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Review article

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Connecting spatial thinking to STEM learning through visualizations

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Abstract

Spatial thinking relates to interest and success in science, technology, engineering and mathematics (STEM) disciplines. In this Review, we suggest that visualizations connect spatial and STEM thinking because all STEM disciplines use visualizations, and visualizations use space to meaningfully organize information. We focus on visualizations to show that their ubiquitous use reflects the importance of spatial thinking in STEM. In building to this point, we discuss different ways to think spatially, as spatial thinking is not a unitary process. With this base, we review the cognitive underpinnings of spatial thinking and visualization comprehension, including attention, perception and memory. We then examine how spatial thinking is involved when processing visualizations, across visualization types and STEM fields. We end by discussing future work to further probe the importance of visualizations and their connection to spatial thinking and STEM success.

Sections

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Introduction

Spatial thinking relates to success in science, technology, engineering and mathematics (STEM) disciplines and is associated with measures of course success and career interests and outcomes[1–3]. Interest in understanding the underpinnings and applications of this cognitive ability has grown[2,4–6] as its role in STEM learning has become apparent. Spatial thinking involves imagining the positions, shapes and locations of objects in space and transformations of these elements to form new spatial relationships. For example, people use spatial thinking when considering how to assemble the parts of a new IKEA chair. Although spatial thinking is clearly related to STEM success, determining a common role that spatial thinking might play across STEM fields has remained elusive because STEM fields cover wide-ranging concepts and each presents unique learning challenges. Further, there are multiple ways to think spatially[7,8]. Yet, because spatial thinking is a malleable cognitive skill[8–10], identifying connections between spatial and STEM thinking can inform STEM education and workforce training to improve spatial thinking[11].

Spatial thinking skills uniquely contribute to STEM success, above and beyond verbal and quantitative skills[12,13]. Longitudinal studies of both intellectually talented and randomly sampled high school students show that spatial skills predict favourite courses, undergraduate majors and STEM career intentions and success[1,12–14]. Yet, spatial skills are often not considered when identifying individuals who would benefit from STEM enrichment programmes[15]. Such talent identification instead focuses solely on verbal and mathematical skills. Individuals with high spatial task scores do not always have high verbal and/or mathematical skills[1] and are often overlooked, yet they have relevant cognitive skills to succeed in STEM fields and help to fill the STEM workforce shortage[2,3,15,16].

An examination of STEM learning tools suggests that visualizations potentially underlie the importance of spatial skills in STEM success. Visualizations are defined broadly as a visual–spatial arrangement of external elements (rather than internal mental visualizations) used to communicate information visually[17]. These external visualizations can be static or dynamic, 2D or 3D, and displayed physically or digitally. They can include images, charts, diagrams, maps, graphs, animations or models that represent objects, processes, situations or other information. This definition includes computer-generated visualizations of complex datasets[18], about which there is a robust literature that is beyond the scope of this Review[19,20]. Visualizations can be used to communicate about both spatial and non-spatial concepts. For example, visualizations showing global temperature increases over time convey non-spatial climate change information. Visualizations have supported scientific discoveries, such as the identification of the helical structure of DNA[21]: Watson described seeing a black cross, which had to correspond to a helix, in the photograph taken by Rosalind Franklin[22].

Visualizations appear in nearly all present-day STEM materials. STEM textbooks across grade levels (primary, secondary and university) and in regions throughout the world include between one and more than two visualizations per page[23,24]. They are also often used in examinations and standardized tests in STEM fields. For instance, the New York State Regents Science Exams (taken by high school students), extensively incorporated visualizations in examination questions and reference resources in all STEM disciplines[25–27]. Although other disciplines also use visualizations, a cross-disciplinary analysis found greater use of content-related visualizations in STEM disciplines than in the humanities or social sciences[28]. Visualizations spatially and meaningfully organize STEM concept components. Further, interpreting visualizations can facilitate STEM concept understanding by promoting higher-level inferencing[29]. The spatial nature of visualizations and their ubiquitous use in STEM fields hint at a relationship between visualizations and spatial thinking in STEM (Fig. 1).

In this Review, we propose that visualizations provide a bidirectional tie between spatial thinking and STEM thinking[10,30,31]. We suggest that spatial cognitive processes are engaged when interpreting STEM visualizations and that this interplay underlies STEM learning and success. This proposed connection parallels a more general argument that people's internal representations (mental models) of ideas strongly relate to external visualizations used during learning[32]. We first discuss different types of spatial thinking and their cognitive underpinnings. Next, we show that visualization understanding involves similar cognitive processes. Then, we discuss spatial thinking processes engaged when interpreting visualizations, considering commonalities across visualizations and differences across visualization types and STEM fields. Finally, we discuss the importance of connecting spatial thinking and visualization use to STEM learning and pose key open research questions.

Spatial thinking

Spatial thinking is involved when one attends to, perceives, remembers, imagines, transforms or mentally manipulates information presented in two or three dimensions. Many everyday activities engage spatial thinking, whether deciding which way to turn at an intersection, figuring out whether a couch fits in the parlour, setting a table with the fork on the correct side of the plate or describing the location of pain on one's body. In this section we build towards visualizations as a link between spatial and STEM thinking by reviewing different ways of thinking spatially and the cognitive processes that underlie spatial thinking.

Tasks and typologies

As the above examples suggest, there is more than one way to think spatially. Several spatial thinking typologies have been suggested[7,33,34]. Many of these typologies include four factors, each with two dichotomous

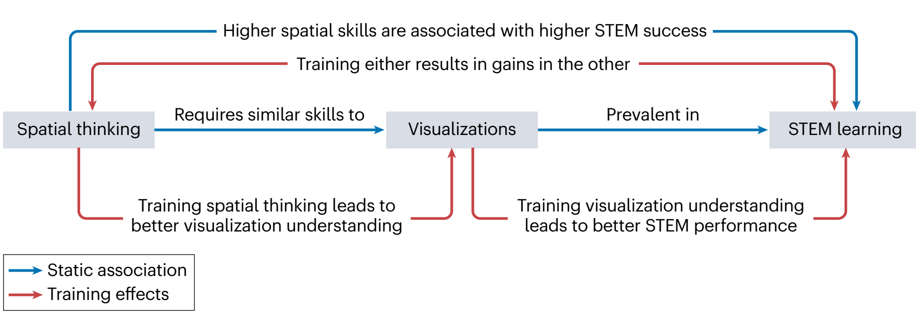

Fig. 1 | The connection between spatial thinking, visualizations and STEM learning. Evidence supports multiple connections between spatial thinking skills, visualizations and science, technology, engineering and mathematics (STEM) learning, including static associations and training effects.

