International Society of the Learning Sciences

Preparing Collaborative Future Learning with Representational-Competency Supports

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Abstract: Collaboration in many STEM domains centers around the collaborative construction and interpretation of visuals. Thus, to become effective practitioners in the STEM disciplines, students need representational competencies: the ability to appropriately use and understand visuals that depict scientific concepts. Although visuals are often used in collaborative contexts, prior research on representational-competency supports has mostly focused on individual learning. To address this limitation, we conducted an experiment with 134 undergraduates who worked collaboratively in 56 small student groups as part of an engineering class. Students were randomly assigned to work with different types of representational-competency supports. The main outcome measure of interest were students' learning gains from a subsequent, novel collaborative learning activity. We found that representational-competency supports can prepare student groups to efficiently learn from novel instructional materials.

Introduction

Many professional practices in STEM domains are collaborative in nature. Indeed, STEM instruction is moving toward active learning, where students are encouraged to collaborate during learning (Freeman et al., 2014). Such collaborative practices often center around joint interpretation and construction of visual representations (Johri et al., 2013) because visual representations can help establish a common ground and make divergent views apparent (Nathan et al., 2013). Hence, collaborative STEM instruction often uses visual representations.

However, research on learning with visual representations shows that students may have difficulties interpreting visual representations (Ainsworth, 2006; Rau, 2017). Students need *representational competencies:* the ability to understand how visual representations depict relevant scientific concepts and use those visuals appropriately (diSessa, 2004; Kozma & Russell, 2005). Indeed, previous research on representational-competency supports found that supporting students' competencies enhanced students' content knowledge both in individual and collaborative learning settings (Berthold et al., 2009; Kellman & Massey, 2013).

However, prior research on the effectiveness of representational-competency supports has two limitations. First, prior research has examined only short-term effects of representational-competency supports. For example, Rau et al. (2017) tested whether adding support for representational competencies to instructional activities enhances students' learning from those activities. It is unclear whether representational-competency supports also enhance students' learning from future instructional activities where students encounter novel visuals they have not seen before. A second limitation is that prior research has mostly focused on individual learning settings even though, as mentioned, visuals are commonly used collaboratively (Rho et al., 2022). To our knowledge, only one study systematically tested the effects of representational-competency supports in a collaborative setting, but focusing on short-term effects on chemistry learning (Rau et al., 2017). In sum, it is unclear whether representational-competency supports enhance *future collaborative learning*. The goal of this paper is to address these limitations by investigating whether representational-competency supports enhance students' collaborative learning from future instructional activities.

Additionally, previous research suggests that spatial skills may affect students' learning with visual representations (Stieff et al., 2020). Visual representations typically depict visuospatial concepts. Students draw on spatial skills when mentally generating, retaining, and manipulating information depicted in visual representations. Students with low spatial skills have fewer cognitive resources to store and process such visuospatial information (Hegarty & Waller, 2005), making them more likely to struggle when learning with visual representations (Kozhevnikov et al., 2007). Hence, a further goal of this paper is to investigate whether representational-competency supports differentially affect students with different levels of spatial skills.

Literature review

Representation competencies

Instruction in STEM domains commonly uses visuals because they can help students understand content knowledge by making abstract concepts accessible (Ainsworth, 2006). However, previous research also showed

that such visuals can impede students' learning if students lack representational competencies. Specifically, students need two types of competencies; sense-making competencies and perceptual fluency (Rau, 2017).

First, sense-making competencies refer to explicit, analytical knowledge that allows students to explain how representational features map to concepts (Bodemer & Faust, 2006) and to connect multiple representations depicting the same concepts (Chang et al., 2021). Since students acquire sense-making competencies by verbally explaining how representational features map to concepts, instructional supports for these competencies ask students to explain relationships between representational features and concepts (Joo et al., 2021). Students should receive support to focus on explaining structurally relevant relationships between the representations instead of surface similarities (Ainsworth, 2006). Second, perceptual fluency refers to implicit, automatic knowledge that allows students to efficiently extract meaning from representations and to quickly translate across representations (Kellman & Massey, 2013). Students acquire perceptual fluency via nonverbal and inductive processes (Koedinger et al., 2012). Consequently, instructional supports for these competencies expose students to a variety of representations while asking them to quickly identify relevant information (Kellman & Massey, 2013).

So far, research has established that these representational-competency supports enhance students' acquisition of content knowledge in individual learning settings (e.g., Rau et al., 2017). However, previous research has focused less on the effectiveness of representational-competency supports in *collaborative* learning settings. Thus, this study investigates whether representational-competency supports help students' acquisition of content knowledge in a collaborative learning setting.

