychology exam: We constructed eight multiple choice questions with four dichotomous answer alternatives each (four questions for each theory). As a total test score, we used the percentage of right answers (= mean).

Results

First, we investigated the descriptive distribution of different problems (see Fig. 2). Overall, the magnitude of problems was low. Even the most pronounced problems seemed to be not severely problematic. The most frequent were technical problems (mostly centered around the recommended mind mapping-software), followed by motivational and comprehension problems regarding the collaboration method, followed by low motivation to study the learning content. Comprehension and coordination problems were very low to almost non-existent.

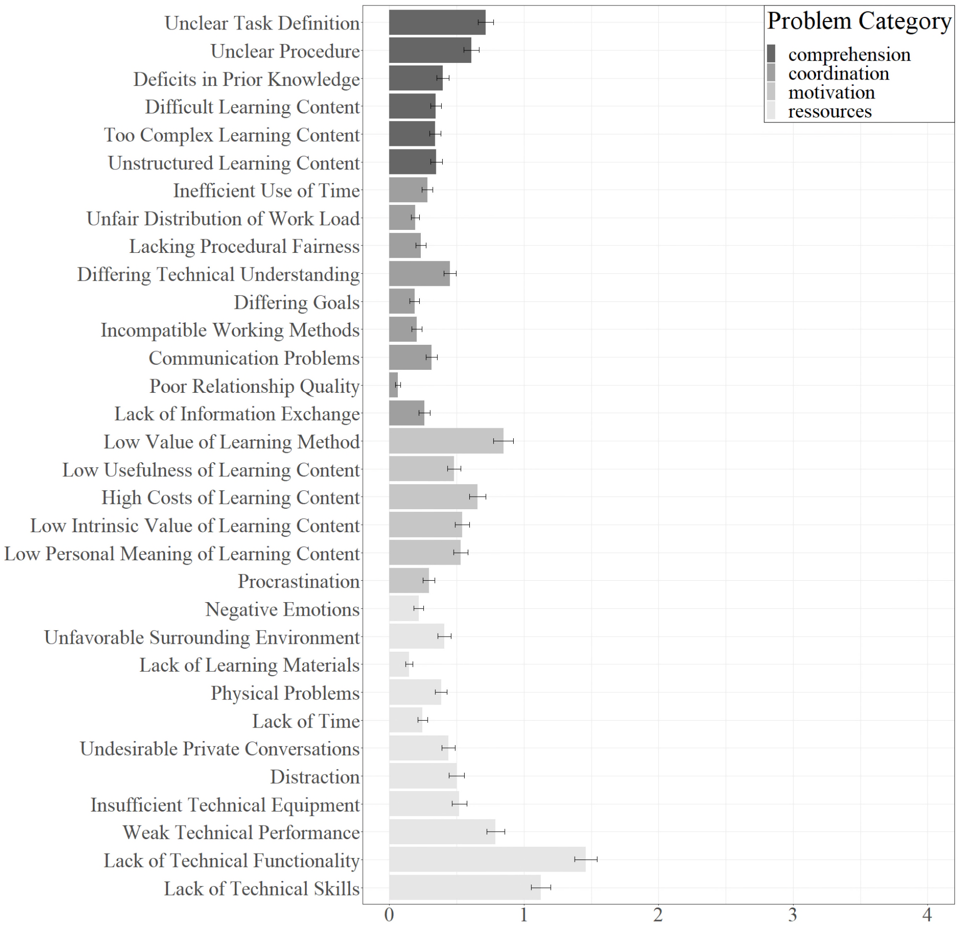

Figure 2. Size of problems during collaborative learning (means and standard errors).

Second, we inspected descriptive statistics of predictor and criterion variables (see Tab. 1). Twenty-one percent of participants located the biggest problem at the same social level within their groups. Regarding immediacy, 71% of the participants applied at least one immediate regulation strategy to remedy the biggest problem. Regardless of the type, about four strategies were reported on average. Successful problem regulation and satisfaction with the group learning experience were estimated to be rather high, while subjective learning success was appraised a bit lower. Of all test questions measuring objective learning success, 75% were solved correctly on average. Predictor variables were not significantly associated with each other, except for immediacy and intensity. The subjective measures for regulation success were associated with each other, but only content-related homogeneity of problem perception was associated with these outcomes. The objective measure of learning success was not related to any of the other variables.

