Preparing Future Learning with Novel Visuals by Supporting Representational Competencies

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Abstract. Many STEM problems involve visuals. To benefit from these problems, students need representational competencies: the ability to understand and appropriately use visuals. Support for representational competencies enhances students' learning outcomes. However, it is infeasible to design representational-competency supports for entire curricula. This raises the question of whether these supports enhance future learning from novel problems. We addressed this question with an experiment with 120 undergraduates in an engineering class. All students worked with an intelligent tutoring system (ITS) that provided problems with interactive visual representations. The experiment varied which types of representational-competency supports the problems provided. We assessed future learning from a subsequent set of novel problems that involved a novel visual representation. Results show that representational-competency support can enhance future learning from the novel problems. We discuss implications for the integration of these supports in educational technologies.

Keywords: Visualizations · Representational competencies · Future learning

1 Introduction

Instruction in STEM domains heavily relies on visual representations because much of the content knowledge in such domains is visuospatial [1]. As a result, students encounter multiple visual representations to learn about foundational concepts [1, 2]. For instance, when learning about sinusoids, engineering students typically encounter the time-domain visual and phase-domain visual shown in Fig. 1.

Unfortunately, students often do not benefit from these visual representations. Students' difficulties in understanding visual representations are a major obstacle to their success in STEM domains [1, 3], including engineering [4]. Such difficulties result from a lack of *representational competencies*, that is, knowledge about how visuals reveal information relevant to scientific concepts and practice [5, 6].

Further, challenges that are caused by lack of representational competencies are particularly severe for students with low spatial skills [7]. For example, when translating between visuals in Fig. 1, students need to mentally rotate a phasor and project a sinusoid's amplitude to the magnitude of a phasor [8, 9].

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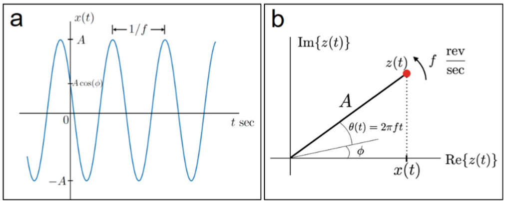

Fig. 1. Visual representations: (a) time-domain visual showing a sinusoid as a function of time; (b) phase-domain visual showing sinusoid as rotating vector.

More crucially, lack of representational competencies could subsequently impede students' future learning because the concepts they learn today are the basis for their later learning from novel problems. For example, students who fail to understand time-domain and phase-domain visuals (Fig. 1) will likely struggle to learn about more advanced concepts building on an understanding of these visuals, such as phasor addition.

Educational technologies offer a solution to this problem. They can provide adaptive support for representational competencies while students interact with visuals [10]. Prior research has established effective technology-based supports for students' representational competencies [10]. However, experimental evidence shows that designing adequate supports requires substantial time and effort [10]. Consequently, it is infeasible to design representational-competency supports for entire curricula. This raises the question of whether the effectiveness of representational-competency supports generalizes by enhancing students' future learning of novel concepts with novel visuals. Addressing this question will yield novel insights into the practicality of integrating supports for representational competencies in technology-based curricula.

Given that issues due to lack of representational competencies are particularly severe for students with low spatial skills, it is important to explore how spatial skills moderate the effects of representational-competency supports on students' future learning. Addressing this question will yield novel insights into how representational-competency supports relate to equity issues in STEM fields because students with low spatial skills are disproportionally women [11] or have low socioeconomic status [12].

2 Literature Review

2.1 Supporting Representational Competencies

Previous research identified two broad types of representational competencies that play an important role in learning with visuals in STEM [6]: sense-making competencies and perceptual fluency. Since these competencies derive from different learning processes, they should be supported by different types of instructional activities [13].

First, sense-making competencies describe explicit, analytical knowledge that allows students to explain how visual features of representations map to domain concepts [14]. Sense-making competencies also involve the ability to connect multiple visuals based on conceptual features [1, 6]. For example, students with sense-making competencies understand that the y-maximum in the time-domain visual (Fig. 1a) shows the amplitude of a sinusoid and can map it to the length of the vector in the phase-domain visual (Fig. 1b), which shows the same concept. Hence, sense-making supports prompt students to explain how the features of visuals represent the same concepts [15, 16].