Table 1 | Spatial thinking examples in the taxonomy of reference frame, dimensionality and scale

	Intrinsic		Extrinsic	
	Small scale	Large scale	Small scale	Large scale
Static	Noting atom positions on a molecule diagram (2D)	Noting relative location of rooms in the same building (3D)	Remembering object locations on a table (3D)	Remembering landmark locations on a map (2D)
Dynamic	Determining the structure of proteins after folding (3D)	Drawing a cross section of subsurface rock layers after geology fieldwork (3D to 2D)	Taking another person's perspective to guide them in constructing a bookshelf (3D)	Determining the relative location of planets within the solar system (3D)

levels: reference frame, activity level, dimensionality and scale (Table 1). Spatial thinking is not a unitary concept and different spatial tasks measure different types of spatial thinking[35,36] (Fig. 2). Thus, the particular spatial tasks used in relation to specific STEM concepts might help to explain inconsistencies in evidence supporting spatial thinking in STEM learning.

The reference frame is the focus for defining spatial relationships[6,7,37]. A reference frame is any structure (such as a viewpoint, concept, value or custom) used to evaluate data or communicate ideas. Spatial reference frames structure location information and can be intrinsic or extrinsic. An intrinsic reference frame defines locations using a single object as exemplified in the sentence 'The damage is on the car's front right fender.' By contrast, an extrinsic reference frame relates spatial information about objects relative to another object, such as setting down a backpack to the left of a chair. Two commonly used spatial tasks, mental paper folding and mental rotation, engage different reference frames. Mental paper folding uses an intrinsic frame that requires assessment of locations of holes punched on a single sheet of paper after the paper has been unfolded. Mental rotation uses an extrinsic frame and has people compare two objects presented at different rotations to determine whether they are the same object or mirror images. Some findings suggest that both intrinsic and extrinsic spatial tasks predict STEM performance, but in different ways[38].

The second factor is activity level, which can be either static or dynamic. Dynamic thinking involves active mental transformation, such as in mental rotation or mental paper folding tasks (Fig. 2). Static thinking involves identifying components within an unchanging visuospatial representation, such as in an embedded figure task. One study identified two ways in which people tend to engage in mental visualization: object mental visualizers and spatial mental visualizers[39]. Object visualizers encode and engage with images as a single object. Spatial visualizers think about images as parts, and the spatial relationship between the parts is meaningful. Scientists were more often classified as spatial visualizers than were visual artists[39].

The final two factors are dimensionality (2D or 3D) and scale (large or small). Both factors influence performance on spatial tasks. In mental rotation, 3D stimuli (relative to 2D stimuli) yield longer response times and larger gender differences that favour male individuals[40]. These gender differences begin in childhood and increase in magnitude through adolescence to adulthood[41,42]. Mental paper folding, which involves mentally transforming information from 2D to 3D back to 2D, engages different neural processes than does either 2D or 3D mental rotation[43,44]. This finding suggests that the dimensionality of a STEM concept engages different spatial thinking. Small-scale (such as about objects on a table) and large-scale (such as about the relative locations of cities in New Hampshire) spatial thinking have been shown to be dissociable, although correlated[35,36,45]. This finding might help to account for variation in the extent to which spatial thinking is related to STEM thinking.

Whereas several spatial thinking typologies use these four dimensions, one typology specifically focuses on two of the factors: reference frame and activity level[7]. A 2013 meta-analysis of the impact of spatial training on spatial thinking provides additional support for this two-factor typology. Although the factors of dimensionality and scale are relevant to both spatial thinking and STEM disciplines, using a more narrowly defined typology makes understanding spatial thinking variations more tractable. Some research supports using a two-factor or even four-factor typology whereas other work questions the extent to which different types of spatial thinking are unique and separable[35,36,38,46].

The number and diversity of STEM concepts is enormous. Some STEM concepts engage spatial thinking and some do not[30,47]. However, research has shown that spatial thinking is involved in all STEM disciplines[1,5,48]. Compelling support for the role of spatial thinking in STEM comes from evidence that training spatial thinking helps in learning a STEM topic, and training in a STEM topic can improve spatial thinking[6,10,30,31]. In some cases, spatial skills mediate STEM learning such that individuals with better spatial skills learn STEM concepts more readily[48]. To narrow this complex relationship into a tractable problem, research often focuses on spatial thinking within a particular STEM domain[49]. By doing so, researchers can reason about spatial thinking using specific examples[50]. However, this approach leaves open the question of how spatial thinking is used more generally in STEM.

Cognitive processes underlying spatial thinking

To relate the cognition underlying visualizations to that underlying spatial thinking, we first discuss the cognitive processes involved in completing spatial tasks, focusing on commonly used and experimentally validated tasks[51] and the roles of attention, perception and memory.

Attention is allocated to permit one to complete a spatial task, whether to identify relevant elements, map details to the bigger picture or compare information in different locations[52]. Attention allocation can involve alternation between visual elements or between a visual element and mentally represented information. For instance, in a standard mental rotation task, one shifts attention between two displayed objects to determine whether they are the same or mirror images[53,54]. Attention allocation also relates to focusing on global or local visual elements or shifting between them. Global focus involves interpreting visual information in an integrated, big-picture way compared with local focus, which involves attending to details[55,56]. How individuals allocate attention relates to spatial task performance. For example, difficulty shifting attention to local details and inhibiting global information, a combination referred to as field-dependent, is associated with poorer spatial thinking on a range of tasks, including perspective taking, mental rotation and map interpretation[57,58]. These points suggest that the attentional processes related to successful spatial thinking have important roles in processing information relevant to task goals.