Role of representation competencies in collaborative learning

Collaborative instruction in STEM often uses visual representations because they can provide common ground for students' discussions (Nathan et al., 2011). Effective collaboration builds on representational competencies. First, collaboration involves sense making of visual representations. When students collaborate, they often verbally share their thoughts about visuals and critically discuss different interpretations of the visual (Kozma & Russell, 2005). Sense-making competencies enable students to verbally explain how visuals show information about problems (Johri et al., 2013). Therefore, sense-making competencies may enhance collaborative learning. Indeed, previous research on sense-making competencies found that providing adaptive collaboration scripts as a supportive tool for sense-making competencies improved students' benefit from a collaborative learning session (Rau et al., 2017). Second, collaboration involves perceptual fluency. When collaborating, students often refer to visual representations (Singer, 2017). This requires students to be perceptually fluent at extracting information from the visuals while also following along with the conversation. Indeed, previous research found that supporting perceptual fluency can enhance collaborative learning (Rau & Patel, 2018).

Thus far, the few studies that examined effects of representational-competency supports on collaborative learning have focused on students' immediate learning outcomes from instruction that contained the supports. However, students may not always have access to representational-competency supports. It remains unknown whether representational-competency supports enhance students' future learning from later instruction when students no longer have access to representational-competency supports. To address this question, this paper investigates whether representational-competency supports prepare students for *future* collaborative learning.

paration for future learning (PFL)

Students build on prior knowledge when learning novel concepts (Singley & Anderson, 1985). Building on this finding, research on preparation for future learning (PFL) examines how instruction can support students to adapt prior knowledge or skills in ways that support their learning of novel concepts (Schwartz et al., 2005). While some research has used the PFL framework to guide specific types of instructional designs, we adopt it as a research framework for investigating whether a given type of instructional design is beneficial beyond its duration (as suggested, for instance, by Schwartz et al., 2005). Although prior research shows that representational-competency supports can enhance students' ability to solve problems they have not encountered before (e.g., using a traditional transfer paradigm; Cromley et al., 2013), little research has investigated whether representational-competency supports prepare students' future learning from novel instructional materials they have not encountered before. To our knowledge, only one study showed that support for sense-making competencies and perceptual fluency enhanced students' future learning from novel instructional materials (Rho et al., 2022). However, this study focused on learning in an individual context, even though, as argued above, students often learn with visual representations in collaborate contexts. Thus, it is unknown whether representational-competency supports prepare students for future collaborative learning.

Collaborative learning may naturally promote discussion among students, which helps students to understand novel visuals in instructional materials (Strickland et al., 2010). Consequently, students may not need extra support for representational competencies in future collaborative learning. However, when students work

manipulating interactive time-domain and phasor graphs. Signals Tutor provides three types of activities, which differ in terms of whether and which types of representational competencies they support.

Regular activities

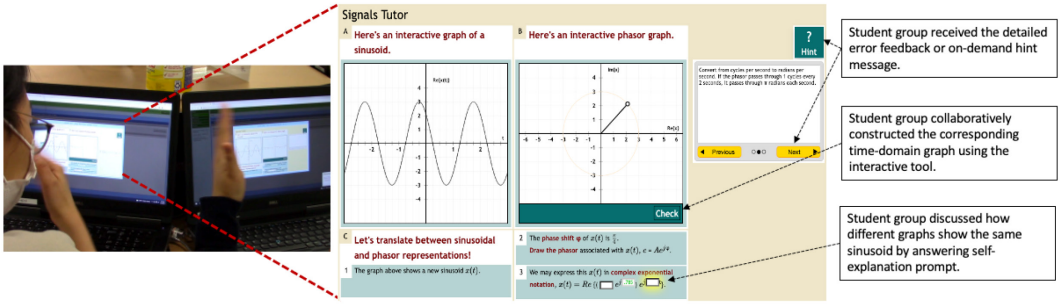
Regular activities do not support specific representational competencies. Following the design of regular instructional activities, they ask students to use time-domain or phasor graphs to answer questions about sinusoids. Regular activities provide detailed feedback and on-demand hints related to the concepts covered in the activities.

Sense activities

Sense activities support sense-making competencies. Prior to working on sense activities, student groups see a brief video instructing them to actively participate in a discussion and come to an agreement before submitting their answers. As shown in Figure 1, students receive step-by-step guidance to build a phasor graph that represents the sinusoid given in a time-domain graph (or vice versa). Then, sense activities ask student groups to verbally explain how specific features of a phasor graph can be translated into a time-domain graph. For example, in Figure 1, the student group is prompted to reflect on how the phase shift shown in the given time-domain graph can be translated to the vector's rotation in the phasor graph. Similar to regular activities, sense activities provide detailed feedback and on-demand hints to guide students.