Second, perceptual fluency describes implicit and automatic knowledge allowing students to quickly and effortlessly see connections among multiple visual representations [17, 18]. For example, perceptually fluent students can quickly and effortlessly translate between time-domain (Fig. 1a) and phase-domain visuals (Fig. 1b). Such perceptual fluency frees cognitive resources that students can invest for higher-order thinking, creative problem solving, or learning advanced concepts [18]. Perceptual-fluency supports expose students to a large number of simple recognition or classification problems that involve various types of visual representations. Through repeated practice, students learn to induce which visual features carry meaningful information [18].

Thus far, research has only examined whether these representational-competency supports enhance learning from the problems that provide these supports [10]. Hence, it remains unknown whether representational-competency supports are effective beyond the duration of the support. This question relates to transfer research that has examined how to prepare students for future learning experiences.

2.2 Transfer and Preparation for Future Learning

Current transfer research focuses on how instruction can prepare students to optimally benefit from future learning experiences [19]. This research developed in response to traditional transfer research, which defined transfer as the direct application of prior knowledge or skills to novel problems [20]. However, students rarely demonstrated this type of transfer, which led to criticisms of the traditional transfer definition [21]. The critiques argued that traditional transfer studies accept only specific evidence as the "right" form of transfer by prioritizing models of expert performance [22]. Instead, students often adapt their prior knowledge in a way that helps them learn about new concepts [20]. In line with this, "preparation for future learning" (PFL) research examines how instruction can support students' knowledge in a way that enhances their future learning from novel problems [19].

However, little research has investigated transfer of representational competencies. The few studies that have investigated this question rely on the traditional transfer framework [23]. For example, Cromley [23] tested whether representational-competency support enhances students' understanding of visuals they did not encounter during instruction, as assessed by a transfer posttest. Results showed advantages of representational-competency supports on the transfer posttest. However, this research leaves open whether representational-competency supports enhance students' learning from novel problems in subsequent instruction. Research on expert problem solving suggests that representational competencies contribute to experts' adaptive thinking about novel problems [17]. First, sense-making competencies enable experts to analyze the deep structure of a problem [24], allowing them to use representations to generate creative solutions [25]. Second, perceptual fluency has been linked to adaptive thinking because the ability to quickly process information from given representations frees cognitive resources to flexibly apply prior knowledge when solving new problems [18]. Thus, supporting students' representational competencies may equip them with knowledge that enhances their subsequent learning.

3 Research Questions

Our review of prior research shows that there is a gap between research on representational-competency supports and research on transfer, especially from a PFL perspective on transfer. Consequently, the following research question (RQ) remains open:

RQ1: Do problems that support sense-making competencies and perceptual fluency enhance students' learning from novel problems?

Further, given that issues due to a lack of representational competencies are particularly severe for students with low spatial skills, we explore:

RQ2: Do spatial skills moderate the effect of representational-competency supports?

4 Methods

4.1 Participants

The experiment was conducted as part of an introductory engineering course on signal processing at a university in the Midwestern U.S. All 120 undergraduate students enrolled in the course participated. The course involved two 75-min class meetings per week. The intervention took place in the first 3 weeks that covered sinusoids.

4.2 Signals Tutor: An ITS for Undergraduate Electrical Engineering

We conducted an experiment in the context of five units of Signals Tutor, an ITS for undergraduate electrical engineering. Signals Tutor provides problems in which students learn about sinusoids by manipulating time-domain and phase-domain visuals (Fig. 1). Both visuals play an important role in learning advanced engineering concepts such as Fourier analysis, circuit analysis, and single-frequency analysis of system. Signals Tutor involves three types of problems.

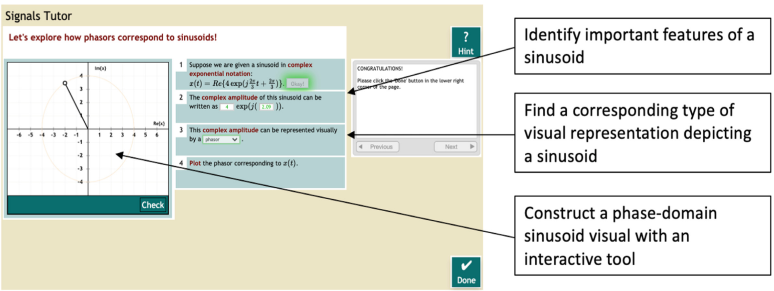

Fig. 2. Example individual problem: students construct a phase-domain visual.