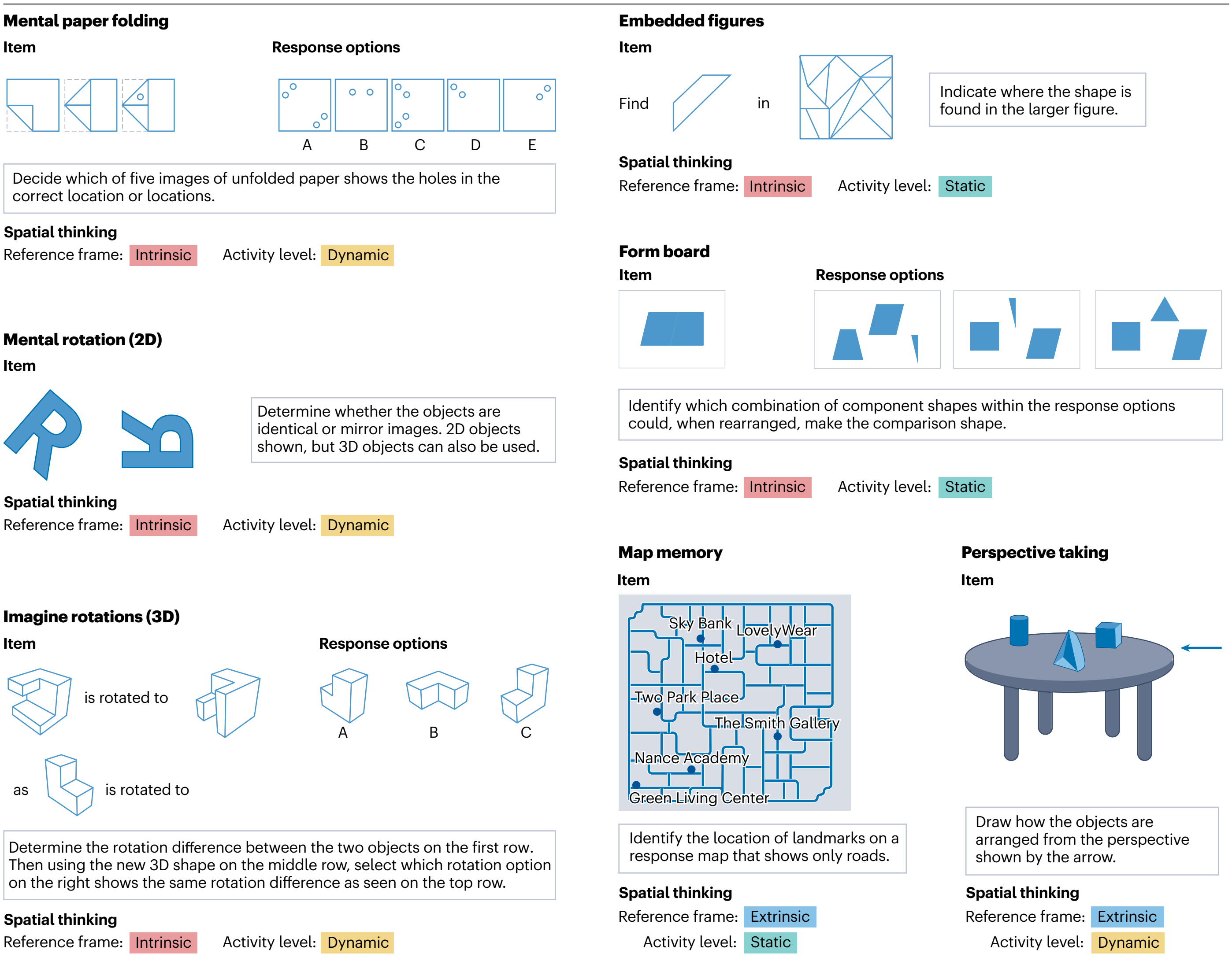

Fig. 2 | Spatial tasks. Spatial tasks can be classified along the dimensions of reference frame, activity level, dimensionality and scale. These tasks exemplify the use of intrinsic (red) and extrinsic (blue) reference frames as well as dynamic (yellow) and static (green) activity levels.

Perceptual processes, including object recognition and pattern identification, also have a role in spatial tasks. Object recognition involves identification of a particular visual input as a specific object, symbol or text. Object recognition and pattern identification also occur in spatial tasks that involve visually identifying the correct response or responses from a presented set of options[59–63]. The options are often systematic modifications of the correct response and might involve the same object in a different rotation, be a mirror-image or depict a similar object[51,62,64].

Properties that influence object recognition and pattern identification also influence spatial thinking performance. Complex compared with simple[65,66], 3D compared with 2D[41,67], unfamiliar compared with familiar[65,67] and large-scale compared with small-scale[68] objects all increase both response times and error rates on spatial tasks. Gestalt grouping principles, such as proximity, similarity, good continuation, closure and symmetry, also guide object interpretation and pattern identification in spatial tasks[69]. Elements that are close together (proximity) and that look alike (similarity) tend to be perceptually grouped. Visual information is perceived as being part of one object when its edges continue smoothly (good continuation) and when gaps in its surface can be interpreted as an occluding object (closure)[70]. Furthermore, mentally rotating objects as grouped wholes (holistic) versus separately by features (piecemeal) yields better performance[71].

Memory, particularly visuospatial working memory, also has a key role in spatial thinking and visualization understanding[72–74]. Visuospatial working memory reflects the mental retention and manipulation of object identities and spatial location[75]. It is engaged with tasks that require mental visualization and mental manipulation, such as in mental rotation[76]. For example, the length of time people hold information in visuospatial working memory was a function of the rotation angle in mental rotation, therefore showing the role of visuospatial working memory in spatial tasks[77].

Thinking spatially uses many of the same cognitive processes as thinking about a STEM concept. STEM learning and reasoning involves building a mental model of the STEM concept to gain understanding or to reason about its application. As an example, a classic physics activity in the USA is the egg drop challenge, in which students build a structure to protect a raw egg from breaking when dropped from a substantial height. In carrying out the challenge, students attend to and perceptually evaluate the height of the drop. They retrieve physics concepts from memory and apply those to the design of the protective structure they build, including considering how to spatially arrange the components of the protective structure. Then they test the structure and evaluate needed adaptations by perceiving where weaknesses emerged on the structure. They might also update their physics knowledge based on the test outcome. As students engage in iterative design and testing, these cognitive processes are used and combined, engaging spatial thinking about physics and engineering concepts.

Spatial thinking with visualizations

STEM learning materials often combine text with visualizations, requiring integration across the information sources (text and visualization)[78]. In other words, STEM materials use a multimedia format, which leads to better learning than either text or visualization alone[78]. Although the overall goal of understanding a visualization is to extract conceptual meaning[79], people can use what they glean from a visualization to engage in visuospatial, algorithmic, memorial and/or verbal reasoning[13–15]. Visualization understanding and creation (Box 1) both require spatial thinking[48,80]. The selection, organization and integration model of text comprehension[81] has also been applied to STEM visualization comprehension[82]. Selection, organization and integration iteratively engage attentional processes, including visual (or spatial) scanning, attention allocation, spatial attention and memory[83]. Visual or spatial scanning involves efficiently looking for relevant information. After identifying relevance, allocating attention to that information aids comprehension[84]. This comprehension process involves organizing information from the visualization in memory and integrating the visualization information with what is already known[82].

Discipline-specific conventions for visualizations, including the symbols used, can introduce ambiguity in how to interpret an element or the entire visualization. For example, in physics, work done in a system receives a negative sign, whereas in chemistry, work done in a system has a positive sign. This difference has implications for visually representing these concepts, such as downward versus upward sloping lines on graphs. Any visualization is likely to have some elements that are familiar to the learner and others that are novel. Novelty increases the cognitive resources required to understand a visualization[85–87].

Attention

Allocation includes directing attention to specific places[88], to global or local information[55] and/or to particularly relevant information[89]. Attention might also need to shift between a visual element and a mental representation. For instance, in organic chemistry, students engage in stereoisomer analysis, which involves determining whether molecules with the same atoms and same connectivity, but different spatial arrangement, are mirror images of one another (enantiomers) or not (diastereomers)[90]. In this case, the attentional shifting often goes between a molecule diagram and memory of another molecule. Field dependence reflects difficulty (dependence) or ease (independence) of shifting attention to local details and inhibiting global information. Field dependence relates to worse perspective taking, spatial orientation and mental rotation performance[57]. Comprehending visualizations is a cyclical process: as one progresses and gathers additional information, spatial attention is engaged to direct attention based on location. Then one might guide one's own attention and return to earlier identified relevant information and integrate it with the new information. Being able to guide attention improves reasoning with visualizations[91].

