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Learning With Diagrams and Visualizations: Visual, Learner, and Contextual Factors

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Abstract

Diagrams and visualizations can be seen throughout educational materials, such that their presence is almost ubiquitous. The assumption is that including visualizations in lessons will lead to greater learning. In this paper, I review the psychological and educational literature to examine how the presence of visualizations influences learning in STEM fields. In particular, I examine how the effectiveness of a visualization depends on characteristics of the visualization, the learner, and the context. Characteristics of the visualization are important insofar as they highlight relevant information and reduce extraneous details. Learner characteristics influence how people learn with visualizations, but more work is needed to isolate these relations. The characteristics of the context are a critical but underexplored area in multimedia learning. This review highlights that visualizations are not universally helpful for learning, but rather their effect depends on a myriad of factors at multiple levels of analysis.

Keywords: Learning, Visualizations, Representations, Instruction, Individual differences, Multimedia learning

Learning With Diagrams and Visualizations: Visual, Learner, and Contextual Factors

Educational materials, such as storybooks (Etta & Kirkorian, 2019; Menendez et al., 2022), textbooks (Woodward, 1993), presentations (Angra & Gardner, 2018), and classroom decorations (Fisher et al., 2014), typically include both text and visualizations. Visualizations are visuo-spatial displays that depict or represent a concept or process (Hegarty, 2002), and can be static (e.g., images, diagrams, maps) or dynamic (e.g., videos, animations). Visualizations can serve different functions in educational settings, including decoration (i.e., increasing the aesthetics or visual appeal of the material), representation (i.e., depicting key aspects of the phenomena), and organization (i.e., integrating the visual and textual information in the material; see Levin, 1981 for a detailed list). The ubiquity of visualizations in educational settings raises the question of whether visualizations improve learning outcomes. Additionally, if visualizations are effective, why is this the case?

Does adding visualizations to a lesson improve learning?

There have been a myriad of studies comparing student learning with just text or with texts and visualizations, generally showing that adding visualizations helps learners: better understand concepts (Butcher & Aleven, 2008; Mayer et al., 1995), better use software (Sweller & Chandler, 1994; Whitley et al., 2006), and increase their interest in the topic (Sung & Mayer, 2012). For example, Schweppe et al. (2015) had undergraduate students learn about pulleys with either text alone or with text and a visualization, and found that students who learned with a visualization outperformed (in terms of retention of information and comprehension of pulleys) those who learned with text only. This difference was present immediately after the test and after a two-week delay. This result is in line with broader learning principles that providing additional relevant information is beneficial for learning (Bransford et al., 1999). Following this principle, multiple visualizations of a concept are even better than including just one (Rau et al., 2015). Therefore, the benefit of visualizations could be due to there being more material available for learners.

If providing additional information in any modality promotes learning, then what makes visualizations special for learning? Isolating the unique effect of visualizations on learning (rather than the effect of providing additional information in any modality) necessitates empirical studies comparing how much students learn on average from lessons with visualization to how much students learn on average from similar lessons where the additional information is provided verbally (or in another form other than visual). However, such a comparison would be difficult to equate, as visualizations by design represent many spatial relations, size information, and relational information that would require lengthy verbal explanations (Gropper, 1963). These relations are easily extracted by our visual system when presented visually (Mandler & Johnson, 1976). This makes comparisons of information presented in multiple modalities challenging. Pursuing this challenge would be a fruitful direction for future research, as identifying the unique contributions (if any) of visualizations on learning would help refine scientific theories on learning. Given the scant research on the uniqueness of visualizations, in this article, I take the approach often taken by scholars of multi-media learning, where the focus is to identify common learning principles that might apply to learning broadly and are particularly relevant when designing lessons with visualizations. Understanding these learning principles could help instructors design lessons that make better use of multimedia learning environments common in modern educational spaces.

One key aspect of research on visualizations is the finding that not all visualizations are equally effective. For example, Kaminski et al. (2008, 2013) found that people were more likely to generalize from a mathematics lesson if they learned with one abstract visualization instead of with several concrete visualizations. Some visualizations are better for novices or advanced students (Clinton et al., 2013; Cooper et al., 2018; Kalyuga et al., 2003; Magner et al., 2014; Rau et al., 2014). In fact, many studies have found that a person's self-rated mental effort (i.e., cognitive load) is an important factor in whether they learn better with a visualization (Eitel et al., 2019; Strobel et al., 2019). Furthermore, sometimes their effectiveness depends on other aspects of the lesson (Kokkonen & Schalk, 2020), such as what and how the linguistic information is presented in the lesson (Chandler & Sweller, 1992; Kalyuga et al., 1999; Son & Goldstone, 2009). The question of whether visualizations are beneficial or not may be too simplistic, as their effectiveness might depend on contextual factors. Likewise, understanding the mechanism for when they are effective might similarly depend on contextual factors.

All of these moderating effects and limiting conditions on the effectiveness of diagrams bring forth some important questions: (1) When are visualizations helpful for learners? And (2) why are visualizations helpful for learners? Please note that I do not make the claim that the answers to these questions have to be unique to visualizations. Rather, it is likely that the answers are common learning principles that are present across modalities. To answer these questions, I review the literature on learning with visualizations to examine the factors that influence whether a visualization is beneficial for learners. I focus specifically on learning with visualizations in formal science, technology, engineering, and mathematics (STEM) education, because the majority of the available research is in these content domains. Hegarty et al. (1991) categorized visualizations into iconic visualizations, schematic visualizations, and graphs. Iconic visualizations, such as photographs and line drawings, attempt to faithfully represent an object. Schematic visualizations, such as cladograms or circuit diagrams, attempt to depict structures or relations without *necessarily* showing the objects involved. Graphs (and charts) are visualizations that depict quantitative relations among variables. I focus on static iconic and schematic visualizations as those are prominent in all STEM disciplines. However, it should be noted that there is evidence that dynamic visualizations can be more beneficial than static ones (Butcher, 2010; Kriz & Hegarty, 2007; Ronfard et al., 2023), but these effects depend on how learners interact with the visualizations (Keehner et al., 2008).

This review is divided into four sections. First, I review some of the major theoretical frameworks in this field. Second, I review work on how the characteristics of a visualization influence its effectiveness. Third, I review research about learner characteristics and individual differences in learning with visualizations. Fourth, I review how the effectiveness of a visualization depends on the context in which it is placed.

Theories of Learning with Visualizations

There have been multiple theories that account for how people learn with visualizations, but their scope varies. For example, Cognitive Load Theory is a general theory of learning with insights into learning with visualizations (Paas et al., 2003; Sweller et al., 1998). Some theories, such as the Cognitive Theory of Multimedia Learning (Mayer, 2009; and its extension the Cognitive-Affective Theory of Multimedia Learning; Moreno, 2005, 2006, 2007), and the Integrated Text and Picture Comprehension Model (Schnotz, 2014; which includes insights from Dual Coding Theory; Clark & Paivio, 1991), focus specifically on learning from lessons that include visualizations as well as textual or other linguistic information. Others focus on a narrow issue such as how learning occurs when there are multiple visualizations (DeFT framework; Ainsworth, 2006). I briefly review each of these theories and emphasize how they propose characteristics of the visualization, learner, and context influence learning with visualizations.