Individual problems provide one visual representation per problem. While these problems do not specifically support representational competencies, they familiarize students with one visual at a time while asking students to relate the visuals to corresponding equations. As shown in Fig. 2. Above, individual problems ask students to answer questions about sinusoids and to construct a visual representation based on an equation by using an interactive visualization tool. Students receive error-specific feedback and on-demand hints on all problem-solving steps, including the visuals they construct.

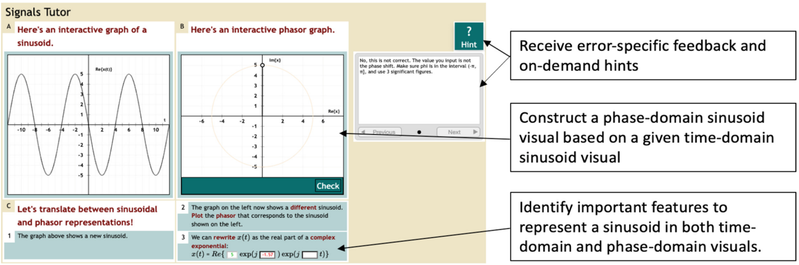

Fig. 3. Example sense-problem: students reflect on time-domain and phase-domain visuals.

Sense problems support sense-making competencies. As shown in Fig. 3 above, sense problems have two parts. First, students are given one visual (e.g., a time-domain visual) and are asked to construct a second visual (e.g., a phase-domain visual) of the same sinusoid. Second, students are prompted to reflect on how the two visuals represent corresponding and complementary concepts related to sinusoids. Similar to individual problems, students receive error-specific feedback and on-demand hints.

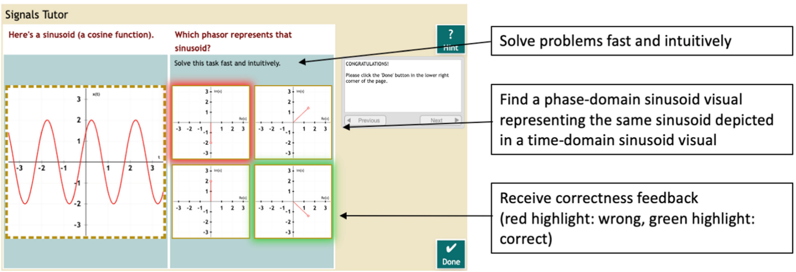

Fig. 4. Example perceptual problem: students quickly choose a phase-domain visual.

Perceptual problems support perceptual fluency by offering practice opportunities to translate between visuals. As shown in Fig. 4 above, students are given one visual (e.g., a time-domain visual) and are asked to quickly choose one of four visuals (e.g., a phase-domain visual) that shows the same sinusoid. The four choices are designed to emphasize features that may confuse students. Perceptual problems do not provide any detailed feedback or hints. Students only receive correctness feedback because explanations could disrupt perceptual processing [26]. Students receive many of these short problems with numerous examples.

4.3 Experimental Design and Procedure

To investigate the effect of representational-competency support on students' future learning, we used a 2 (sense problems: yes/no) × 2 (perceptual problems: yes/no) design. This yielded four conditions: (1) The *control condition* received only individual problems without representational-competency supports. (2) The *sense condition* received individual and sense problems. (3) The *perceptual condition* received individual and perceptual problems. (4) The *sense-perceptual condition* received individual, sense, and perceptual problems. Across conditions, we adjusted the number of steps in each problem so that all conditions received the same number of problem-solving steps.

The sequence of problems was organized as follows across the five Signals Tutor units. As detailed in Table 1, Units 1–4 provided time-domain and phase-domain visuals. Unit 1 was an introductory unit that familiarized students with basic sinusoids and with time-domain and phase-domain visuals. Unit 1 was identical across conditions.

Unit 2 provided only time-domain visuals. Because individual problems ask students to translate between equations and visuals, there were no sense problems for Unit 2. Yet, Unit 2 offered perceptual problems that asked students to quickly translate between equations and time-domain visuals. Students in the control and sense conditions received only individual problems. By contrast, students in the perceptual and sense-perceptual conditions received individual problems followed by perceptual problems.