Box 1

Generating visualizations

Generating visualizations of one's understanding of a concept is a common educational activity. This generation process can benefit understanding of the science, technology, engineering and mathematics (STEM) concept, later interpretation of visualizations made by others and spatial thinking. Generating visualizations gives students an opportunity to spatially organize their current understanding of a concept, which can enable them to learn to detect errors and identify gaps in their understanding[246,247]. Further, hand-drawn visualizations might externalize the cognitive functions that support scientific thinking[248]. Creating visualizations with computers serves similar functions[249]. Creating visualizations can also improve understanding of STEM concepts[250]. Drawing engages self-regulated learning, or a process of learning in which students plan, monitor and reflect on their learning progress[246]. Furthermore, the extent to which individuals spontaneously draw visualizations while taking notes on a STEM concept predicts learning outcomes[251].

The idea that generating visualizations can improve spatial thinking forms the basis of a spatial training programme targeting engineering[10,252]. In this 10-week programme, students engage in drawing activities in 8 of the weeks[252]. Versions of this programme have been implemented since 1993, and participation leads to gains in spatial thinking tasks, better grades in STEM courses and higher retention rates in STEM majors[10,252,253].

It is common for STEM diagrams to represent 3D concepts in two dimensions, and understanding these 2D representations can be difficult[254,255]. Generating one's own visualizations can improve interpretation of diagrams requiring 2D-to-3D transformation. One study found improvement in 3D diagram interpretation when participants drew sketches predicting the internal 2D structure of a 3D diagram slice[255]. Students were asked to focus on spatial relationships in their predictive sketches. Importantly, predictive sketching improved performance over imagining the 2D structure or sketching without predicting the structure.

However, spatial thinking and STEM success from visualization creation might require forming concrete mental associations between the visualization and the topic. In an undergraduate-level biology course, students who received pre-drawn visualizations, drew visualizations based on text or drew visualizations without text showed similar learning[256]. These results suggest that while creating their visualization, students need to relate it to the concept they are learning. This connection can be successfully accomplished by later comparing the created visualization with those provided by the instructor[256,257], by attending to spatial aspects of drawn visualization[255] or by using visualizations to reason through problems[258]. Thus, it is important to engage with the visualization beyond merely creating it.

Some aspects of visualizations influence how successfully attentional processes are engaged. With well-designed visualizations, the spatial organization can help to guide attention to relevant information[92]. With such guidance, one can more easily determine and process relevant, rather than all, information, thereby keeping the cognitive load manageable[93]. The density and complexity of a visualization also impacts attentional processes[94]. In general, visualizations with more information and greater complexity require more effortful integration, which in turn increases cognitive load and decreases comprehension[95,96]. This relationship has been termed the split attention principle and is relevant to visualizations[97]. The spatial organization of a visualization can reduce split attention and improve processing[98,99], in particular, by using Gestalt grouping principles to guide attention[100–104]. Further, juxtaposing visual elements with text can speed search, a phenomenon known as a spatial-contiguity effect. Search is facilitated because people can use the visualization to anchor information integration and/or use the text to guide visualization interpretation[105]. Taken together, spatial properties of visualizations can facilitate spatial scanning and attention allocation.

Perception

Object recognition, pattern recognition and Gestalt groupings also influence visualization understanding. Visualization interpretation involves comparison across multiple visual elements, including many that are spatially defined (relative position, height, length and grouping)[106]. Elements are spatially distributed in meaningful ways, and meaning is identified via perceptual matching, pattern identification and visual comparison[107]. Meaningful organization within and across visualizations can facilitate identification of commonalities and/or differences[103,107]. For instance, interpreting components of a remote sensing or satellite image involves object recognition within the larger spatial context of the image[108]. Through pattern recognition one finds regularities or interpretable changes in the visual signal. For example, plotting cancer occurrences on a map can help to identify patterns and support inferences, which is a potential benefit of using visualizations instead of using descriptions or data alone[109].

The spatial organization of a visualization, including arranging elements according to a scheme (schematizing) and Gestalt perceptual grouping, can sometimes induce misinterpretations. For instance, lines on graphs tend to be interpreted as closer to the horizontal and vertical axes or 45° than they actually are[110]. When schematizing with symmetry, people interpret elements of diagrams as more symmetrical around vertical and horizontal axes than they actually are[110,111]. Such schematization suggests that people use reference frames such as diagram axes to interpret visualization elements. This idea is consistent with the Gestalt principle of symmetry, which suggests that people perceptually group symmetrical elements of a display[112]. Other Gestalt grouping principles also guide visualization understanding[103,104]. For example, people use closure to help to interpret the overall message of a visualization[104]. Further, similarity and proximity have strong roles in final visualization interpretations, both separately and combined with other Gestalt cues[103].

Some aspects of visualizations can make interpreting their features more difficult, including complexity and ambiguity. Visualizations can range from perceptually rich to relatively sparse[79]. As with spatial thinking tasks[41,67], adding visual complexity (such as adding the third dimension) to visualizations increases cognitive processing requirements, which has consequences for understanding[113,114]. Three-dimensional graphs increase visual ambiguity relative to 2D graphs, leading to distorted interpretations[115]. For example, people estimate values on a bar graph less accurately when they have 3D cues than when they are purely 2D[113].

Memory

The integration aspect of the selection, organization and integration model within visualizations involves working memory[116–118], including visuospatial working memory. Location memory requires less effortful processing than semantic memory, which suggests that remembering where to return to process relevant information is not cognitive resource heavy[119–121]. To understand a visualization, its component parts need to be integrated with each other and with any accompanying text and/or existing knowledge. Integration of elements requires more working memory resources than simply evaluating the same elements[118].

In parallel with findings from spatial thinking research[122], visuospatial working memory capacity impacts visualization use. Individuals with greater visuospatial working memory capacity more accurately interpret visualizations and are more likely to use them to reason[123]. By contrast, individuals with lower visuospatial working memory capacity tend to be distracted by irrelevant diagram details[124]. Visualizations with more graphic elements engage greater visuospatial working memory processes[125]. Further evidence for visuospatial working memory processing with visualizations can be seen in reduced benefits of a visualization when visuospatial working memory is also needed for a secondary task[73]. Visuospatial working memory is also engaged when processing verbal material that describes visual or spatial concepts[126–128]. Given the nature of STEM concepts, these findings suggests that visuospatial working memory has a role in processing STEM visualizations and the accompanying descriptions.

Visualizations reflect the visuospatial nature of STEM concepts and serve as a cross-cutting tool. The underlying attentional, perceptual and memorial processes used in STEM learning make use of space to guide attention, perceptually group related ideas and engage working memory, particularly visuospatial working memory.

Categorizing visualizations

Nearly all STEM information sources, whether textbooks, journal articles, TED talks, news articles, class materials or teachers' resources, use visualizations[27]. The prevalence of visualizations in STEM materials supports their utility in communicating STEM concepts[129]. STEM communications often include visualizations to convey structure and relationships, either spatially or metaphorically. When accompanying textual descriptions, STEM visualizations support comprehension by using visual and spatial relationships to organize and emphasize conceptual relationships[130].

To connect STEM and spatial thinking, it is important to understand how spatial thinking is used in interpreting STEM visualizations in both general and discipline-specific ways. Conventions for some visualization types overlap across STEM disciplines, whereas others vary[131,132]. A STEM discipline's content focus predicts the most commonly used visualization types[27,133]. In this section, we discuss visualization types and commonalities across these types.