Cognitive Load Theory

Cognitive Load Theory (Paas et al., 2003; Paas & Sweller, 2014; Sweller, 2005; Sweller et al., 1998) is motivated by memory research, in particular Baddeley's (2000) model of memory and Miller's (1956) research on working memory. The central idea is that there are limits to an individual's working memory (i.e., the amount of information they can actively hold in mind), and once this limit is reached, the learner cannot take in more information. The term cognitive load describes the extent to which a learner's working memory is taxed by the task at hand. As such, this theory is not specific to visualizations, as overtaxing working memory can be done in any modality. Cognitive Load Theory takes into account the complexity of the learning task, also called *intrinsic cognitive load*. Some tasks, such as memorizing a couple of key terms, are simpler than others, like learning how to solve a physics problem. More complex tasks create more load, as the learner needs to spend more resources just performing the task. Cognitive Load Theory also differentiates between load that is relevant to learning (i.e., *germane cognitive load*) and load that is irrelevant (i.e., *extraneous cognitive load*). Although this distinction of types of cognitive load has been criticized (de Jong, 2010; Gerjets et al., 2009; Kalyuga, 2011), some research still makes this distinction (Debue & van de Leemput, 2014; Sweller et al., 2019).

The predictions of Cognitive Load Theory center around reducing extraneous load (Castro-Alonso et al., 2019). Therefore, visualizations that maximize the amount of relevant information and minimize the irrelevant information will be beneficial. This theory also places great importance on one learner characteristic, prior knowledge. If learners already know some of the information (thus have high prior knowledge), then they do not have to process as many details, and it will be easier to add the information from the lesson to their long-term memory. Finally, this theory also makes predictions about the context. Most notable is the idea that when learning with visualizations, spoken lessons are preferred over written lessons (Chandler & Sweller, 1992; Kalyuga et al., 1999). Written lessons are not ideal as the learners have to split their attention between the text and the visualization.

The biggest critique of Cognitive Load Theory has been on how to measure cognitive load (Kirschner et al., 2011). Although there are behavioral and physiological measures for cognitive load (Skulmowski & Rey, 2017), the standard approach has been to use self-report measures after a lesson, in which learners rate how much mental effort they had to put in the lesson (Bartholomé & Bromme, 2009; Paas, 1992; Park et al., 2011). One issue with these self-report measures is that it is difficult to separate whether the lesson required little mental effort or whether the learner was not engaged during the lesson. Another criticism of Cognitive Load Theory is how to differentiate between the three types of loads. A big question for this distinction is whether the information is relevant. I provide a working definition for relevance in the section on characteristics of the visualization, but it is worth noting that some definitions of relevance can be circular. Additionally, it is not clear how the different types of load interact. For example, highlighting relevant information might add germane cognitive load for some learners because they might not attend to the right elements without the highlighting. However, for learners who know where to attend, this highlighting might add extraneous cognitive load.

Cognitive Theory of Multimedia Learning and Cognitive-Affective Theory of Learning with Media

The Cognitive-Affective Theory of Learning with Media (Moreno, 2005, 2006, 2007; Moreno & Mayer, 2007) expands the Cognitive Theory of Multimedia Learning (Mayer, 1997, 2009; Mayer & Gallini, 1990). Given their similarity, I will only discuss them together. These theories have identified several principles for effective multimedia instruction (Mayer & Moreno, 2003). Some of these principles stipulate that related information should be close together in space (spatial contiguity principle) and/or time (temporal contiguity principle), redundant information should be omitted (redundancy principle), irrelevant information should be reduced or omitted (coherence principle), and interactive media is better than non-interactive media (interactivity principle).

These theories outline that learners perceive all the information present during the lesson and select part of this information to be processed more deeply in working memory. Then, learners create a mental model that contains information from both the text and the visualizations and integrate this with the information in their prior knowledge. Critically, this theory posits that learners can use their metacognition to regulate their attention and working memory. The role of metacognition in this theory is to allow learners to reflect and regulate their learning. Motivation (the affective component of the Cognitive-Affective Theory of Learning with Media) influences how much the learners engage with the lesson. Thus, learners with greater motivation will engage more with the lesson and process it more deeply, resulting in greater recall of the information in the lesson than learners with less motivation.

The Cognitive Theory of Multimedia Learning makes very specific predictions about how characteristics of the visualization influence learning (Mayer, 2009). Each of the ten principles outlined by Moreno (2005) makes a specific design recommendation that will lead to better learning (e.g., reducing extraneous information, placing text close to visualization, making interactive visualization, etc.). This theory emphasizes three characteristics of the learner (i.e., prior knowledge, motivation, and meta-cognition), but the most care is given to motivation. In this theory, learners' motivation is crucial as it determines how deeply they will process the information from the lesson. Many of the design principles are intended to boost learners' motivation by personalizing the lesson (personalization principle) or providing explanatory feedback (guidance principle). The theory makes only one prediction in terms of the characteristics of the context. According to the modality principle, with all other factors being equal, a spoken lesson will lead to better learning than a written lesson. This is because the learner can focus on both the words and visualizations simultaneously during a spoken lesson as they are processed in different channels of their working memory. However, in a written lesson, the words and visualization use the same channel in working memory.

One criticism of these theories is that it does not explain how people interpret visualizations. The model details that learners select information from the visualization to further process, but how do they choose this information? Additionally, this theory suggests that if two visualizations comply with the same design principles, then they will be equally effective. However, this is not always the case because the effectiveness of different features of a visualization depends on the characteristics of the learner (Cooper et al., 2018; Hegarty & Sims, 1994; Kriz & Hegarty, 2007). Additionally, there are features of the visualizations, such as the spatial arrangement of the elements in the visualization, that are missing from the design principles (Novick et al., 2011).

Integrated Text and Picture Comprehension Model

Schnotz and colleages (Schnotz, 2002, 2014; Schnotz & Bannert, 2003) proposed the Integrated Text and Picture Comprehension Model, in which text and pictures are not only different external representations, but also lead to different internal representations. Grounded in Dual Coding Theory (Clark & Paivio, 1991; Paivio, 1991), this model argues that texts, and all other symbolic representations, lead to description-based internal representations organized in terms of propositions and are therefore based on logical relations and not based on perception.

Visual representations lead to perception-based internal representations. The learner has the challenge of integrating these two internal representations to form a cohesive mental model for the topic at hand.

In order to learn from a lesson that contains texts and visualization, learners first select the relevant information from the text and the visualization separately. The learner creates separate internal representations for the text and the visualization. The information selected from the text and visualizations activates relevant prior knowledge. Then, the learner combines the information presented in both formats with their prior knowledge to create a new mental model. This model construction is done through analogical structure mapping (Gentner, 1983; Gentner & Markman, 1997), through which learners make connections between the representations. Therefore, the integrated text and picture comprehension model predicts that how much visualizations improve learning, compared to the same lesson without a visualization, depends on (1) how much relevant information the learner gets out of the visualization and how much overlap there is between this information and the information obtained in the text or already present in their prior knowledge, and (2) whether learners can make connections between the different representations.

The integrated text and picture comprehension model makes predictions about the characteristics of the visualization, learner, and context. Characteristics of the visualization matter as learners construct their mental models based partly on the visualization. Thus, how the information is depicted influences the mental model. Two visualizations that contain the same information but differ in what information they make more salient will lead to different mental models. This model emphasizes prior knowledge as a key characteristic of learners. Learners with little prior knowledge might benefit more from the inclusion of a visualization, as there might be less overlap between their prior knowledge and the information in the visualization. For learners with a lot of prior knowledge, the overlap might be greater, so they do not benefit as much from having the visualization. Finally, given that this model is about text and picture integration, it is not surprising that it makes predictions about the context in which the visualization is presented, particularly about the text (or accompanying lesson). If learners cannot get much out of the text because it is too complex or not very legible, then the visualization will have a larger role in determining the resulting mental model.

The main criticism of this theory is the sharp distinction between text and visualizations. Although this distinction is based on Dual Coding Theory (Paivio, 1991), current work in cognitive science has noted that changing the perceptual features of text and mathematical expressions influences how people represent them (Hornburg et al., 2025; Jiang et al., 2014; Landy & Goldstone, 2007; Marghetis et al., 2016). Therefore, the distinction between the internal representations might be less stark than previously thought, as information in any modality can be perceptual and symbolic.