Units 3 and 4 provided both types of visuals. For each of these units, students in the control condition received only individual problems. Students in the sense condition received individual problems followed by sense problems. Students in the perceptual condition received individual problems followed by perceptual problems. Students in the sense-perceptual condition received individual, then sense, then perceptual problems. Across Units 3–4, we implemented sense problems before perceptual problems following prior research suggesting that this sequence is more effective [27].

Finally, Unit 5 provided instructional problems on phasor addition, a novel, more complicated concept that builds on the content covered in Units 2–4. Students used a vector graph, a novel type of visual. Unit 5 served to assess students' preparation for future learning and was identical across conditions.

In the first course meeting, students were greeted by the research team and informed about the study. Then, they worked on one Signals Tutor unit per meeting for the first five meetings of the course. For Units 2–5, students received a pretest prior to the Signals Tutor problems and a posttest immediately after. As Unit 1 was an introductory unit administered in the first course meeting, it did not include a pretest or posttest. The spatial skills test was given prior to the Unit 2 pretest.

Table 1. Overview of Signals Tutor units

Unit	Content	Sinusoid visuals	Experimental factors
1	Sinusoids, sinusoid visuals	Time/phase domain	None
2	Sinusoids as function of time	Time domain	Perceptual (y/n)
3	Multiple sinusoid visuals	Time/phase domain	Sense (y/n); perceptual (y/n)
4	Complex numbers	Time/phase domain	Sense (y/n); perceptual (y/n)
5	Sum of sinusoids	Vector graph	None

4.4 Measures

We assessed students' learning gains with pretests and posttests for each unit (except for the introductory Unit 1). Isomorphic test versions were counterbalanced across test times (i.e., the versions had structurally identical items but used different examples). Each test had ten multiple-choice items assessing students' ability to internally visualize and manipulate sinusoids. Some items provided a visual of a sinusoid and asked students to mentally modify it to answer questions about the sinusoid. Other items provided an equation and asked students to mentally visualize the corresponding sinusoid to answer questions. Students were not allowed to draw or use calculators. We computed accuracy scores as the percentage of correctly answered items on each test. We computed efficiency scores to take response time into account following [28]:

$$\text{efficiency score} = \frac{\text{Z(average correct responses)} - \text{Z(average response time per test item)}}{\sqrt{2}} \tag{1}$$

Finally, we assessed spatial skills with the Vandenberg & Kuse mental rotation test [29], which is a common measure in engineering education research [30].

5 Results

We excluded students from analysis who were absent from any test, whose test performance was a statistical outlier (i.e., 2 standard deviations above or below the median), or who dropped the course. As a result, a total of $N = 117$ students were included in the data set (control: $n = 28$, sense: $n = 28$, perceptual: $n = 32$, sense-perceptual: $n = 29$). We report partial η^2 (p. η^2) for effect sizes, with .01 corresponding to a small, .06 to a medium, and .14 to a large effect [31]. Table 2 shows efficiency scores by unit.

5.1 Prior Checks

First, we checked for differences between conditions on the pretests for Units 2–5. A multivariate ANOVA showed no significant effects of condition ($ps > .10$). However, each unit's pretest significantly correlated with the posttest (ranging from $r = .274$ to $r = .726$; $ps < .01$). Thus, we included pretest as a covariate in the analyses for each unit.

Second, we checked whether students showed learning gains after working with Signals Tutor. We used a repeated measure ANOVA with test-time (pretest, posttest) as the repeated, within-subject factor and average test scores across units as the dependent measure. Results showed significant gains, $F(1,116) = 87.871$, $p < .001$, p. $\eta^2 = 431$. Separate repeated measure ANOVAs for Units 2–5 showed significant gains for all units (ps $< .01$) with effect sizes ranging from p. $\eta^2 = .09$ to p. $\eta^2 = .24$.

Third, we checked whether representational-competency supports enhanced students' learning from Units 2–4; that is, on the units where these supports were present. We conducted separate ANCOVAs for Unit 3 and 4, with pretest as covariate, the sense (y/n) and perceptual (y/n) factors as independent variables, and posttest as dependent measure. For Unit 2, we conducted similar ANCOVA but used only the perceptual factor (y/n) as an independent variable. For accuracy, results revealed a significant interaction between the sense and perceptual factors in Unit 4, $F(1,116) = 4.499$, $p = .036$ p. $\eta^2 = .039$. Predefined contrasts showed that students in the sense condition showed marginally higher accurate posttest performance than students in the sense-perceptual condition ($p = .09$). No other effects were significant (ps $> .10$). For efficiency, we found no significant effects (ps $> .10$).