Figure 1

Example of student group collaboratively working on a sense activity

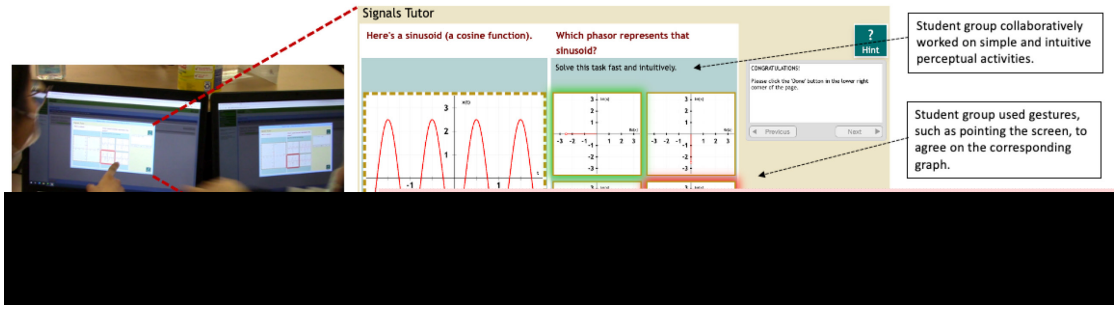


Perceptual activities

Perceptual activities support perceptual fluency. Prior to working on these activities, student groups see a brief video instructing them on perceptual learning. They are instructed to solve the activities quickly and intuitively. Further, the video asks students to collaborate using nonverbal communication, such as pointing gestures, because verbal communication interferes with perceptual learning processes (Schooler et al., 1997). As shown in Figure 2, perceptual activities ask student groups to find one out of four time-domain graphs which represent the same sinusoid depicted in the given phasor graph (or vice versa). The four choice options are designed to direct students' attention to important visual features. Perceptual activities only provide correctness feedback so that students focus on perceptual processing (Kellman & Massey, 2013).

Figure 2

Student group collaboratively working on a perceptual activity



Experimental design

Student groups were randomly assigned to one of four conditions resulting from a 2 (sense activities: yes/no) x 2 (perceptual activities: yes/no) experimental design. To control for time on task across conditions, we ensured that all conditions solved the same number of problem-solving steps.

The sequence of instructional activities was organized as follows across five Signals Tutor units. Unit 1 was identical across conditions because it introduced to time-domain and phasor graphs. Unit 2 covered time-domain graphs and their corresponding equations. Because time-domain graphs were the only type of visual used in this unit, Unit 2 did not provide sense activities. However, Unit 2 provided perceptual activities where students practiced quick translation between equations and visuals. Units 3 and 4 involved both time-domain and phasor graphs. Thus, each group received representational-competency supports according to the assigned condition.

Finally, Unit 5 provided regular activities on a novel concept, phasor addition, which is depicted in a novel visual, a vector addition graph. Working on activities about phasor addition required student groups to apply concepts and representational competencies they practiced in previous Units 2-4.

Measures and analyses

To investigate the effect of representational-competency supports on students' future collaborative learning (RQ1), we assessed learning gains with pretests and posttests for each unit (except for the introductory Unit 1). The tests for Units 2-4 served as an implementation check. Our main outcome of interest were the tests for Unit 5, which assessed students' learning from future instruction that did not offer representational-competency supports. Students solved all tests individually. We computed learning gains through accuracy and efficiency scores. Accuracy scores were computed as the percentage of correct answers. Efficiency scores were computed to take account how long it took students to achieve correct answer, following as: efficiency = (z-score of accuracy – z-score of duration) / √2, (Van Gog & Paas, 2008). We used statistical analyses to compare students' learning gains scores (i.e., efficiency and accuracy scores) across four conditions. To investigate the moderation effect of spatial skills (RQ2), we assessed spatial skills with the Vandenberg & Kuse mental rotation test (Peters et al., 1995), which is prevalent measure of spatial skills in engineering education. We used statistical analyses to see students' level of spatial skills moderate the effect of representations-competency supports across conditions. To investigate how students experience collaborative work on representational-competency support activities (RQ3), we qualitatively examined interview responses for themes that emerged across dyads.

