Do you see what I see?

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Abstract

Researchers often use visual representations (e.g., graphs, diagrams, pictures) to communicate scientific data, especially when supporting instruction. This style of visual communication relies on the intended receiver's ability to make sense of the visual inputs in manners consistent with scientific thinking. Unfortunately, learners are not always comfortable communicating with visualizations, and they do not always interpret and understand the represented science as intended. We refer to how well learners make sense of and use visual depictions of science as their representational competence. Low levels of representational competence can limit learning outcomes. Ignoring students' self-efficacy and ability to use and develop scientific representations can prevent them from developing expertise in their field. I developed and tested a 20-item Likert-type instrument to measure participant **E**fficacy in **C**ommunicating **S**cientific with **V**isualizations (ECSV). I used rigorous approaches to establish the content and face validity and reliability ($\alpha \geq 0.94$) of the instrument. I used biology student mean scores on the ECSV pre/post instruction to document statistically significant differences in science communication self-efficiency using visualizations. By identifying the self-efficacy involved in communicating science visualizations, we can better inform instructional practices. Improvements in representational competence are one step in maximizing our potential to improve science literacy.

Introduction

Science concepts and data are often communicated via visual means, be it graphs, symbolic equations, models, diagrams, or simulations, especially when supporting instruction. Visualizations can enhance learning from texts, improve problem-solving, and facilitate connections between new knowledge and prior knowledge (Cook, 2006). Various forms of visual representations can support an understanding of different, yet overlapping, aspects of a phenomenon or entity. Given that so many examples in science use visual representations to illustrate concepts, it is critical to consider the different ways students use and make sense of these representations. This style of visual communication relies on the intended receiver's ability to make sense of the visual inputs in manners consistent with scientific thinking. There is no doubt that using visual representations enhances learning (e.g., Reiner & Gilbert, 2008). Unfortunately, there is also no doubt that students often have difficulties understanding and interacting with visual representations (e.g., Halverson et al., 2011). Learners are not always comfortable communicating with visualizations, do not always express high self-efficacy regarding their ability to think and learn using visual representations of science (Hung & Wu, 2018; Uchinokura, 2020), and they do not always interpret and understand the represented science as intended.

Student self-efficacy has been positively linked to academic performance in STEM (Ballen, et al., 2018; Lent et al., 1984; Manzano-Sanchez et al., 2018). The manner by which we communicate science in the classroom may change student self-efficacy (Hung & Wu, 2018;

Uchinokura, 2020). However, we do not yet know how self-efficacy relates to communicating science using visual representations.

How learners make sense of and use visual depictions of science is referred to as their representational competence. As people build their representational competence, they can transfer ideas across representations, draw meaning from multiple representations, and generalize across different representations. Competence can be investigated as an outcome, condition, or developmental stage, with students' understanding of content based on their interactions with representations. It has been suggested that students' representational competence can change with task difficulty (Halverson & Friedrichsen, 2013; Kozma & Russel, 2005; Saleh & Daniel, 2018). When a learner achieves the highest level of representational competence across tasks, it is thought that they can begin shifting the external representation into an internal representation, or a mental image that can be manipulated (e.g., scanned and rotated) to improve performance on visual tasks, memory tasks, and cognitive problem solving (Gilbert, 2005). Whereas, underdeveloped representational competence can limit learning outcomes and may prevent learners from developing expertise in their field (Chiu, 2015).

Phylogenetic trees are a common biological visualization that serves as a central metaphor for evolution. The branching patterns within these diagrams illustrate testable hypotheses about the evolutionary histories of different species lineages. And, these diagrams are known to be challenging for students to learn how to interpret and compare (Halverson, 2010; Halverson et al., 2011). As such, I have chosen to use trees as the focal model for the treatment intervention of this study.

Research Questions

The purpose of this investigation was to develop and test a new instrument for measuring learner efficacy in communicating science with visualizations and explore the relationship between efficacy and tree-thinking learning outcomes. This study was guided by the following research questions:

- To what extent can we capture student self-efficacy in communicating science using visual representations?
- How does ECSV change after explicit instruction aimed at building representational competence in tree-thinking?
- To what extent does student confidence and tree-thinking performance impact ECSV outcomes?