Although the specifics of STEM visualizations differ across disciplines, the same visualization types appear in multiple disciplines[24]. STEM visualization types vary in detail and abstraction. High-fidelity images (henceforth images) have the greatest detail and the least abstraction. Images can represent various scales, from large-scale images taken through a telescope (a nebula in astronomy), to visible scale (a stratified cliff in geology), to small-scale taken through a microscope (cells in biology). Image overlays (henceforth overlays) apply features to an image, such as adding topographical lines to satellite images or functionally active areas to brain images. Overlays can appear with the base image or alone. They have less detail than images, but still directly represent the STEM concept at a low level of abstraction.

Diagrams are the most frequently used visualization type across STEM disciplines. They include maps, process models and cycles, and generally have less detail than images. Instead, they focus on what is relevant, presenting information with higher abstraction, but therefore require some inference about the concept represented. Diagrams use information from images and overlays but can show relationships not visible in either. They can reflect concrete and abstract relationships, thereby covering a wide range of STEM concepts[134]. A molecule diagram in chemistry illustrates the bond structure between atoms, a concrete relationship. Another chemistry diagram might be used to explain different particle identities, an abstract concept. All diagrams use spatial locations to impart conceptual information. The information imparted might denote location or other spatial properties, but can instead reflect other concepts such as structure, time, quantity, processes or movement.

Diagrams, with their reduced detail, have less visual complexity than images or overlays. Reduced complexity can ease the mental resource demands needed to complete a task (cognitive load)[95,135]. Many diagrams have domain-specific conventions, which must be learned, making interpretation non-intuitive (such as topographical maps in geology[136]). Models, which generally represent three dimensions rather than two, have a similar level of detail and abstraction to diagrams. By directly representing the third dimension, models can facilitate interpretations about concepts such as height and depth. Finally, graphs show relationships between variable quantities (change in disease rate over time). Thus, unlike the other visualization types, they primarily represent abstract ideas. They are the visualization type with the least detail and greatest abstraction. Graphs take many different forms (point, bar, line and area) and can represent two or three dimensions.

Visualizations of certain STEM processes align with the spatial thinking typology discussed earlier[137]. These processes include actions, conversions, classifications and analytical processes[138]. Action processes involve events that change or alter spatial arrangements, such as how geological faults alter relative locations within a rock structure. Understanding action processes engages either intrinsic-dynamic or extrinsic-dynamic spatial thinking, depending on the concept[139]. Conversion processes involve changes between a starting point and end point or across a cycle (such as a chemical process resulting in change of chemical make-up) and involve intrinsic-dynamic spatial thinking[38]. Classification processes involve categorization of objects, processes, situations or other information relative to related information (such as evolutionary trees). Classification processes engage extrinsic-static thinking. Finally, analytical processes reflect how parts make up the whole of an object or process (the arrangement of atoms in a molecule), which involves intrinsic-static spatial thinking[140].

In the research literature, categorizations of visualizations aim to capture broad trends across the visualization types. One categorization identifies three categories (iconic, schematic, and charts and graphs), based mostly on abstraction level[141]. A refinement of this scheme that aims to highlight commonalities across STEM disciplines has just two categories: iconic (or pictorial) and relational[68]. Iconic visualizations include images, overlays and some diagrams; these are visualizations in which the use of space represents space

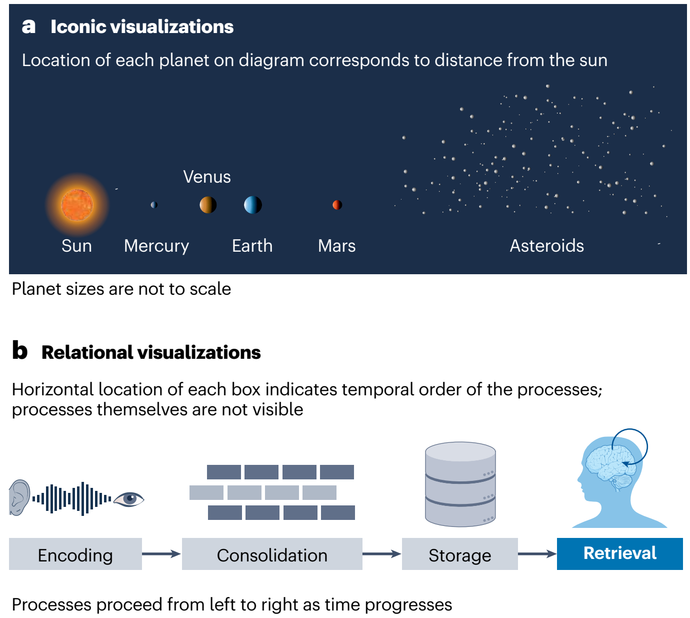

Fig. 3 | Differences between iconic and relational visualizations. Iconic visualizations (including images, image overlays, and some diagrams) use space to depict spatial properties (part **a**), whereas relational visualizations (some diagrams, models and graphs) use space to depict non-spatial properties (part **b**). Part **a** adapted from ref. 238, Springer Nature Limited. Part **b** adapted from ref. 239, Springer Nature Limited.

in the world (Fig. 3a). Although iconic visualizations represent real-world spatial relationships, the depicted spatial relationships need not map accurately to those in the real world. By contrast, relational visualizations use visual and spatial properties to represent non-spatial concepts, such as time or processes (Fig. 3b). The spatial relationships convey meaning about the relationship between components. Schematized diagrams are considered relational diagrams as they depict non-physical ideas[141]. A similar categorization defines visualizations as pictorial or semantic (or a combination)[142], which map onto the iconic and relational categories. The same typology of spatial thinking (intrinsic or extrinsic, and static or dynamic) can be used to discuss different inferences that can be made from different iconic (pictorial) visualizations[142]. In the remainder of this Review we adopt the terminology of iconic and relational[68] as it captures spatial thinking in the context of visualizations.

Visualizations are used across STEM disciplines to depict certain concepts. Next Generation Science Standards, a US-based programme focused on establishing research-based guidance for STEM education from ages 5 to 18 years, has identified several cross-cutting STEM concepts including patterns, scale, proportion and quantity, structure and function, and stability and change[143]. These and other cross-cutting concepts (such as boundaries, branching and paths) can be easily identified using visualizations[144]. Indeed, these concepts are in some cases better represented visually than verbally or with equations[145–148], but sometimes multiple representations (visual, verbal and equation) are needed[149,150]. For instance, branching concepts appear across biology, chemistry and earth sciences and are easily represented visually[144]. Visualizations of similar ideas across STEM fields use similar visualization types with similar visual features.

Field-specific visualizations

Much of the literature examining spatial thinking in STEM pertains to discipline-specific visualizations[49]. In this section, we discuss use of different visualization types across specific STEM disciplines and how the visualizations reflect spatial thinking. The differences across STEM disciplines reflect the uniqueness of concepts and visualization conventions within each discipline. We discuss geosciences, biology, chemistry, physics and mathematics. These disciplines cover concepts that range in scale, abstractness and the extent to which the disciplines themselves reflect spatial information. Although we do not explicitly discuss computer science or engineering fields, much of our discussion generalizes to visualizations used in these fields.