DeFT framework

The DeFT framework is an approach used to determine whether presenting multiple representations is useful (Ainsworth, 2006, 2008). The DeFT framework argues that the usefulness depends on the **De**sign characteristics of the representations, their pedagogical **F**unctions and the **T**ask. In terms of design characteristics, the framework focuses on the number of representations, their form (e.g., text, animations, images), and whether the representations are presented simultaneously or sequentially.

When combined, multiple representations should have a complementary, constraining or constructive function. Multiple representations *complement* each other when they present different information that cannot be presented in only one representation. By providing different views on the same phenomenon, the learner can get a more thorough understanding of the concept. One representation can also *constrain* the interpretation of another, particularly when one of them is ambiguous. To borrow Ainsworth's (2006) example, "[t]he phrase 'the cat is by the dog', is ambiguous about which side of the dog the cat is sitting, but in a picture, the cat must be either on the left or the right of the dog. So, when these two representations are presented together, interpretation of the first (ambiguous) representation may be constrained by the second (specific) representation" (pp. 189). Finally, multiple representations can help the learner *construct* their understanding of the phenomena. For example, an instructor might present multiple representations that are increasingly more abstract to show the learners how the elements in a very concrete representation map to the elements in a more abstract representation (Fyfe et al., 2014). The task that the learners need to accomplish can also vary. In some situations, learners need to relate the information in the representations to a concept in the domain. In other situations, learners need to select or construct a representation, as when they are asked to create a diagram or concept map. These different tasks might be facilitated by different representations.

The DeFT framework focuses primarily on the context in which a visualization is presented. The functions are not about individual visualization, but about how one representation influences the interpretation of another. The framework argues that if multiple representations have a complementary, constraining, or constructive effect, then learning is enhanced by adding the representations. The framework also mentions some characteristics of representations, such as their form, but does not make specific predictions about one form being better than the other. The framework also incorporates prior knowledge, as learners might use their prior knowledge in the domain to interpret the different representations. However, it does not discuss prior knowledge or other learner characteristics at length.

Having examined some of the main theoretical approaches in this field, I now turn to a narrative review of how characteristics of the visualization, learner, and context influence how people learn with visualizations in multimedia environments.

Characteristics of the visualization

Researchers have examined many different characteristics of visualizations that could influence learning. I focus on how much irrelevant information visualizations contain (Siler & Willows, 2014), how visualizations highlight information (Alibali et al., 2018; Ozcelik et al., 2009), and how realistic or detailed the visualizations are (Wiley et al., 2017). I discuss each of these characteristics below. Although not a comprehensive review of all features of visualizations, this review provides an overview of why certain characteristics influence learning.

Removing irrelevant information

Visualizations often contain a lot of information, but not all the information is equally pertinent to the lesson at hand. Learners might find it difficult to differentiate the information that is critical for their understanding of a concept from the more tangential information. The same information in a diagram could be critical or tangential, depending on what the instructor wants to teach and what will extend to other situations. I will use the term *relevant information* to refer to the information that is needed to understand the lesson, that generalizes beyond the exemplar used in the lesson, or that will be assessed on a later test. I will use the term *irrelevant* *information* to refer to information that is not needed to understand the lesson, that does not extend beyond the exemplar in the lesson, or that learners are not going to be tested on later.

Omitting irrelevant information is a simple way to have learners focus only on the relevant information in the visualization. Irrelevant information can capture learners' attention and lead them to spend time and cognitive resources on material that is not relevant (Garner, 1992). This is known as the "seductive details" effect, and it has been applied to both text and visualizations (Garner, 1992; Garner et al., 1989, 1991; Harp & Mayer, 1998; Rey, 2012). Eliminating irrelevant information from a visualization or lesson (and still including relevant information) helps learners focus on the more important concepts (Mayer & Jackson, 2005; Strobel et al., 2019), leads to better learning (Eitel et al., 2019; Sung & Mayer, 2012) and promotes generalization (Kaminski et al., 2013; Kaminski & Sloutsky, 2013; Siler & Willows, 2014). Thus, sparse diagrams that omit irrelevant details might be better at promoting generalization than more detailed diagrams that include irrelevant details. This is in line with Cognitive Load Theory, which predicts that the irrelevant information is still processed by the learner, increasing the effort required to understand the lesson without the benefit of providing new germane information, thus increasing extraneous load and decreasing learning.

Given that the topic learners need to understand is often an abstract process or concept, many of the details in visualizations can be considered irrelevant. For example, if one wants children to understand the numerosity "two", whether one focuses on two animals or dots should not matter. Petersen and McNeil (2013) found that children who were asked to count dots performed better than those who were asked to count animals. Based on this and other studies, it has been argued that visualizations should contain the least amount of information while conveying their central point. (Lehman et al., 2007; Mayer et al., 2008; Park et al., 2011;

Schneider et al., 2019; Zacks et al., 1998). A similar argument has been made for graphs, where the idea is to maximize the data-ink ratio, where most of the ink spent on printing a graph should be used to display data (Tufte, 1983). These recommendations should not be taken as law, as the extreme point of eliminating information would result in the absence of any visualization. Rather, the focus on the tradeoff between relevant and irrelevant information. In situations where the details are relevant, preserving them in the visualization can serve as a retrieval cue for students (Skulmowski & Rey, 2020a). Thus, retaining relevant information while removing irrelevant information could maximize learning.

Highlighting relevant information

Removing all irrelevant information is not always feasible. In these cases, one way to encourage learners to attend to the relevant information is to highlight it (Richter et al., 2016). Highlighting important information can be done through bottom-up attentional mechanisms by making certain elements more salient. For example, Canham and Hegarty (2006) showed participants weather maps that made either pressure or temperature salient and then asked them to determine the direction of the wind (a property dependent on pressure). Participants who saw the weather maps in which pressure was salient spent more time looking at relevant details and were more accurate at determining wind direction at posttest. This result is in line with the Integrated Text and Picture Comprehension Model, as participants' mental models were shaped by the information that was more apparent in the visualization. Other methods of highlighting include changing the color of relevant elements (Alibali et al., 2018; Clinton et al., 2013; Kalyuga et al., 1999; Skulmowski & Rey, 2018) or adding arrows pointing at relevant information (Kriz & Hegarty, 2007).

Additionally, as predicted by the Integrated Text and Picture Comprehension Model, different types of visualizations emphasize or highlight different features or characteristics of the depicted information. The features that are depicted in a visualization relate to the message that the designer of the diagram wants to convey (Wood, 1968). Schnotz and colleagues (Rasch & Schnotz, 2009; Schnotz & Kürschner, 2008) showed that when visualizations highlight information, learners are more prone to use that information to solve problems. For example, Alibali and Booth (2002) asked college students to solve mathematical word problems where a quantity was changing continuously. The problems were accompanied by visualizations that schematized the change as either continuous or discrete (see Figure 1). They found that students who saw the visualizations that showed the problem as continuous were more likely to use mathematical strategies that treated the change as continuous. Students who saw the visualizations that showed the problem as discrete were more likely to use strategies that treated the change as discrete. Thus, students' mental models were influenced by the visualization, and in turn, that shaped their problem-solving strategies. According to the Integrated Text and Picture Comprehension Model, the wording of these mathematical problems should also be able to modify students' mental models. Using the same type of problems, Menendez et al. (2023) showed that using continuous versus discrete *wording* had a similar effect on problem-solving strategies. These results provide support for the Integrated Text and Picture Comprehension Model, as students' mental models are shaped by information in all modalities. This shows how visualizations highlight different aspects of the material and thus promote different mental models of the information.