Methods

I developed a Likert-type instrument to measure participant self-efficacy in their use of scientific visualizations (the current 20-item version of this instrument is included as an Appendix). I assessed the validity of this new instrument in two ways: content validity and face validity. I initially developed the original 21-item ECSV and asked five experts in the field of science communication and the field of learning with representations to review and review the instrument items for content validity (Moskal & Leydens, 2000). Through this process, I identified one item to eliminate due to a lack of fit within the intended construct being measured. Additionally, I administered the updated version of the ECSV to a small group of introductory biology students (n = 67) to assess face validity. I used these students to evaluate the overall appearance, structure, and wording of the instrument. Students reported that the wording of each item was understandable and appropriate for their level of education. Students also reported that the overall appearance of the diagnostic was uncluttered and organized, providing face validity (Moskal & Leydens, 2000). I also measured the instrument's reliability using Cronbach's alpha score for internal consistency. Internal consistency measures compare the responses of each participant to all other participants to determine if the diagnostic produces similar answers among similar participants (Kline, 2005). The ECSV has a strong overall reliability score of $\alpha \geq 0.95$ with the initial sample data set, which is considered strong and well above the minimum reliability score of $\alpha \geq 0.80$ (Field, 2009).

To test the ECSV in a practical setting, I surveyed 883 university and high school students studying biology. I ran a principal component analysis (PCA) to identify potential components within the ECSV and measured the reliability of each emergent factor with the new sample population. Next, I used a quasi-experimental design to explore changes in student ECSV component mean scores. I grouped students into treatment groups as follows: a control group wherein students were provided no explicit tree-thining instruction and treatment groups wherein students engaged in explicit, active-learning tree-thinking instruction (Leone, 2017). Within my treatment group, I surveyed Advanced Placement Biology high school students (AP), and introductory biology university students (UNI). I asked all participants to complete a pre- and post-questionnaire that included items from the Basic Evolutionary Tree-Thinking Skills Inventory ([BETTSI] Jenkins et al., 2021), ECSV, a confidence question, and demographic questions administered via Qualtrics. The BETTSI is an 11-item multiple-choice instrument (Reliability: $\rho KR20 = 0.80$) that captures participant tree-thinking accuracy. I removed student responses from the data set who did not complete both surveys, resulting in a reduced sample size (Control $n = 88$; AP $n = 72$; UNI $n = 42$). I then calculated participant responses for the full instrument mean average on the BETTSI (one score per participant), tree-thinking confidence score (one score per participant), and component average mean scores on the ECSV (three scores per participant).

To avoid the potential confounding variable of differences in response scores prior to instruction, I calculated the change in ECSV paired scores (post minus pre) for each participant by component. I found a significant difference in the *Learning & Recall* component mean change score between the two treatment groups ($F = 9.192$, $p = 0.003$, AP = 0.058, UNI = -0.087). While there were no significant differences in student scores between the AP and UNI groups for the other two components (*Diagram Use*, $F = 2.759$, $p = 0.099$, AP = 0.140, UNI = 0.162; *Metacognition*, $F = 3.781$, $p = 0.054$, AP = -0.097, UNI = -0.032). Thus, I elected not to combine the AP and UNI groups and treated them as separate treatment groups for analysis. I then ran an ANOVA to compare changes in ECSV mean scores by component between participants in the control group to participants in the two treatment groups. Lastly, I ran three linear regression analyses to identify significant relationships among post-BETTSI, post-Confidence, and post-ECSV component mean scores.

Findings

I conducted a principal component analysis (PCA) on the 20 items with orthogonal rotation (varimax). I measured the Kaiser-Meyer-Olkin (KMO) to verify the sampling adequacy for the analysis, KMO = 0.954 ('superb' according to Field, 2009), and all KMO values for individual items were > 0.85, which is well above the acceptable limit of 0.5 (Field, 2009). Bartlett's test of sphericity $X2\ (190) = 10567.21$, $p < 0.001$ indicated that correlations between items were significantly large for PCA. I ran an initial analysis to obtain eigenvalues for each component in the data. Three components had eigenvalues over Kaiser's criterion of 1 and, in combination, explained 62.19% of the variance. The scree plot groupings further justified retaining all three components. Given the large sample size, and the convergence of the scree plot and Kaiser's criterion on three components, I retained all three components in the final analysis. Table 1 shows the factor loadings after rotation. The items that cluster on the same components suggest that Component 1 represents self-efficacy affiliated with *Diagram Use* (14 items), Component 2 *Learning and Recall* (3 items), and Component 3 *Metacognition* (3 items).