Geosciences

Visualizing the earth and its processes, including its evolution, is fundamental to the geosciences. Many geoscience concepts are inherently spatial[37,151]. An analysis of the New York State Regents earth science examinations found that more than 70% of questions addressed spatial concepts[151]. Further, the earth science examination used the most visualizations out of the science examinations (earth science, life science, chemistry and physics)[27]. The geosciences use all the visualization types described above.

High-resolution images of real-world settings (derived from field observations and aerial and satellite remote sensing) are central to many lines of enquiry in geoscience. Such images are iconic visualizations. Overlays are added to these images to draw attention to features, reveal processes and connect information across different primary sources. Two geoscience map overlay styles cause students particular trouble in interpretation: topographical maps and choropleth maps. Interpreting both map types involves extrinsic-static spatial thinking.

Topographical maps use contour lines to designate 3D information such as change in height or depth. Thus, interpreting topographical maps involves 2D-to-3D intrinsic-dynamic spatial thinking, which can be challenging[136,152,153]. Some classroom approaches can help students to develop the spatial thinking skills needed to understand these map overlays[154]. Focusing attention on the spatial features directly or indirectly can bolster the spatial thinking involved. Direct approaches specifically present depth cues, using models or virtual or augmented reality (VR or AR) together with the 2D map rather than requiring the 3D information to be inferred. For instance, improvements in topographical map interpretation were found when students placed 3D-printed map sections on top of a 2D map[155]. Furthermore, giving 3D cues to students through stereo visualization helped them to better comprehend topographical maps compared with using 2D cues such as shading[136]. However, directly providing depth information is not always effective; adding depth through AR has had mixed results[156]. Some studies using AR-enhanced topographical maps find they do not aid understanding[157–159]. Indirect approaches to focusing attention on depth involve guiding students to mentally visualize the third dimension. For instance, focusing student attention on contour lines and shape information through pointing and gestures improved topographical comprehension[153].

Cloropleth maps use contour lines with shading or colours to represent the spatial variation of a third variable, such as temperature, migration patterns or time. Interpreting these maps involves applying the spatial arrangement of features (lines, symbols and colours) to a non-spatial concept, a process that can be challenging[160,161]. Choropleth maps challenge students to interpret spatial variation of a non-spatial variable. One approach that aids interpretation of these overlays involves making the non-spatial variable information more intuitive. For instance, teaching students intuitively coloured maps (for temperature: blue = cold and red = hot) first, compared with starting with grey-shaded maps, helped students to later interpret grey-shaded choropleth maps more accurately[160]. By contrast, colours not intuitively connected to the concept had little impact on comprehension and were often ignored[162]. Overall, these studies suggest that difficulties in interpreting 2D geoscience representations arise when additional information, either spatial or non-spatial, needs to be interpreted or integrated for full understanding.

Iconic diagrams are commonly used to infer geological structures or processes beneath the Earth's surface based on visible surface features. Tasks of this nature require penetrative thinking – imagining and extending the internal structure of a solid object – and engages intrinsic-dynamic spatial thinking. Iconic diagrams can support penetrative thinking by representing phenomena that are difficult to observe directly (Fig. 4a). The ability of novices to engage in penetrative thinking with such diagrams is associated with their visuospatial skills in combination with their geological knowledge[163,164]. Furthermore, spatial thinking skills predict learning in structural geology courses[165]. Geologists who more often engage in mapping activities during fieldwork more quickly identify geological structure than geologists with less experience[166]. Finally, as with topographical maps, directing attention to spatial signals in iconic diagrams improves penetrative thinking[167].

The geosciences commonly use relational diagrams to represent geological time (Fig. 4a). Students struggle to understand geological timelines[168,169]: they learn the relative order of geological time periods, but think of them categorically rather than quantitatively (as reviewed in ref. 170). This finding is consistent with other findings that indicate that remembering information categorically is separable from remembering fine-grained spatial details[171]. Categorizing in this way is also consistent with visuospatial grouping processes that people use when processing and remembering visualizations; both involve combining information based on some commonality[110,172].

In summary, understanding hidden aspects of the Earth's structure and processes relies on spatial inferences[173], and geoscience visualizations can serve as a basis for these inferences. Many iconic geoscience visualizations aid inferences about the Earth's structure, helping to promote penetrative thinking. Relational visualizations support thinking about geoscience processes and timelines.

Biological sciences

Biological sciences also use the full range of visualization types. Images range in scale from cells to organs to organisms to habitats. Overlays highlight image features relevant to scientific questions. For example, an overlay of cartoon ribbons indicating protein structure on a cross section of an enzyme helps to guide reasoning about how the enzyme catalyses reactions[79]. Diagrams, both iconic and relational, are also common in biology (Fig. 4b). They are used to highlight specific information (such as parts of the human circulatory system), relate changes over time (cell division), show different viewpoints on a 3D structure, connect components of biological systems at different scales or group organisms by shared characteristics.

Learning in the biological sciences frequently involves reasoning about 3D structure from 2D representations. This penetrative thinking process can be supported by iconic diagrams[174]. Penetrative thinking and 2D-to-3D transformations involve intrinsic-dynamic spatial thinking. Diagrams that use canonical instead of oblique axes aid comprehension, such as when an eye is depicted using a vertical cross section[175].

Mental visualization and spatial thinking abilities positively relate to anatomy learning, particularly from static diagrams[174,176,177]. Individuals who score higher on spatial tasks are better at matching spatial positions represented in different viewpoints by engaging in mental rotation[178]. Findings that relate spatial thinking to imagining 3D structure from 2D visualizations led researchers to propose that dynamic 3D models that animate sequential viewpoints would negate the need to mentally rotate and thereby support learning. However, dynamic diagrams did not uniformly improve learning: only individuals with high spatial ability learned the anatomy content better with dynamic diagrams[179]. This finding suggests that engaging in mental transformations benefits learning, consistent with the finding that augmented reality to show three dimensions in geoscience diagrams does not aid learning. Instead, doing the mental transformations oneself, even with guidance, leads to better understanding than watching the transformation in an animation.

Relational diagrams in the biological sciences depict non-spatial ideas, such as fetal development stages, levels of analysis (molecular, cellular, organism, ecosystem and biome) or organisms' shared characteristics. Carefully designed spatial layouts are key to effectively conveying complex and/or changing information through diagrams[180]. Layouts that coincide with how people interpret space, for example, using left-to-right organization to reflect changes over time or verticality coinciding with magnitude, are more effective than other arrangements.