Table 1. Means, standard deviations, and correlations.

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Homogeneity problem type	0.00	0.30							
2. Homogeneity social level	0.21	0.41	.06						
3. Immediacy	0.71	0.45	.07	−.06					
4. Intensity	3.99	2.39	−.00	.10	.34**				
5. Successful problem regulation	4.12	1.07	.21**	.11	.09	.08			
6. Satisfaction with group learning	4.12	0.84	.42**	.06	.11	.09	.53**		
7. Subjective learning success	3.76	0.89	.29**	−.01	.04	.04	.33**	.33**	
8. Objective learning success	0.75	0.10	.10	−.08	.06	.11	.02	−.05	.06

Note. ***p* < .01.

Third, we conducted multilevel regression analyses to account for the two-level structure (students in groups) and covariations between predictor variables (see Tab. 2, all variables standardized before analysis). However, the pattern of findings remained the same as with the bivariate correlations reported above. To check if the results would remain stable when covariations between dependent variables were considered as well, we also conducted a structural equation model with all eight predictor and dependent variables in one model and group as a cluster variable, which led to an identical pattern of effects.

Table 2. Multilevel modeling of four different measures of regulation success.

	Satisfaction with learning		**Successful problem regulation**		**Subjective learning success**		**Objective learning success**	
Predictors	β	(*SE*)	β	(*SE*)	β	(*SE*)	β	(*SE*)
(Intercept)	.00	(0.07)	.00	(0.08)	.00	(0.08)	.02	(0.08)
Homogeneity problem type	.42 ***	(0.07)	.19 *	(0.08)	.30 ***	(0.08)	.08	(0.08)
Homogeneity social level	.04	(0.07)	.10	(0.08)	–.03	(0.08)	–.10	(0.08)
Immediacy	.03	(0.07)	.03	(0.08)	–.03	(0.07)	–.01	(0.08)
Intensity	.09	(0.02)	.03	(0.07)	.03	(0.07)	.03	(0.07)
Random Effects								
σ^2	0.70		0.89		0.82		0.84	
τ^00	0.12 (GrNr)		0.08 (GrNr)		0.12 (GrNr)		0.17 (GrNr)	
ICC	0.15		0.08		0.13		0.17	
N	74 (GrNr)		74 (GrNr)		74 (GrNr)		74 (GrNr)	
Observations	193		193		193		193	
Marginal R^2 / Conditional R^2	.187 /.307		.048 /.127		.086 /.204		.014 /.181	