Table 1.
Summary of exploratory factor analysis results for the ECSV questionnaire (n=883)

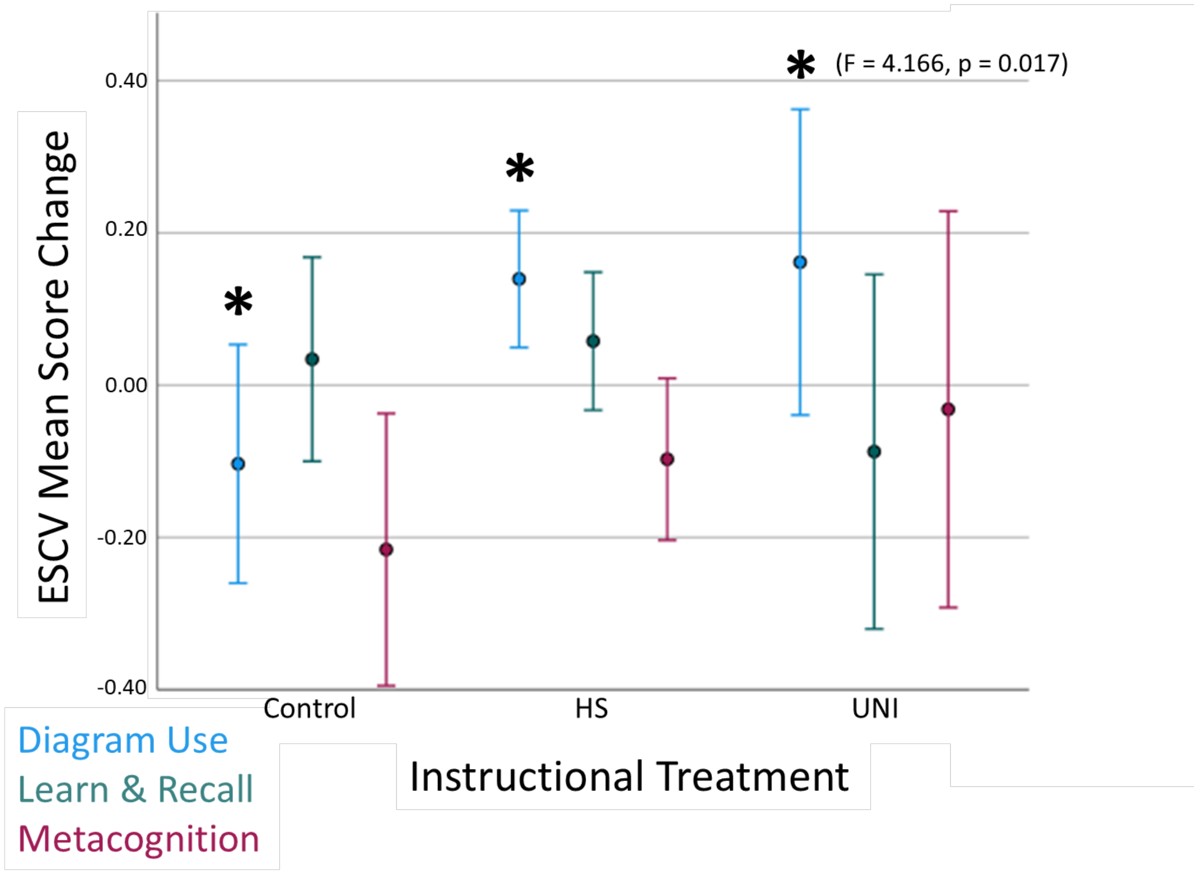
	Rotated Factor Loadings		
Item	Diagram Use	Learning & Recall	Metacognition
I can use scientific diagrams to explain ideas	0.80		
I can create a scientific diagram to show my understanding of a concept	0.79		
I can explain any scientific diagram I find in a textbook to a teacher	0.79		
I can explain difficult science concepts with visual diagrams	0.77		
I can find appropriate scientific diagrams to explain an idea	0.77		
I can create multiple scientific diagrams to show my understanding of a concept	0.76		
I can compare scientific diagrams and select with is best to show an idea	0.71		
I can explain any scientific diagram I find in a textbook to a friend	0.67		
I can solve problems using scientific diagrams	0.66		
I can interpret what concept a scientific diagram is representing	0.66		
I can explain scientific diagrams I have been taught in class to someone else	0.63		
I can compare scientific diagrams and identify what is different about them	0.62		
I can explain simple science concepts with visual diagrams	0.61		
I can understand when someone explains a scientific idea to me using a diagram	0.54		
I can learn science		0.82	
I can learn biology		0.81	
I can easily remember information presented in class		0.67	
I can recognize when I do not understand a scientific diagram			0.84
I can recognize when I understand a scientific diagram			0.68
I can get someone else to explain a scientific diagram I do not understand			0.58
Eigenvalues	7.22	2.96	2.26
% of variance	36.10	14.79	11.30
α	0.95	0.79	0.65