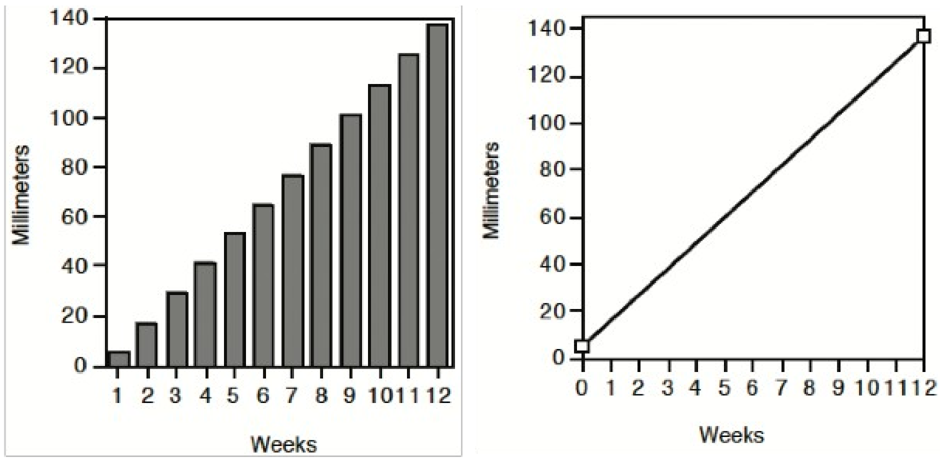

Figure 1. Visualizations that accompanied word problems in Alibali and Booth (2002). The left graph shows a discrete representation of how change occurs over time, and the right graph shows a continuous representation of change over time.

Detailedness

One particular feature of visualizations that has received a lot of attention in the psychological literature is their detailedness. Detailed visualizations are those that include a great number of visual features, whereas sparse visualizations have a small number of visual features. The detailedness of a visualization is closely related to other terms such as concreteness, complexity, and perceptual richness, but whether these terms are distinct or separable is not clear (Castro-Alonso et al., 2016; Menendez, Rosengren, et al., 2020; Skulmowski et al., 2021; Skulmowski & Rey, 2018).

Many studies have found that learners generalize more from lessons with sparse visualizations than from lessons with detailed visualizations (Butcher, 2006; Goldstone & Sakamoto, 2003; Goldstone & Son, 2005; Kaminski et al., 2008, 2009; Menendez, Rosengren, et al., 2020; Petersen et al., 2014). For example, Goldstone and Son (2005) taught adult learners about complex adaptive systems through an example of ants' foraging behavior. In this study, some learners saw a detailed interactive visualization depicting the ants and the fruit, and others saw sparse points and patches (which could represent anything, see Figure 2). Then, learners had to apply what they learned from this simulation to a similar scenario (learning) and a very different scenario, pattern recognition (generalization). Learners who saw the sparse visualization learned just as well as those who saw the detailed visualization, but critically, those who saw the sparse visualization were more likely to generalize from the ant scenario. The hypothesis is that sparse representations are less tied to a specific context or scenarios, so learners are more likely to apply the information to other new scenarios, yielding better generalization.

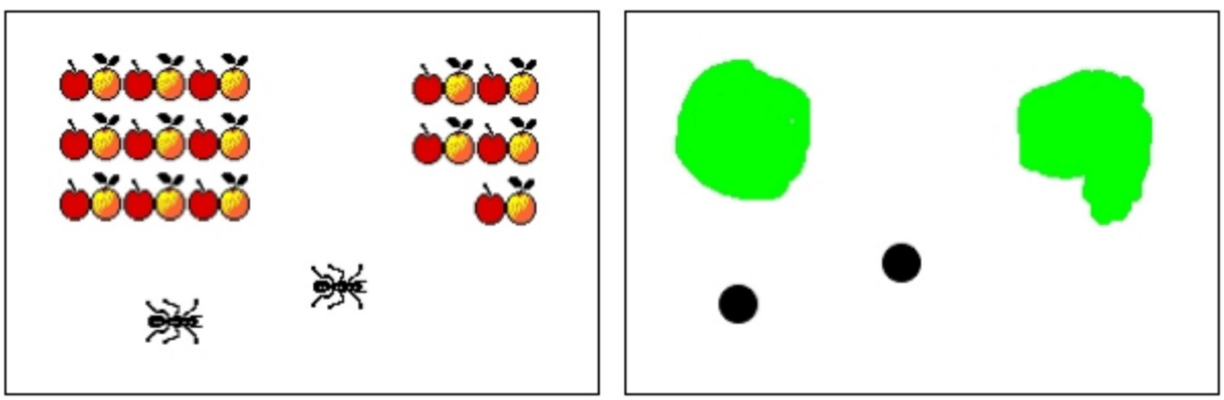

Figure 2. Visualization used in Goldstone and Son (2005). Left visualization is concrete and detailed, and the right visualization is abstract and sparse.

There are reasons to doubt that abstract sparse visualizations are always better than detailed concrete ones. Recent work shows that using detailed visualizations is beneficial for recall, learning, and generalization (Siler & Willows, 2014; Skulmowski, 2024; Skulmowski & Rey, 2020b; Trninic et al., 2020). For example, Siler and Willows (2014) found that teaching learners about modular arithmetic with a visualization that had concrete, but relevant details led to greater generalization than teaching with an abstract visualization. Similarly, Menendez, Donovan, Mathiaparanam, Klapper et al. (2024) taught undergraduate students about genetic inheritance with either detailed, sparse or abstract diagrams (see Figure 3), and found that students transferred more if they learned with the detailed diagram. Additionally, recent work on concreteness fading, a procedure in which learners first learn with a concrete representation and then abstract representations are slowly introduced, suggests that this progression leads to better transfer than when learners see only abstract representations (Fyfe et al., 2014; Fyfe, McNeil, & Borjas, 2015; McNeil & Fyfe, 2012; Ottmar & Landy, 2017). Therefore, it is possible that in some situations, detailed visualizations are better for learning and generalization.

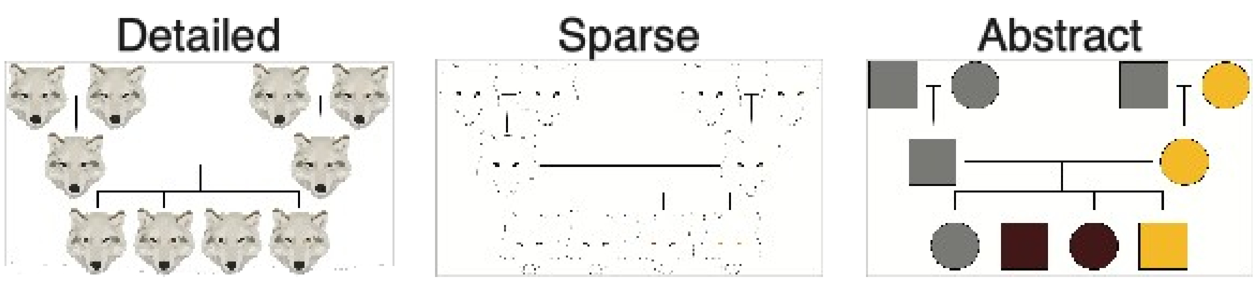

Figure 3. Diagrams used in Menendez Donovan, Mathiaparanam, Klapper et al. (2024), from left to right, the figure shows a detailed pedigree diagram, a sparse pedigree diagram, and an abstract pedigree diagram.

Summary

This review of research on characteristics of visualizations suggests some key takeaway points. Omitting details from visualizations can increase learning if the details omitted are irrelevant. Reducing the amount of information that learners need to process may free their cognitive resources to spend on other aspects of the lesson. Omitting details can also make visualizations more abstract, which can increase the likelihood that learners will generalize the information. Finally, omitting details could also increase the likelihood that learners focus on the relevant details (as those are the only ones remaining). This can also be achieved by highlighting the relevant information.

This review suggests that characteristics of the visualization matter when they make it easier for the learner to discern the relevant information. Guiding the learner's attention to relevant information can be done by removing the irrelevant information or highlighting the relevant information. Therefore, visualizations *support* learning by making relevant information more prominent.