Table 2. Each unit's means and standard deviations (in parentheses) of efficiency scores

Unit	Test	Control	Sense	Perceptual	Sense-perceptual
2	Pre	−0.199 (0.691)	−0.127 (0.882)	−0.681 (1.046)	0.108 (1.023)
	Post	0.302 (0.927)	0.032 (0.778)	0.097 (.782)	0.528 (1.037)
3	Pre	−0.338 (0.891)	−0.495 (1.017)	−0.345 (1.172)	−0.341 (0.923)
	Post	0.216 (0.958)	0.312 (1.135)	0.359 (1.011)	0.621 (0.823)
4	Pre	−0.464 (1.190)	−0.380 (1.014)	−0.526 (.987)	0.100 (1.085)
	Post	0.064 (1.057)	0.380 (0.881)	0.273 (1.010)	0.564 (0.886)
5	Pre	−0.267 (1.160)	−0.575 (1.013)	−0.529 (.927)	−0.401 (0.880)
	Post	0.608 (1.036)	0.223 (1.235)	0.210 (1.167)	0.763 (1.118)

5.2 Effects on Future Learning

To test whether representational-competency supports enhance students' learning from novel problems (RQ1), we used an ANCOVA with Unit 5 pretest as covariate, sense and perceptual factors as independent variables, and Unit 5 posttest as dependent measure. On the accuracy measure, results showed no significant effects (ps $> .10$). On the efficiency measure, students who had received sense problems in Units 3–4 (i.e., students in sense and sense-perceptual conditions) had significantly higher posttest efficiency than students who had not received sense problems (i.e., students in control, perceptual conditions), $F(1, 116) = 7.366$, $p = .008$, p. $\eta 2 = .063$. Further, the sense and perceptual factors interacted, $F(1, 116) = 5.386$, $p = .022$, p. $\eta^2 = .047$. As shown in Fig. 5a, students who had received both sense and perceptual problems in Units 3–4 had the highest posttest efficiency in Unit 5.

Next, we tested whether students' spatial skills moderate the effect of representational-competency supports (RQ2). To this end, we included spatial skills as a covariate to the ANCOVA and an aptitude-treatment interaction of spatial skills with the sense factor and the perceptual factor. This tests whether the continuous spatial skills variable moderates the effect of sense problems and perceptual problems. For efficiency, there was a significant interaction between spatial skills and the sense factor, $F(1,116) = 8.989$, $p = .003$, p. $\eta^2 = .076$ (Fig. 5b). To understand this effect, we computed effect slices that estimate the effect of the sense factor for specific levels of spatial skills. Students with high spatial skills ($\geq 80^{\text{th}}$ percentile of the sample, $p = .026$) showed a significant benefit from receiving sense problems (i.e., sense and sense-perceptual conditions). By contrast, there was no significant benefit of sense problems for students with low spatial skills ($\leq 20^{\text{th}}$ percentile of the sample, $p = .207$).

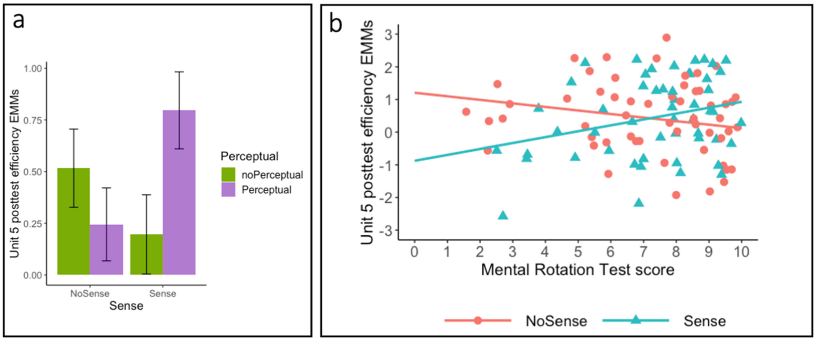

Fig. 5. (a) Interaction between sense and perceptual factors on posttest efficiency. Error bars show standard errors of the Estimated Marginal Means (EMMs); (b) effect of sense factor for levels of spatial skills. EMMs were computed controlling for covariates.