Note: Only factor loading over 0.40 appear in table.

Furthermore, I found that the *Diagram Use* self-efficacy subscale of the ECSV had high reliability (Cronbach's α = 0.95), and the *Learning and Recall* subscale had moderate reliability (Cronbach's α = 0.79). However, the *Metacognition* subscale had relatively low reliability, Cronbach's α = 0.65 with this new sample population. Overall, the full instrument maintained high reliability, Cronbach's α = 0.943.

When comparing outcomes across quasi-experimental groups post-instruction, I found a significant change in student self-efficacy of *Diagram Use* after instruction compared to the control group (DF = 2, F = 4.166, p = 0.017). There were no significant changes in student self-efficacy of *Learning and Recall* (F = 0.878, p = 0.417) or *Metacognition* (F = 1.066, p = 0.346) compared to the control group (Figure 1).

Figure 1
Change in Student ESCV Scores by Component after Treatment (n=202)



The linear regression model shows that with every increase of one standard deviation in a student's tree-thinking score via the BETTSI or their confidence in tree-thinking, their efficacy also significantly rises. With an increase of one standard deviation in student BETTSI tree-thinking score, efficacy of *Diagram Use* will rise 0.044 (p = 0.020), *Learning and Recall* will rise 0.037 (p = 0.034), and *Metacognition* will rise 0.037 (p = 0.034). Likewise, with an increase of one standard deviation in student tree-thinking confidence, efficacy of *Diagram Use* will rise 0.252 (p < 0.000), *Learning and Recall* will rise 0.160 (p < 0.000), and *Metacognition* will rise 0.117 (p < 0.000).

Discussion

We can effectively measure aspects of student self-efficacy involved in communicating science with visualizations. This current investigation has also provided evidence that explicit active tree-thinking instruction can lead to significant increases in student self-efficacy in *Diagram Use*, *Learning and Recall*, and *Metacognition*. As students begin to have a higher belief in themselves that they are capable of learning through visual communication means, they will likely begin to demonstrate increased representational competence, which in turn will support gains in self-efficacy (a positive learning cycle). Improvements in representational competence are one step in maximizing our potential to improve science literacy. Thus, if educators highlight self-efficacy and representational competence within STEM instruction, we can facilitate students developing expertise in their field. Ultimately, this type of instructional approach may lead to stronger retention in STEM.

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Appendix A

Efficacy in Communicating with Science Visualizations (ECSV)

Please rate how certain you are that you can do each of the things using a scale of 1-5:

1	2	3	4	5

I Cannot Do At All - - - - - - - Moderately Certain I Can Do - - - - - - - Highly Certain I Can Do

1. I can learn science
2. I can easily remember information presented in class
3. I can explain any scientific diagram I find in a textbook to a friend
4. I can recognize when I do not understand a scientific diagram
5. I can get someone else to explain a scientific diagram I do not understand
6. I can compare scientific diagrams and select which is best to show an idea
7. I can explain difficult science concepts with visual diagrams
8. I can explain scientific diagrams I have been taught in class to someone else
9. I can learn biology
10. I can recognize when I understand a scientific diagram
11. I can find appropriate scientific diagrams to explain an idea
12. I can use scientific diagrams to explain ideas
13. I can create a scientific diagram to show my understanding of a concept
14. I can explain any scientific diagram I find in a textbook to a teacher
15. I can interpret what concept a scientific diagram is representing
16. I can explain simple science concepts with visual diagrams
17. I can solve problems using scientific diagrams
18. I can compare scientific diagrams and identify what is different about them
19. I can create multiple scientific diagrams to show my understanding of a concept
20. I can understand when someone explains a scientific idea to me using a diagram