Characteristics of the learner

Just as not all visualizations are equally beneficial, visualizations might not benefit all learners equally. Much research has examined the factors that influence whether visualizations are beneficial for learners. Some work has focused on domain-general characteristics such as age (Menendez et al., 2022), working memory (Padilla et al., 2018; Sanchez & Wiley, 2006), or spatial ability (Bartholomé & Bromme, 2009), whereas other studies have focused on domain-specific characteristics such as prior knowledge (e.g., Booth & Koedinger, 2012). Some scholars have even argued that learners differ in their diagrammatic or visual literacy, their ability to take in, understand, and parse visualizations, as a way to explain differences in performance (see Novick, 2006; Peeck, 1993 for more information on this).

The idea that certain domain-general characteristics influence how people learn from visualizations is closely linked to proposed mechanisms explaining why certain features of visualization influence learning. For example, if the reason why having irrelevant details leads to lower learning is *because* these details capture learners' attention away from the relevant information (Garner et al., 1991), then learners with better inhibitory control might not be influenced by these features as much, as they can disengage from these details and refocus on the relevant information. Likewise, if the hypothesis is that learners spend cognitive resources on irrelevant details, then learners with greater working memory capacity might be less influenced by such details because they can hold both relevant and irrelevant features in mind. In this way, theories of why certain features of the visualization matter can inform us about which individual differences to explore.

Research on individual differences has not yielded consistent results. For example, some studies find that working memory or spatial ability influences how people learn with visualizations (Höffler, 2010; Lusk et al., 2009; Sanchez & Wiley, 2006), but other studies fail to find an effect (Bartholomé & Bromme, 2009; Hegarty & Sims, 1994). In this review, I explore a subset of factors that have received considerable attention in the literature: prior knowledge age/grade, working memory capacity, spatial ability, and motivation.

Prior knowledge

Prior knowledge has received the most attention as a moderating variable, as many theories hypothesize that it influences how people learn with diagrams. The typical result has been that learners with low prior knowledge are influenced by a particular feature of a diagram, and learners with high prior knowledge succeed regardless of the visualization or benefit more from not having that feature (Booth & Koedinger, 2012; Clinton et al., 2013; Cooper et al., 2018;

Goldstone & Sakamoto, 2003; Magner et al., 2014; Mayer et al., 1995; Novick et al., 2011; Rau et al., 2014; Richter et al., 2016, 2018). This is consistent with predictions from Cognitive Load Theory and the Integrated Text and Picture Comprehension Model, as learners with low prior knowledge might benefit from more visual scaffolding, but for learners with high prior knowledge, that scaffolding can be distracting or additional information that needs to be processed without a clear benefit. This is a surprisingly robust finding given that studies vary greatly in how they measure prior knowledge; some studies use a pretest that targets the specific topic of the lesson (e.g., knowledge of genetics) and others look at prior coursework in the entire domain (e.g., all biology or science classes). There is also work that shows that learners look at different aspects of a visualization depending on their prior knowledge (Harsh et al., 2019), which is in line with other findings on the expertise literature where experts attend to different features than novices (Chi et al., 1981, 1994). Prior work has also found that learners with high prior knowledge benefit from different visualizations than learners with low prior knowledge, termed the expertise reversal effect (Kalyuga et al., 2003). For example, Richter et al. (2018) conducted a field study with 8^{th} graders on the effects of color coding on learning chemistry. They found that learners with low prior knowledge, assessed via a pretest, benefitted from color coding, but learners with high prior knowledge did not benefit from color coding. Therefore, prior knowledge might be an important factor to consider when examining how people learn with visualizations. However, why would learners with low prior knowledge benefit more from a certain feature than learners with high prior knowledge? Why might it be that the visualizations that are not beneficial for beginners serve advanced learners?

To answer these mechanistic questions, it is important to remember that visualizations *support* learning by connecting ideas or making relevant information more prominent (as discussed in the earlier sections). Visualizations might do this by guiding learners' attention through bottom-up attentional mechanisms (e.g., highlighting relevant information). Learners with high prior knowledge might already have an idea of what the important information is, and they can therefore use top-down mechanisms to focus on the relevant information even when it is not highlighted (Harsh et al., 2019; Kriz & Hegarty, 2007). This claim is supported by eye-tracking research (Manning et al., 2006; Ponce & Mayer, 2014; Strobel et al., 2018, 2019), which shows that, for example, learners with high prior knowledge spend more time looking at relevant information in a visualization than learners with low prior knowledge (Harsh et al., 2019). This would lead learners with high prior knowledge to learn equally well from visualizations with different features. However, adding irrelevant information seems to be detrimental for learning (Rey, 2012). For learners with high prior knowledge, having highlights or arrows pointing to key concepts adds information that they need to process, but has no added value for them, as they were already attending to the relevant information. Removing the highlights or arrows (i.e., removing the scaffolds) might be more beneficial for learners with high prior knowledge, as it decreases the amount of perceptual information they need to process. This would lead learners with high prior knowledge not to learn as well from the diagram that benefited the learners with low prior knowledge.

Age or grade level

Diagrams and other visualizations can be found in educational materials for all ages and grade levels (Menendez, Mathiaparanam, et al., 2020). Therefore, it is practically important to determine if students at all ages benefit similarly from the inclusion of visualizations, and whether visualizations with particular features benefit different age groups more. Although there have been studies examining the benefits of different visualizations for almost every age group, age has not been consistently studied as a moderating factor. One reason for this omission is that it is challenging to design lessons suited to students in different grades or age groups. Thus, many researchers interested in age differences in the effect of visualizations focus on a small range of contiguous age groups or grades. For example, Booth and Koedinger (2012) had 6-8th-grade students solve mathematical problems with a relevant diagram or no diagram. They found that diagrams helped older students but not younger students solve the problems correctly. Similar findings were observed by Menendez et al. (2022) in studies on learning about metamorphosis with detailed or sparse visualizations. They found that, when controlling for prior knowledge, children in early elementary school learned more about metamorphosis with rich visualizations, but that children in late elementary school generalized metamorphosis to more animals when they saw sparse visualizations. These studies suggest that older students might learn or benefit more from seeing visualizations, but the type of visualization might not matter. However, further work may be needed on how features, other than detailedness, might have differing effects on students at different grade levels.

When considering age as a moderating factor, it is essential to examine why these age differences may exist. Differences based on age could be due to students' familiarity with visualizations broadly (Menendez, 2023; Zhu et al., 2025), differences in their cognitive development (Siegler & Alibali, 2019), or a myriad of other factors. Therefore, future work should not only examine developmental differences in the effect of visualizations, but also the mechanisms behind these differences. In particular, future work should measure several of these possible mechanisms (familiarity, working memory capacity, spatial ability, motivation, etc.) to find out which factors in isolation or in combination with other factors explain age differences in learning from visualizations.

Working memory capacity

Working memory capacity is the amount of information someone is able to hold in their mind and manipulate at any given moment (Baddeley, 2000). Working memory capacity has been hypothesized by Cognitive Load Theory to influence learning with visualizations (Paas & van Merriënboer, 2020). Higher working memory capacity could help decrease the detrimental effect of lessons that induce high cognitive load (but see Anmarkrud et al., 2019 for a review of conceptual and methodological issues with this approach). For example, Sanchez and Wiley (2006) found that working memory capacity moderates the effects of irrelevant details in visualization. This is in line with Cognitive Load Theory as higher working memory as people with higher working memory capacity would experience proportionally less load from having to process the same information (Kozan et al., 2015; Lehmann et al., 2016). When they examined possible mechanisms, they found that people with higher working memory capacity spend less time looking at the irrelevant details. This suggests that working memory may influence how people process diagrams in the moment.