6 Discussion

The goal of this paper was to investigate whether representational-competency supports enhance students' future learning from novel problems with novel visuals (RQ1). We examined the effects of two types of representational-competency supports that were provided in the form of sense and perceptual problems. Our results show that students who received a combination of both problems showed more efficient posttest performance after learning from novel visuals, compared to students who received problems with no or with only one type of support. We interpret these findings in terms of the preparation for future learning (PFL) transfer framework [19]. Students learned how to make sense of representations through sense problems and how to quickly see meaning in the visuals through perceptual problems. Students appeared to be able to adapt these representational competencies when learning about sums of sinusoids using an unfamiliar vector graph. The finding that the combination of sense-making and perceptual-fluency supports was most effective suggests that both types of representational competencies are relevant to future learning experiences. Based on expertise research [18, 24, 25], we conjecture that sense-making competencies allow students to analyze a novel problem to generate a solution, whereas perceptual fluency frees cognitive resources for them to adapt prior knowledge to novel problems.

Further, we investigated whether spatial skills moderate the effect of representational-competency supports (RQ2). We found that students with high spatial skills benefited from sense problems, whereas students with low spatial skills did not. This suggests that the sense problems disadvantaged students with low spatial skills; that is, students who are already at a disadvantage in STEM domains such as engineering. What might explain this unfortunate effect? Sense problems support students in constructing mental models of multiple visuals [32]. Students with high spatial skills might have the necessary cognitive resources to spatially integrate multiple visuals in their mental models. This may have allowed them to efficiently incorporate a new visual in their mental model when learning from Unit 5. In contrast, students with low spatial skills may find it more cognitively demanding to integrate new visuals into their working memory. This finding suggests that research needs to focus on students with low spatial skills. It is possible that our sense problems did not offer optimal support for these students. For example, sense problems could visually highlight correspondences between visuals after students make mistakes in connecting the visuals. This may help low-spatial-skills students to understand spatially distributed correspondences. Future research should examine whether redesigned sense problems are effective for low-spatial-skills students. In the absence of redesigned sense problems, low-spatial-skills students may need continued sense-making support when they encounter novel visuals.

Finally, the results on the PFL assessment (Unit 5) differ from the results on the manipulation checks (Units 2–4), where we only found an advantage of sense problems on posttest accuracy (Unit 4). It is possible that the effectiveness of the sense problems only appeared after students had sufficient practice in reflecting on how the two visuals show sinusoid concepts (i.e., after Unit 4). However, the effectiveness of perceptual problems was not apparent immediately in Units 2–4, but only when students encountered novel problems with a novel visual in Unit 5. Thus, it seems that the ability to process familiar visuals quickly and effortlessly did not pay off when the visuals were familiar. However, it enabled students to solve novel problems more efficiently.

In sum, our study highlights the importance of assessing future learning. An intervention that seems effective for all may lack long-term benefits for some students (e.g., low-spatial-skills students). An intervention that seems ineffective (e.g., perceptual problems) may have long-term benefits, including for students with low spatial skills. These findings also have important implications for the design of adaptive educational technologies. Designing supports in a way that ensures long-term benefits may resolve the impracticality of providing representational-competency supports for entire curricula, which is infeasible because of the significant development costs.

Our study has several limitations. First, if focused on individual learning, whereas STEM instruction often involves collaboration. Future research should test effects of collaborative representational-competency supports on future learning. Second, our study only assessed students' improvement of content knowledge. Future research should additionally assess students' learning sense-making competencies and perceptual fluency. Finally, our study revealed the risk of disadvantaging students with low spatial skills. Future research should examine how representational-competency supports can prepare these students for future learning experiences.

To conclude, our findings suggest that integrating sense-making supports and perceptual-fluency supports in educational technologies enhances students' learning with novel visuals in novel tasks. This study is the first to show that representational-competency supports have the potential to enhance future learning. However, our study cautions that sense-making supports need to be designed in a way that better serves low-spatial-skills students. Without research that examines long-term effects of representational-competency supports, we may widen rather than close the achievement gap in STEM domains.

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