Note. **p* < .05 ****p* < .001

Discussion

This study investigated which problems occurred during one session of (relatively) self-organized online collaborative learning and how groups regulated these problems. Descriptive analyses of problem ratings and means of regulation success variables draw a picture of a rather successful learning experience: All problems were reported as being small or very small, and at the same time, subjective measures of regulation success indicated successful regulation of these problems, high satisfaction and solid subjective learning success. This is good news for university teachers who are forced to move their regular classrooms into the online domain: In general, students seem to be prepared to successfully collaborate in this realm. This finding is in contrast to Capdeferro and Romero (2012), for example, who found students to report frustrations about online collaborative learning more frequently. The main question of this study was how homogeneity of problem perceptions within study groups and immediacy and intensity of regulation strategy use would be associated with different measures of regulation success. In sum, homogeneity of problem perception was the only significant predictor of subjective measures of regulation success. This might mean that groups who have a commonly shared perspective on what their problems are were more successful in regulating their problems. This finding replicates the same finding of Melzner et al. (2020). Contrary to Melzner et al. (2020), we did however not find immediacy and intensity of strategy use to be associated with regulation success. This also contrasts with Engelschalk et al. (2016), who found strategies to be selectively used for different kinds of problems, but is in line with Schoor and Bannert (2012), who also did not find an effect of intensity of regulation strategy use on regulation success. To better interpret this finding, it is informative to take the difference between the two studies into account: Melzner et al. (2020) investigated completely self-organized groups preparing for important exams for an extended period of time, while the present study explored a single session of collaborative learning during a regular lecture. Thus, we compare an extensive, high stakes setting to a less extensive, lower stakes setting. In addition, the level of autonomy and instructional support differed: In Melzner et al. (2020), the learning content, materials, and method were completely self-selected, while in the present study, all this was fixed. In other words, in the present study, the instructional context might have helped to pave the road for collaborative learning enough, so that the specific strategy choice and intensity of its application did not matter for regulation success as much, because just any regulation strategy (applied with random intensity) might have been good enough to overcome a (rather) insignificant problem. We conclude that the full model of problem regulation shown in Fig. 1 might only apply to truly self-organized learning contexts with sufficient prevalence of problems, while problem regulation might follow a simpler process only relying on a shared problem perception when problems are low due to effective instructional support. The fact that the instructional support in the present study seemed to be sufficient is slightly surprising: When taking recommendations for instructional design of instances of collaborative learning (Strauß & Rummel, 2020) into account, only few principles were realized here. The same is true for the technical realization: Only three out of seven affordances for computer supported collaborative learning (Jeong & Hmelo-Silver, 2016) were observed here (video chat as communication means, concept map as representational tool, and facilitation of group formation). And when considering the concrete actions of students themselves, it remains unclear if students applied more than two strategies out of 10 (MacMahon et al., 2020), namely scheduling uninterrupted work and creating a shared concept map. This may mean that a low-level instructional support already makes a big difference and helps to simplify the dynamics of self-organized collaborative learning in a way that students cope successfully with upcoming problems.

When interpreting the results, we have to take the following limitations into account. First, neither the predictor variables nor the subjective measures of regulation success were associated with the results of the objective knowledge test. There are several explanations for this: It might be that the actual knowledge is influenced by many other variables not in the scope of this study which might increase unsystematic error variance making it difficult to find small effects. Alternatively, the lack of a significant association might be due to the low prevalence of problems which might have created a ceiling effect, therefore reducing variance and possible covariation. Second, all measures (except the knowledge test) were based on self-report, though regulation strategies were measured by open-ended questions at least in order to reduce social desirability bias. True associations might be different.

The interpretation of the different findings in the previous study by Melzner et al. (2020) and the present study has important implications for theory building: A new theoretical model of problem regulation during collaborative learning has to be developed that includes problem intensity and variety as moderator of the relations between problems, their regulation, and learning outcome. For teaching practice, the study might imply that recommendations of good instructional design for collaborative learning (see above) also apply to relatively self-organized online collaborative learning and that simple and few scaffolding aids might already help to reach satisfying knowledge gain.

References

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. In K. W. Spence & J. T. Spence (Eds.), *The Psychology of Learning and Motivation: Advances in Research and Theory* (Vol. 2, pp. 89–197). Academic Press.

Bellhäuser, H., Müller, A., Konert, J., & Röpke, R. (2019). Birds of a feather learn well together? An experimental study on the effect of homogeneous and heterogeneous learning group composition on satisfaction and performance. In K. Lund, G. Niccolai, E. Lavoué, C. Hmelo-Silver, G. Gweon, & M. Baker (Eds.), *A*

Wide Lens: Combining Embodied, Enactive, Extended, and Embedded Learning in Collaborative Settings, 13th International Conference on Computer Supported Collaborative Learning (CSCL) (Vol. 2, pp. 721–722). International Society of the Learning Sciences.

Capdeferro, N., & Romero, M. (2012). Are online learners frustrated with collaborative learning experiences? *International Review of Research in Open and Distributed Learning*, *13*(2), 26–44.

Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219–243. https://doi.org/10.1080/00461520.2014.965823

Eckerlein, N., Roth, A., Engelschalk, T., Steuer, G., Schmitz, B., & Dresel, M. (2019). The role of motivational regulation in exam preparation: Results from a standardized diary study. *Frontiers in Psychology*, *10*, 81. https://doi.org/10.3389/fpsyg.2019.00081

Engelschalk, T., Steuer, G., & Dresel, M. (2016). Effectiveness of motivational regulation: Dependence on specific motivational problems. *Learning and Individual Differences*, *52*, 72–78.