However, it is important to remember that many domain-general traits are correlated with each other (Van Der Maas et al., 2006), and thus, due to the correlational nature of this research, it cannot be determined whether the difference in performance is because of the difference in working memory capacity. For example, working memory is correlated to inhibitory control (Roncadin et al., 2007). Because Sanchez and Wiley (2006) did not measure inhibitory control, it is possible that their working memory measure is explaining variance that is due to both working memory and inhibitory control. This is important as it could inform instructional interventions to support student learning. If working memory is indeed causally related to learning from diagrams, then instructors should build a diagram piece by piece, which would help students with less working memory capacity slowly make sense of the information without overtaxing their cognitive resources (Zhang et al., 2025). However, if inhibitory control is the reason behind this relationship, then instruction on the irrelevant aspects of a visualization could help students with low inhibitory control prioritize relevant information (Eitel et al., 2019). Thus, disentangling the causal relations in this observational work can lead to effective practical recommendations for instructors. Future work should measure a variety of individual differences and analytically control for them. While these findings would still be correlational, controlling for other learner characteristics can strengthen causal claims that the difference in performance is due to differences in working memory capacity or some other factors. Then, testing manipulations that should decrease the impact of that individual difference can advance theories of learning and provide practical recommendations.

Spatial ability

Spatial ability is an individual difference in people's processing of visual information, particularly in their ability to encode and mentally manipulate visual information (Hegarty & Kozhevnikov, 1999; Höffler, 2010), and it is often measured with a mental rotation test (see Castro-Alonso & Atit, 2019 for an overview). The hypothesis has been that individuals with high spatial ability will be better at processing information from visualizations (Kozhevnikov et al., 2007). A meta-analytic review suggests that, across 29 studies, spatial abilities moderate the effectiveness of visualizations, such that learners with high spatial ability benefit more from visualizations than learners with low spatial ability (Höffler, 2010). One potential reason is that because visualizations arrange information in space, individuals who are better at decoding this spatial information would be better at learning from visualizations. However, in three studies, Hegarty & Sims (1994) found no differences between participants with low and high spatial ability in their eye movements or strategies to decode a visualization. And Korbach et al. (2016) also did not find evidence that spatial ability was related to eye movements. Therefore, even though there is support for the moderating role spatial ability, the mechanism for why this might be the case has not been well established.

Motivation

Another domain-specific trait that has been studied is motivation. However, the majority of the studies examine how visualizations influence a learner's motivation, which in turn influences learning (Durik & Harackiewicz, 2007; Magner et al., 2014; Moreno, 2007; Moreno & Mayer, 2007; B. Park et al., 2014; S. Park et al., 2005; Sung & Mayer, 2012). Therefore, the majority of this literature, in line with the Cognitive-Affective Theory of Multimedia Learning, proposes that one reason why visualizations influence learning is by increasing motivation. This means that the majority of the studies treat motivation as an outcome or mediator variable rather than an individual difference that influences how people learn with visualizations. Some work does suggest that attitudinal and motivational factors influence which visualizations are more effective. Cooper et al. (2018) had undergraduate students solve trigonometry problems with either text only, text + diagram, text + illustration (decorative photos that represented the problem but not the quantitative relations), or text + diagrams with illustrations. As students' attitudes towards math increased, they were more likely to answer the questions correctly. But the relation was moderated by features of the visualization. Diagrams were helpful for all learners, but particularly for learners with positive math attitudes who were more likely to solve problems correctly if there was a diagram compared to if there was none. Cooper et al. (2018) also found that problems with illustrations were beneficial (i.e., led to correct problem solving) for learners with positive attitudes towards mathematics and detrimental for learners with less positive attitudes who benefited from not having an illustration. Although attitudes towards a domain are not the same as a motivation to learn, the two concepts are related, with a learner's attitudes towards a domain influencing their motivation to learn in that domain (Wigfield, 1997). However, few studies have investigated how motivation might influence the effectiveness of a visualization.

Summary

The research on how learner characteristics influence learning with visualizations is not conclusive. This research suggests that domain-general traits could influence how people learn with visualizations. One possible problem with the research on individual differences is that it has been too narrowly focused. Many of these studies measure only one individual difference, and when they measure multiple individual differences, they are not included in the same model. Individual difference measures are typically correlated, and domain-general traits like inhibitory control, working memory capacity, and spatial ability are typically strongly correlated (Van Der Maas et al., 2006). Measuring multiple constructs and controlling for them could clear up some of the confusion in the literature. For example, Korbach et al. (2016) measured both spatial ability and prior knowledge in the domain, and found that when both of them were included in the regression models, prior knowledge was related to both learning outcomes and eye fixations on the visualization, but spatial ability was not. Suggesting that prior findings on the influence of spatial ability might have been due to prior knowledge. Measuring multiple individual differences might create more robust evidence for the importance of any given characteristic.

Characteristics of the context

Visualizations used in education are not presented in isolation. They are normally presented as part of a multimedia lesson and therefore are accompanied by instructional texts

(Woodward, 1993), verbal lessons (Mayer & Anderson, 1991), or other visualizations (Rau, 2017a). Additionally, instructors can use non-verbal behaviors, such as hand gestures, to convey new information or connect these different elements (Alibali et al., 2014; Nathan et al., 2013). Finally, the visualizations are also embedded in a particular social context, and so interactions between learners or between learners and instructors can influence the effectiveness of visualizations (Carbonneau et al., 2020; Rau, 2017b). This is also reflected theoretically, as three of the four theories discussed (the Cognitive-Affective Theory of Multimedia Learning, the Integrated Text and Picture Comprehension Model, and the DeFT framework) focus on how visualizations work in the context of other elements in the learning environment. First, I consider context as the other information available to the learner during the lesson, focusing on the presence of other linguistic or visual information. Then, I consider context as it relates to different strategies that an instructor might use when designing or teaching the lesson. Finally, I consider context in terms of the social interactions that occur when multiple learners (or a learner and an instructor) engage with the same visualization.

Other Representations

The effectiveness of a visualization depends on whether other visualizations are presented. For example, Rau et al. (2015) presented fourth- to sixth-grade students with multiple types of visualizations of fractions across consecutive problems or the same type of visualization in an intelligent tutoring system. They found that presenting learners with multiple visualizations increased their learning. Other studies have shown a similar effect whether the visualizations are presented at the same time or sequentially (Rau, 2017a; Zahner et al., 2017). As discussed earlier, the DeFT framework suggests that presenting multiple representations helps learners constrain their meaning (Ainsworth, 2006). Thus, by showing multiple visualizations, learners can infer which features generalize to all examples and which are unique to each example (Matlen et al., 2011). Presenting multiple visualizations can also lead to a more thorough understanding of the concept, as the different representations might highlight different information. For example, there are multiple ways to visualize a water molecule; see Figure 4 for an example. Although similar, these different visualizations make more apparent different information, such as the three-dimensional shape or the bonds, providing the learner with a more comprehensive picture of the concept.

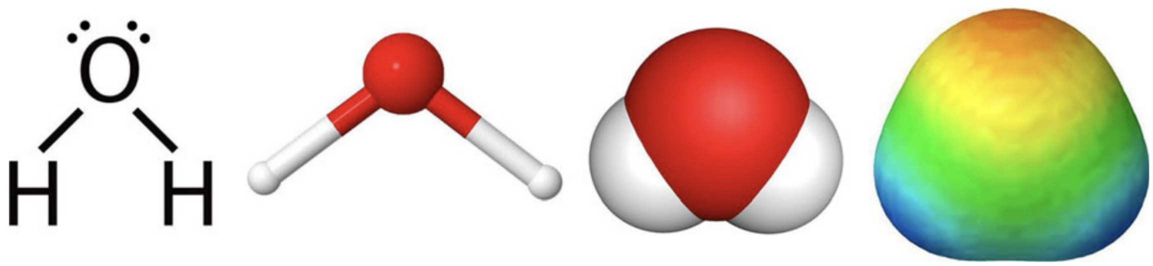

Figure 4. Visualizations of water molecules. From left to right the visualizations are a Lewis structure, a ball-and-stick model, a space-filling model, and an electrostatic map.