Procedure

On the first course meeting day, students were briefly informed about the study and instructed to collaborate on problems in Signals Tutor. In the following course meeting days, students completed the instructional activities according to their experimental condition, with Unit 2 being assigned in class in the second course meeting day, Unit 3 in the third meeting day, Unit 4 as homework, and Unit 5 in the fourth meeting day. Students worked collaboratively on Units 2, 3, and 5. We also conducted a semi-structured interview asking students to reflect on their collaboration experiences with peers in Unit 2, 3, and 5. We randomly chose one student from each condition. The interviewers asked questions about what was difficult and what was helpful and, how a group collaborated.

Results

Student groups were excluded from analysis if one of the group members absent from any test, failed to complete the instructional activities, or dropped the course. As a result, a total of N = 134 students and 56 small groups were included in the data set (control: n = 37;15 groups, sense: n = 39; 16 groups, perceptual: n = 30; 12 groups, and sense-perceptual: n = 28; 13 groups). We report p. η2 as a measure of effect size, p. $\eta^2 \geq 01$ being a small effect, p. $\eta^2 \geq .06$ being a medium effect, and p. $\eta^2 \geq .14$ being a large effect (Cohen, 1992). Table 1 shows the mean and standard deviation of efficiency scores for Units 2, 3 and 5, on which students collaboratively.

Table 1

Means and standard deviations (in parentheses) of efficiency scores for each unit

Unit	Test	Control	Sense	Perceptual	Sense-Perceptual
2	Pre	-0.197 (0.874)	0.106 (0.807)	-0.093 (0.761)	-0.559 (0.938)
	Post	0.231 (1.097)	0.426 (0.989)	0.514 (0.692)	0.320 (0.802)
3	Pre	-0.460 (0.866)	-0.225 (1.040)	-0.435 (1.048)	-0.276 (1.058)
	Post	0.419 (0.989)	0.178 (0.870)	0.957 (0.978)	0.506 (0.891)
5	Pre	-0.480 (0.720)	-0.238 (0.820)	-0.402 (0.993)	-0.088 (0.854)
	Post	0.086 (1.056)	0.727 (0.938)	0.620 (1.072)	0.928(0.914)

Effects on future collaborative learning

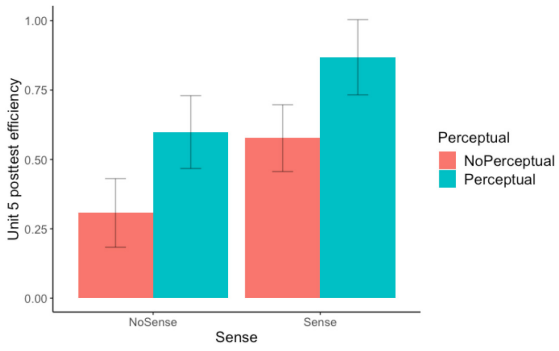
Following Cress (2008), we tested if adjustments were necessary for that fact that students were grouped together during learning with Signals Tutor. We calculated intraclass correlations (ICCs), which provided an estimate of how much clustering occurred due to factors such as group, TA, professors or sections. The ICCs score for our

primary outcome variable, Unit 5 posttest scores, were very low (ICCs < .10). Therefore, adjustments for non-independence were not required. We investigated whether representational-competency supports prepare students future collaborative learning (RQ1) by conducting an ANCOVA with Unit 5 posttest as dependent measure, sense and perceptual factors as independent variables, and Unit 5 pretest and spatial skill as covariates. For the accuracy measure, we found no significant effects. For the efficiency measure, as shown in Figure 4a, we found that student groups working on perceptual activities showed significantly more efficient performance on the posttest than groups which did not work on perceptual activities, $F(1, 133) = 3.941$, $p = .049$, p. $\eta^2 = .030$. Similarly, student groups working on sense activities showed marginally more efficient performance on posttest than groups which did not, $F(1, 133) = 3.239$, $p = .074$, p. $\eta^2 = .024$.

To test whether students' level of spatial skills moderate the effect of representational-competency supports (RQ2), we tested for aptitude-treatment interactions of spatial skills with the sense and perceptual factors by adding these effects to the ANCOVA model described above. To be consistent with previous research on aptitude-treatment interaction, we did not categorize spatial skills into separate group, but instead modeled how sense and perceptual factors interacted with continuous variable of spatial skills. In Unit 5, we found no significant interaction between sense or perceptual factors and spatial skills ($p > .10$).

Figure 4

Student groups that worked on both sense and perceptual activities showed the higher efficiency on posttest.



Collaboration experiences

To understand how students experience collaboratively working on representational-competency supports activities in Signals Tutor, we examined students' collaborative experiences. We found that three themes emerged: confidence, comfort, and helpfulness.