A cladogram is a relational diagram that uses a hierarchical structure to reason about evolutionary theory. Ladder cladograms have a single diagonal line from which different species or lineages diverge. Tree cladograms do not have a single diagonal line and instead visually represent species divergence horizontally before continuing vertically (Fig. 4b). In the tree representation, horizontal divergences lower on the diagram represent common ancestors, and lower on the diagram corresponds to earlier in evolutionary time. Although the content of these cladogram types is isomorphic, the spatial structure influences reasoning about evolutionary relatedness showing that tree cladograms result in more accurate reasoning[181]. For instance, ladder cladogram presentation can facilitate a misconception that certain current species evolved from other current species (such as that humans evolved from apes), owing to the continuous diagonal line located at the bottom of the figure and the series of rungs leading to the top of the diagonal[182]. This misconception is avoided in tree cladograms because the horizontal divergence of species breaks up the continuity of the vertical progression of evolutionary time, spatially segregating divergent species. Greater exposure and specific training on ladder cladogram conventions can circumvent incorrect, albeit intuitive, interpretations based primarily on the spatial organization of the diagram[183].

In summary, format and feature differences of the iconic and relational diagrams in biological sciences reveal characteristics of spatial thinking. Specifically, iconic diagrams can influence how people mentally visualize 3D structure from 2D diagrams. Relational diagrams aid reasoning about commonalities between biological processes or evolutionary characteristics. As a cautionary note, any diagram that violates intuitions about how space designates relationships between concepts will be more difficult to understand.

Chemistry

Chemistry involves reasoning about things too small to be visible, such as atoms and molecules, the structure of those things, reactions happening between them and results of those reactions[184]. Chemistry

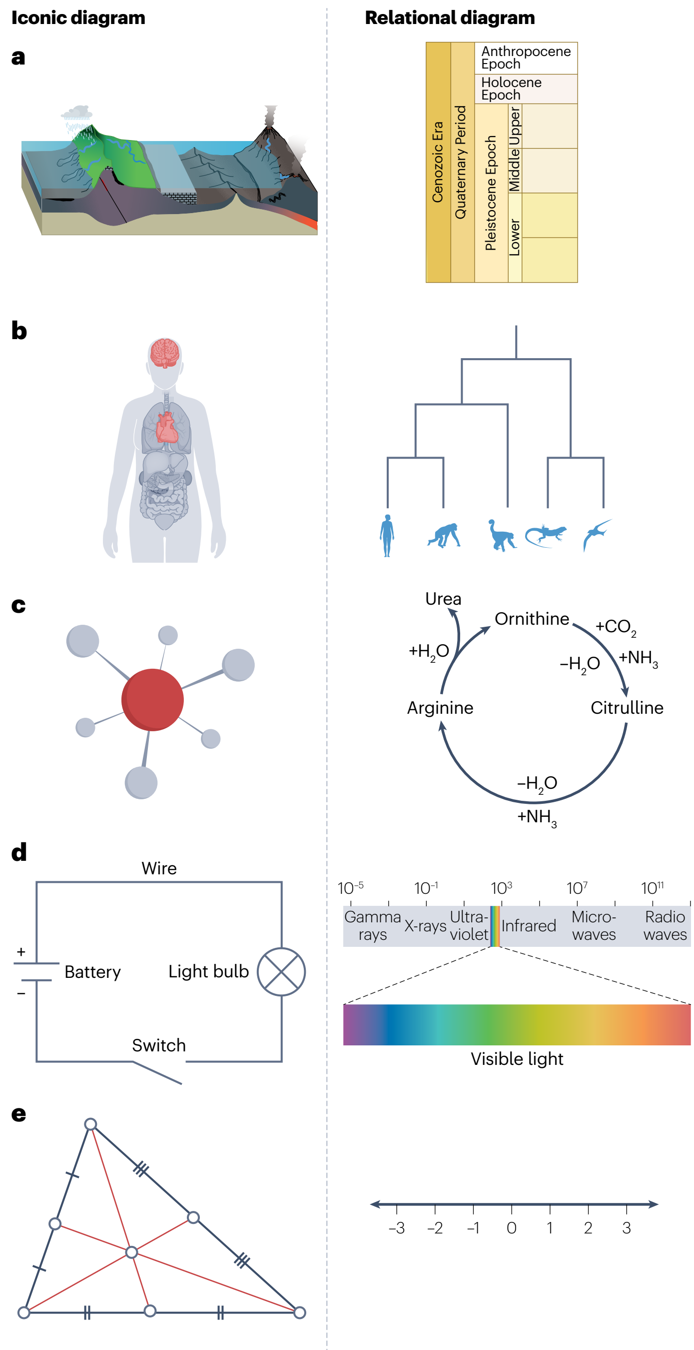

Fig. 4 | Sample iconic and relational diagrams across different science, technology, engineering and math fields. a, Geosciences: a cross section of the earth and a geological timeline. **b**, Biological sciences: an organ diagram and a tree cladogram. **c**, Chemistry: a molecule diagram and a cycle diagram. **d**, Physics: a circuit diagram and an electromagnetic spectrum. **e**, Mathematics: a geometry diagram and a number line. Part **a** (left) adapted from ref. 240, Springer Nature Limited. Part **a** (right) adapted from ref. 241, Springer Nature Limited. Part **b** (left) adapted from ref. 242, Springer Nature Limited. Part **c** (left) adapted from ref. 243, Springer Nature Limited. Part **c** (right) adapted from ref. 244, Springer Nature Limited. Part **d** (right) adapted with permission from ref. 245, Wiley.

commonly uses iconic diagrams to represent molecules, including component atoms and structure (Fig. 4c). There are several diagram conventions, which differ in how they represent 3D structure and highlight different structural aspects of the molecule. Common tasks undertaken by chemistry students, such as determining whether two depicted molecules are the same or isomers (when the order of atom bonding is the same but the spatial arrangement is different) and deciding whether two different diagram types represent the same molecule, require 2D-to-3D mental transformation[185]. When asked to narrate their thoughts ('think aloud') while reasoning about molecule diagrams, students' reasoning approach and use of spatial thinking changed with task complexity[186]. With simpler tasks, students used mental imagery. With more complex tasks, they based their reasoning on the diagram, either with it available or from memory. This shift in reasoning approach might reflect cognitive offloading: creating or using information in the world to reduce mental processing demands[187]. Chemistry reasoning with molecular diagrams engages mental rotation, but with fewer memory demands when the diagram is present[188]. Physical 3D models further support reasoning, eliminating the need to engage in 2D-to-3D transformation[189].

Relational diagrams in chemistry represent a range of concepts, such as chemical cycles and how states of matter change as a function of pressure and temperature (Fig. 4c). A challenge that students face in understanding these diagrams comes from a tendency to think of the components separately, rather than of the spatially represented relationships between them[190]. In the context of the selection, organization and integration model, the challenge lies in integrating the spatially distributed parts of a diagram. Training in mapping non-spatial concepts to the spatial layout of diagrams can facilitate understanding of the diagram[191].

Chemistry communication often incorporates diagrams that combine iconic diagrams and relational diagrams, together with textual descriptions. Combined diagrams can show connections between microscopic and macroscopic levels, helping to promote conceptual understanding[184]. However, even more so than with relational diagrams in chemistry, it is challenging to integrate the components of these combined format diagrams both to one another and to the concept being related[192].

In summary, chemistry makes extensive use of iconic and relational visualizations. Molecule diagrams are often used to convey spatial structure, to compare that structure between molecules or between different diagram types of the same molecule and to predict how the spatial structure changes with chemical reactions. In other words, these diagrams can be used in service of understanding chemistry concepts that engage intrinsic-dynamic spatial thinking.