The effectiveness of a visualization may also be influenced by accompanying linguistic information. The linguistic information can be provided either visually (written text) or orally (speech). The modality in which this linguistic information is presented influences learning (Bobis et al., 1993; Chandler & Sweller, 1991, 1992; Mayer, 1997; Moreno & Mayer, 1999; Sweller et al., 1990). For example, Moreno and Mayer (1999) had undergraduate students learn about meteorology from animations accompanied by the same linguistic information either orally (a narration) or visually (text). Participants were also randomly assigned to see the linguistic information before, after or during the animation. Those who had the narration learned the most for the lesson (regardless of whether the narration was before, during or after the animation). Those who had to read the text during the animation learned the least (with those reading the text before or after the animation being in between). This finding has been explained in terms of competition for visual attention, which has been termed the split attention effect. This finding is in line with Cognitive Load Theory, as it emphasizes the limited capacity of cognitive resources, and the Cognitive-Affective Theory of Multimedia Learning, as it emphasizes how having both sources of information integrated can help learners construct a unified model of the lesson. When the linguistic information is in written text, the text and the visualization are competing for visual attention, thus leading to lower learning compared to when the information is presented orally (when there is no competition for visual attention Chandler & Sweller, 1992; Kalyuga et al., 1999; Skulmowski, 2023).

The specific content of the linguistic information can influence how people interpret visualization and interact with features of the visualization (Arndt et al., 2015; Schüler et al., 2015). As discussed in earlier sections, abstract sparse visualizations promote generalization more than concrete detailed visualizations. However, concrete visualizations do promote transfer if they are accompanied by abstract labels (Fyfe, McNeil, & Rittle-Johnson, 2015; Son & Goldstone, 2009). For example, Menendez (2023) had students read biological facts that were phrased as being about an entire animal category (e.g., "Giraffes have blue tongues") or about an individual animal (e.g., "This giraffe has a blue tongue"). It was accompanied by either a colorful, detailed visualization or a sparse visualization, and asked students how broadly the fact applies to other animals. They found that students extended the facts more broadly when the phrasing was about the entire category and the visual was sparse. In line with the DeFT framework, the linguistic and visual information constrained each other, such that a category phrasing with a detailed visual was not interpreted as broadly (Menendez, 2023). This work suggests that how and what linguistic information is presented alongside visualizations can influence learning and generalization.

The effectiveness of a visualization does not only depend on the information presented at the same time; it can depend on the information that preceded the visualization (Arndt et al., 2019). This is illustrated in research on concreteness fading. In concreteness fading procedures, learners are presented with a concrete representation, and over the course of instruction (see Figure 5), the concrete representation (i.e., the aspects of the visuals that make it specific to the example at hand but not required to understand the lesson; in Figure 5 this would be the animals and sticker) is removed (or faded) and abstract representations are introduced (Fyfe et al., 2014; Kokkonen & Schalk, 2020; McNeil & Fyfe, 2012; Ottmar & Landy, 2017; Royer & Cable, 1976, 1976). By starting with concrete representations, people can ground their learning on their prior knowledge. So, although the animals and stickers are not necessary to solve the problem, they might help children ground their understanding of the problem on something tangible. By transitioning to abstract representations slowly, learners are able to easily make connections between the representations. Fyfe, McNeil, and Borjas (2015) showed this by teaching second- and third-grade students about mathematical equivalence with either only concrete visuals, only abstract visuals, a concreteness fading procedure, or a concreteness introduction procedure (these are the same materials as in the concreteness fading condition but in the reverse order). Children learned and generalized more when they were taught using concreteness fading than when they were taught with only concrete or abstract representations (Fyfe, McNeil, & Borjas, 2015). Even though the final visualization that learners see, in both abstract-only and concreteness fading, is abstract, the previous representation that they saw influences their learning. This shows how students interpret and learn from visualizations is shaped by the visualizations they saw in previous lessons. The concreteness introduction condition is of great importance here, as students in that condition saw all the same materials, just in a different order. Without this condition, it would be impossible to tell whether the difference is due to the sequence of the visuals or simply the fact that students in the concreteness fading condition saw more different types of visuals (Xie et al., 2020). They found that concreteness introduction was not as effective at teaching students as the concreteness fading procedure (Fyfe, McNeil, & Borjas, 2015). Therefore, the sequencing of visualization in a lesson can help students understand and make sense of visualizations.

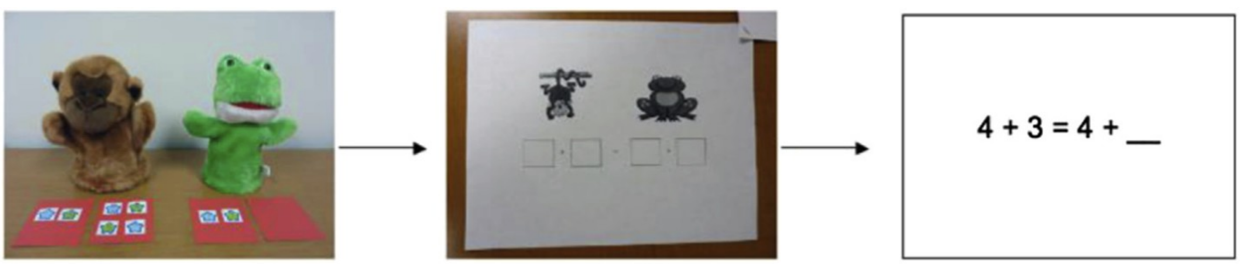

Figure 5. Concreteness fading procedure applied to mathematical equivalence problems by Fyfe, McNeil, and Borjas (2015). First panel shows a visualization of numbers with physical stickers and puppets. Second panel shows two-dimensional visualizations of the same puppets with boxes underneath to place numbers (an abstract representation of quantities). Third panel shows an equation.

Social interactions and instructor support

One key contextual factor in formal educational settings is the instructor. Instructors can guide learners' attention explicitly by telling learners which information is relevant (Eitel et al., 2019). Instructors also often guide attention in more subtle ways by highlighting different parts of a visualization with either their speech or their gestures (Alibali et al., 2013; Cook et al., 2013; Valenzeno et al., 2003). One area where instructional supports can help is in situations when there are multiple visualizations present. With multiple visualizations, it might be challenging for students to know where to attend, how to use their cognitive resources effectively, or how the information in one visualization connects to another. Instructors help ease this process by guiding students' attention or directly connecting elements across information in several modalities (Alibali et al., 2014; Nathan et al., 2013). For example, Alibali et al. (2013) trained teachers on how to use gestures to connect elements of a lesson on slope and intercept. Teachers were recorded giving a lesson on this topic before and after the training, and those videos were later shown to students to examine which they learned best from. They found that after the training, the teachers expressed information in multiple modalities (e.g., through speech, gesture, or creating visualizations on the whiteboard) at the same time. This multimodal redundancy might have helped highlight the critical information and help students connect ideas across multiple representations. Students who saw the post-training lesson learned more about intercepts than students who saw the pre-training lesson. Although instructors can highlight and connect material in any modality, this study exemplifies that instructors' gestures can aid in students' learning from visualizations (Alibali et al., 2013; Ping & Goldin-Meadow, 2008; Singer & Goldin-Meadow, 2005). Future work should examine other ways in which instructors scaffold students' learning with visualization across multiple modalities. Additionally, future work should examine how the timing of these instructional supports affects learning, as it is possible that certain scaffolds are more effective when students first encounter a visualization (thus the support can aid their sense making process about what the visualization is showing). Others might be better later in the lesson (when students have to use visualization to help them solve a problem or abstract new ideas).