First, with respect to *helpfulness*, students commented that they were able to cement their understanding through verbally explaining the concepts to her partner during collaboration. Similarly, another student commented that collaboration was helpful because they were able to explain each other about the confusing points during Unit 2: "we spoke out our thoughts and it was helpful because the parts I missed or got confused was the part he knew how to solve."

Second, regarding *confidence*, all students reported that collaborative working increase their confidence: "Collaboration gives me confidence, because when you think you know how to do the problem and you get the same answer as your partner, it shows that two brains are better than one." Collaborative working also released self-doubt: "Sometimes there's self-doubt, especially when answering a complicated question and having someone else agree with you makes you feel more confidence and feel like you understand the material better."

Lastly, regarding *comfort*, students reported that they become comfortable about working with their partners in Unit 5: "Yes, we got more comfortable with each other now, like, we are not strangers anymore so that helped." Students were able to find each one's strengths based on previous collaboration experiences in Units 2 and 3: "From the past experiences, we got to know each other.", which leads to more comfortable collaborative work on Unit 5: "We now kind of know who's explaining what, so I think that it got easier [in Unit 5]."

Discussion

This study investigated whether representational-competency supports enhance students' future collaborative learning (RQ1). Specifically, we provided sense and perceptual activities to student groups and tested whether these activities have an effect on students' learning of a novel concept with a novel visual in Unit 5. We found that student groups who worked on sense or perceptual activities showed higher learning efficiency in Unit 5 than student groups who did not receive these activities. These results extend previous findings about the effectiveness of representational-competency supports to collaborative learning. Further, our findings expand prior research by

showing that representational-competency supports are an effective intervention to prepare students for their future learning.

Our finding that perceptual activities alone were effective stands in contrast to the prior research on representational-competency supports in individual learning contexts, which showed that students benefit from perceptual activities when they were combined with sense activities (Rho et al., 2022). While prior research found perceptual activities to be effective only when they were preceded by sense activities first, student groups in the present study benefited from perceptual activities even if they had not previously received sense activities. A possible explanation for these divergent findings is that student groups in the present study learned in an active learning format, which encourages students to engage in co-construction of explanations and inferences (Freeman et al., 2014). The active learning format may have supported students in making sense of visual representations so that additional sense activities were no longer necessary to enable students' learning from the perceptual activities. Indeed, our interviews revealed that students who worked on perceptual activities had an active discussion, which supports our interpretation.

Further, we investigated whether spatial skills moderate the effect of representational-competency supports (RQ2). We found no evidence that spatial skills affected students' benefit from sense activities or perceptual activities; in other words, all students benefitted equally. This finding differs from our unfortunate previous finding (Rho et al., 2022), where sense activities were effective for high-spatial-skill students in preparing for future learning. It is possible that collaboration alleviated the moderation effects of spatial skills. As mentioned, the active learning setting of our encouraged students to help one another, which might have particularly benefitted students with low spatial skills. Our findings related to students' experiences of collaborative learning with representational-competency supports activities (RQ3) supports this interpretation. We found that students received *help* from each other while having an active discussion. Through such discussion, students felt *confidence* and *comfort* about collaboratively working on activities. As a result, students created a supportive environment where low-spatial-skill students can ask for and receive timely help from their peers. Further, high-spatial-skill students were able to enhance their understanding by providing an elaborated explanation to their peers.

Our findings should be interpreted considering the following limitations. First, we conducted our experiment as part of an electrical engineering course. While the naturalistic context of a real classroom enhances the external validity of the experiment, it might have reduced its internal validity. For instance, students might have received help other than our intervention in an unknown way, for example from teaching assistants. Thus, future research should replicate our findings in a more controlled environment. Second, we did not test whether collaborative work on representational-competency activities is more effective than individual work on activities for preparing for future learning. Future research could address this limitation by comparing individual to collaborative learning from representational-competency supports.

To conclude, our research is, to the best of our knowledge, the first to demonstrate that representational-competency supports in collaborative learning are effective for preparing future learning with novel visuals. This finding provides new evidence that fills the existing research gap between representational-competency supports and preparation for future learning. Our findings also provide practical contributions to instructional design in collaborative learning. Considering many STEM instruction activities moving toward collaborative learning, our study demonstrated that collaborative work occurring in a supportive environment has potential to evenly distribute the effect of representational-competency support, especially for preparing future learning.

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Acknowledgments

We thank Bhuvana Krishnaswamy, Eduardo Remero Arvelo, and their teaching assistants for their help with this study. This work was supported by NSF DUE 1933078.