Glaesmer, H., Grande, G., Braehler, E., & Roth, M. (2011). The German version of the Satisfaction with Life Scale (SWLS). Psychometric properties, validity, and population-based norms. *European Journal of Psychological Assessment*, *27*(2), 127–132. https://doi.org/10.1027/1015-5759/a000058

Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist*, *48*(1), 25–39. https://doi.org/10.1080/00461520.2012.748006

Järvenoja, H., Näykki, P., & Törmänen, T. (2019). Emotional regulation in collaborative learning: When do higher education students activate group level regulation in the face of challenges? *Studies in Higher Education*, *44*(10), 1747–1757. https://doi.org/10.1080/03075079.2019.1665318

Järvenoja, H., Volet, S., & Järvelä, S. (2013). Regulation of emotions in socially challenging learning situations: An instrument to measure the adaptive and social nature of the regulation process. *Educational Psychology*, *33*(1), 31–58. https://doi.org/10.1080/01443410.2012.742334

Jeong, H., & Hmelo-Silver, C. E. (2016). Seven affordances of computer-supported collaborative learning: How to support collaborative learning? How can technologies help? *Educational Psychologist*, *51*(2), 247–265. https://doi.org/10.1080/00461520.2016.1158654

Koivuniemi, M., Panadero, E., Malmberg, J., & Järvelä, S. (2017). Higher education students' learning challenges and regulatory skills in different learning situations. *Journal for the Study of Education and Development / Infancia y Aprendizaje*, *40*(1), 19–55.

MacMahon, S., Leggett, J., & Carroll, A. (2020). Promoting individual and group regulation through social connection: Strategies for remote learning. *Information and Learning Sciences*, *121*(5/6), 353–363.

Melzner, N., Greisel, M., Dresel, M., & Kollar, I. (2020). Regulating self-organized collaborative learning: The importance of homogeneous problem perception, immediacy and intensity of strategy use. *International Journal of Computer-Supported Collaborative Learning*, *15*(2), 149–177.

Noroozi, O., Bayat, A., & Hatami, J. (2019). Effects of a digital guided peer feedback system on student learning and satisfaction. In K. Lund, G. Niccolai, E. Lavoué, C. Hmelo-Silver, G. Gweon, & M. Baker (Eds.), *A Wide Lens: Combining Embodied, Enactive, Extended, and Embedded Learning in Collaborative Settings, 13th International Conference on Computer Supported Collaborative Learning (CSCL)* (Vol. 2, pp. 809–810). International Society of the Learning Sciences.

Ritzmann, S., Hagemann, V., & Kluge, A. (2014). The Training Evaluation Inventory (TEI)—Evaluation of Training Design and Measurement of Training Outcomes for Predicting Training Success. *Vocations and Learning*, *7*(1), 41–73. https://doi.org/10.1007/s12186-013-9106-4

Schoor, C., & Bannert, M. (2012). Exploring regulatory processes during a computer-supported collaborative learning task using process mining. *Computers in Human Behavior*, *28*(4), 1321–1331.

Springer, L., Stanne, M. E., & Donovan, S. S. (1999). Effects of small-group learning on undergraduates in science, mathematics, engineering, and technology: A meta-analysis. *Review of Educational Research*, *69*(1), 21–51. https://doi.org/10.3102/00346543069001021

Strauß, S., & Rummel, N. (2020). Promoting interaction in online distance education: Designing, implementing and supporting collaborative learning. *Information and Learning Sciences*, *121*(5/6), 251–260.

Wecker, C., & Fischer, F. (2014). Lernen in Gruppen [Learning in groups]. In T. Seidel & A. Krapp (Eds.), *Pädagogische Psychologie* (6th ed., pp. 277–296). Beltz.

Weinberger, A., Stegmann, K., & Fischer, F. (2012). Learning to argue online: Scripted groups surpass individuals (unscripted groups do not). *Computers in Human Behavior*, *26*(4), 506–515.

Zimmerman, B. J., & Moylan, A. R. (2009). Self-regulation: Where metacognition and motivation intersect. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Handbook of Metacognition in Education* (pp. 299–315). Routledge. https://doi.org/10.4324/9780203876428