Understanding how instructors teach with visualizations is critical to understanding when visualizations are effective in educational settings. Rau (2017b) examined interactions between groups of students in grades 7 to 12 and their instructor during lessons on chemical bonding. During the lessons, students were presented with multiple representations of chemical bonds (e.g., Lewis structures, ball-and-stick models, electrostatic potential maps) both physically and virtually through an intelligent tutoring system. Interactions between the students and between the students and the instructor (in both speech and gestures) were analyzed to identify the social processes that promote learners making connections between different representations. They found that across physical and virtual representations, instructors' prompting questions helped students make connections. Instructors' questions encourage students to elaborate on concepts they had just mentioned and how those concepts could be seen in the visualization. Additionally, other students also influenced this sense-making process. One student, noting that they did not understand a concept, was typically followed by explanations from the other students, and in these explanations, the students often made explicit connections between the concept and the visualizations. This study highlights the importance of social mechanisms, which are not unique to visualizations, in helping students connect visualizations to the concepts they represent. However, the research on learning with visualizations has overlooked these social mechanisms, leaving a scant literature on the topic. Future work should examine how instructional supports, such as using analogies or metaphors (Jee & Anggoro, 2019; Rau, 2017b; Rau et al., 2015), help students connect information across visualizations (rather than only examining whether they support learning). There is also a need to examine how these social mechanisms interact with learner characteristics, such as prior knowledge. For example, future work could examine whether activating students' prior knowledge, in the form of a warm-up activity (Sidney & Alibali, 2015), aids them in making sense of visualizations.

Instructors can also explicitly teach learners how to interpret visualizations. For example, geography instructors have been reported to spend more time explaining how to understand visualizations in their field than instructors of other subjects (Constable et al., 1988; Schroeder et al., 2011). These explanations can help students build their meta-representational knowledge (i.e., their knowledge of symbols and conventions used in visualizations in a particular field, diSessa & Sherin, 2000; Kozma et al., 2000; Stieff, 2011). Explicitly teaching these conventions ensures that students are aware of the conventions and their meaning, which should help students make sense of the visualization. One potential barrier for this explicitly teaching conventions in a field is that instructors often assume that instructors often assume that their students can understand the visualizations. Future work should examine how instructor beliefs and attitudes influence how they teach with visualizations, and whether teacher trainings (similar to Alibali et al., 2013 discussed above) increase explicit teaching of conventions. Additionally, explaining how to make sense of visualizations might be more beneficial for younger students, who are still developing their understanding of images as representations (DeLoache, 2004; DeLoache et al., 1998). Therefore, future work should examine how teachers and parents support young learners' understanding of information depicted in visualizations and how they support their sense-making process.

Instructors can also set up the learning environment to allow learners to collaborate and learn with visualizations. Collaboration has been shown to promote learning with visualizations (Carbonneau et al., 2020). However, the quality of the collaboration can influence how much learners get out of it (Schwarz et al., 2000). For example, learners might get more out of a collaborative event in which they support each other's reasoning, rather than if they do not discuss their ideas with each other (Rau, 2017b). But students' social identities influenced these social mechanisms, as who is perceived as an expert in a particular discipline can be gendered and racialized (Esmonde & Langer-Osuna, 2013). Social identities like gender and race can thus affect who is positioned as a knower and given a great time to express their ideas, shaping how collaborative activities unfold (Gutiérrez et al., 2018; Langer-Osuna et al., 2020). Social hierarchies and power dynamics in the classroom are issues broader than learning with visualizations, but they can still shape how students make sense of visualizations. Thus, this is an area where more work is needed, both to understand how these dynamics shape learning and motivation broadly, but also how learners' different identities shape the collaborative events when discussing visualizations.

Summary

Although there has been considerably less research on how context influences learning from visualizations, we can still draw some preliminary conclusions. When thinking of context narrowly defined as the other information that is presented alongside a visualization, we can see that presenting multiple visualizations might allow learners to distinguish between features that are relevant and likely to generalize to other contexts and features that are idiosyncratic to the example. The content of the linguistic information presented alongside a visualization can provide learners with cues as to how to interpret the visualization (e.g., how broadly to apply the information). When thinking of context broadly defined as the social interactions that occur around a visualization, it is clear that instructional scaffolds (e.g., highlighting relevant information or asking prompting questions) help learners make connections between the concept and the visualization. These scaffolds could even be as explicit as teaching what conventions are used in a field. Finally, I highlight the need for further research on how social interactions and power dynamics influence the way that students learn from and make sense of visualizations.

Conclusions

Modern educational environments, be it schools, museums, or virtual reality, are characterized by an abundance of information in multiple modalities, including many visualizations of the concept to learn. Therefore, theories of learning need to explain how students learn with visualizations in these environments. Additionally, insights from these theories need to make concrete recommendations for how to structure these learning environments in order for students to learn from them. To address these theoretical and applied questions, in this paper, I reviewed the literature on how people learn with visualizations in STEM domains. I first discussed different theoretical frameworks for how people learn with visualizations. Then, I reviewed empirical work on how the effectiveness of a visualization depends on characteristics of the visualization, the learner, and the context. Overall, my review of the empirical work showed at least partial support for all theoretical accounts, but it also highlighted several areas where the theoretical accounts lack precision or left out important topics. For example, the different theoretical accounts explained why different features of visualization influence learning, but aside from prior knowledge, there were few mechanistic explanations as to why characteristics of the learner would influence this process. Additionally, although several theoretical accounts discuss the role of contextual factors, these were often limited to narrow definitions of context that focused on the other information presented alongside visualizations. These theories provide little information on how social interactions among students or between students and instructors influence the processes of making sense of or learning with visualizations. Building on this review of the empirical literature, I identified four key takeaway points.

The first takeaway is that the function of visualizations is to make relevant information salient for learners. Although it may appear obvious, explicitly stating this function highlights the role of attention, such that eliminating irrelevant information and decreasing competition for attentional resources by conveying linguistic information orally can lead to better learning for most learners. Of course, the attentional mechanism will likely be visual due to the modality of visualizations. When using other representations, such as tactile graphs (Sheppard & Aldrich, 2001), other attentional processes will be more relevant. Attentional mechanisms are thus central to learning with visualizations, and suggest that individual differences should matter if they influence these attentional mechanisms. Practically, this means that lessons with visualizations should minimize distractions, highlight aspects that are central to the concept being learned, and align the information in different modalities so that students can properly attend to each.

The second takeaway is that although there has been prior work on individual differences in learning from or with visualizations, these studies have not attempted to isolate the causal mechanism involved in these learning processes. As such, more work is needed on why and when some students learn more from visualizations than others. Identifying these causal links could have implications for future instructional interventions. The third takeaway is that there needs to be greater emphasis on the sense-making processes. Understanding how learners make sense of visualizations will involve examining both narrow and broad definitions of context.

Narrowly, other information in the lesson may help constrain or expand the interpretations of a visualization. Broadly, questions and explanations from instructors and peers might help facilitate making connections between the concept and the visualization. Practically, this means that it is important to attend to how the linguistic and visual information support each other to present an accurate and cohesive view of the concept. However, this sense-making process does not occur in isolation. The fourth takeaway is that visualizations are not always clear, meaning that students often benefit from scaffolding that helps them notice the connections between the visualization and the real-world analogs it represents. Practically, this means that it can be beneficial to explain how students should decode or interpret the visualization. This way, they understand the visualization before they need to use it to support their learning. The social aspects of learning with visualization are one area that requires more attention from future research. Future work should examine how students learn how to make these connections in both formal and informal environments, and how explicit and subtle scaffolds facilitate this process. Overall, this review highlights that visualizations are not universally helpful for learning, but rather their effect depends on a myriad of factors at multiple levels of analysis. As such, theoretical accounts might need to further explore how these factors interact with one another to shape learning.

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