Physics
Physics deals with the largest range of spatial scales – from the atomic to the celestial. Images are used to depict elements too small to be viewed directly (such as images at the atomic or subatomic level) and those too large to view (such as images from space telescopes). Overlays depict how non-visible elements, such as X-ray and radio contours, align spatially with what is shown in high-resolution images. Diagrams (iconic and relational) often depict forces and spaces invisible to the unassisted eye.

Reasoning with physics diagrams often involves mentally animating the physics processes, which engages extrinsic-dynamic spatial thinking. For instance, circuit diagrams use specific conventions to reflect the flow of electricity between the components and across the connections (Fig. 4d). An accurate understanding of the circuit's function and the role of the components requires mental animation of the electricity flow, which is not explicitly represented in the diagram. Novice students, and sometimes their teachers, commonly misunderstand circuit diagram conventions and the concepts they need to reason about[193,194]. Many of these misunderstandings reflect intuitive understanding of the diagram's spatial elements. For instance, students often think distance from battery, direction of current or element order alters voltage[195]. Additionally, undergraduate students struggle to reason about complex circuits involving two batteries, probably because they require mental animation of electricity flow from two different sources[196]. Similar evidence that people are engaging in mental simulation and influences of complexity have been found with mechanical system diagrams, such as for pulley systems[197,198].

Relational diagrams are commonly used to represent unobservable physical quantities, such as using directional arrows to represent the vector of a force or the mapping of perceived colours to light wavelengths (Fig. 4d). People often engage in mental animation with such diagrams[199]. These mental animations need to be carried out within the conceptual context: vectors and rays are interpreted differently in ray diagrams that depict light movement in different contexts and free-body diagrams that depict the magnitude and direction of forces acting on an object[200]. Further complicating understanding, vectors can be either relational or iconic diagram elements depending on their context[200]. Vectors that represent displacement are iconic; their magnitude and direction necessarily imply a defined spatial relation between object instances. By contrast, vectors that represent velocity, acceleration or force are relational; their magnitude corresponds to an abstract property of the object. In the case of relational vectors, information about spatial relations between object instances requires an additional level of analysis, such as incorporating non-spatial properties such as mass or time, which challenges learning[201].

Graphs in physics, such as those representing data relative to velocity–time, acceleration–time, force and kinematics, depict the outcomes of physical phenomena. This type of reasoning engages intrinsic-static spatial thinking. It can be difficult to connect the data to the concept because the graph's spatial elements have only an abstract relationship to the actual system dynamics; students struggle to interpret or reason about the represented data, including line slopes[202,203]. For example, students confuse slope with y-axis height or fail to interpret the significance of the area under the slope[204].

In summary, physics uses the full range of visualization types, often to represent information that cannot be directly perceived. Iconic diagrams show spatial relations at scales too large or too small to observe, and relational diagrams include non-spatial influences on physics processes, such as time. Thus, visualization elements and the spatial relations between them make ideas visible. At the same time, physics visualizations use many of the same symbols (such as arrows) configured in similar ways to present different ideas. These challenges in physics mean that accurate interpretation of visualizations benefits from the ability to flexibly map non-visible and non-spatial concepts to visualization elements[199].

Mathematics
Mathematics is more abstract than many other STEM disciplines; although visualizations are commonly used, images are rare. Diagrams can facilitate mathematical solutions by spatially representing the relationships between problem elements[205], from simple arithmetic to advanced structural equation modelling[206,207].

Within mathematics, geometry makes the most use of iconic diagrams, which enable the shapes and structures of 2D and 3D geometric objects to be easily related visually (Fig. 4e). Interpreting these diagrams involves intrinsic-static spatial thinking. For example, a diagram of different triangle types provides a visual reference for comparison between them. Showing 3D objects constructed from triangles (such as a pyramid) illustrates ways to combine and structure 2D shapes and suggests possible 2D-to-3D transformations, engaging intrinsic-dynamic spatial thinking. Spatial thinking both impacts and is impacted by geometric reasoning[208]. After elementary school geometry lessons that included a range of spatial training activities (drawing geometric shapes, building 3D shapes with cubes from both visual and oral instructions, and identifying spatial relations), students showed improvements in distinct tasks including spatial language use, mental rotation, geometry understanding and symbolic magnitude comparison[209]. In another study, having individuals interact directly with geometric shapes led to improved spatial thinking on a mental rotation task[208]. Furthermore, mental rotation skills tested at age 6 years predicted success learning geometry in the same children at age 10–11 years[210,211]. Spatial skills (including mental rotation, perspective taking, cross-section identification, diagram interpretation, decomposition of geometric shapes and spatial scaling) identified at age 6–7 years predicted later mathematics gains at age 8–9 years[74]. This work showed that intrinsic spatial skills were strongly related to later arithmetic operation performance, and extrinsic spatial skills were related to numerical logic, spatial functions and geometry understanding.

Relational diagrams are also common in mathematics[212]. The number line is a relational diagram presented early in Western mathematics education (Fig. 4e). This mapping of numerical magnitude to spatial location forms the base of developing numerical and spatial estimation skills[213]. To master this spatial mapping, children must first learn numerical order and then map it onto a line such that rightward movement denotes increasing magnitude[214]. Mapping numbers onto the line involves intrinsic-static spatial thinking. Once mastered, the mental number line can be used to reason about mathematical concepts, such as negative numbers, using intrinsic-dynamic spatial thinking[215]. Children can use a mental number line in one of two ways — as divided or continuous[216]. With the divided number line model, children considered the positive and negative halves as separate and started calculations from zero. With the continuous number line model, students moved easily between positive and negative numbers, which aided their spatial understanding of negative numbers. Spatial visualization skills of children at age 5 years and their number line knowledge at age 6 years predicted how accurately they estimated addition problems at age 8 years[217]. Spatial scaling, mental rotation and embedded figures performance all predict number line estimation[211]. Some researchers argue that number line understanding mediates both spatial and mathematical skills[217].

In more advanced mathematics, relational diagrams illustrate geometry theorems and aid reasoning through proofs[218]. Evidence supporting spatial thinking with such diagrams emerges in the gestures and verbalizations students make when interacting with them[219]. For example, when publicly explaining a geometric proof, students use spatial gestures such as pointing to angles, tracing geometric shapes and showing change in distance by moving pointer finger and thumb further apart. Some researchers and educators have even argued that diagrams without any accompanying text can guide mathematical reasoning. This idea has been explored through 'proofs without words', the idea that diagrams show a student the truth of a mathematical statement and guide them to prove that truth[220]. Generalizing from this idea, diagrams can make abstract concepts more concrete and therefore aid reasoning[221].

Graphs are the most abstract visualization type and use spatial properties to convey and compare numerical information[222]. Although even simple graphs use spatial properties, the extent of spatial processing required to effectively interpret graphs increases with conceptual and graphic complexity and/or when information must be inferred from the graph[223,224]. Compatibility between intuitive conceptions about space and how data are presented improves graph comprehension[222]. For example, students showed greater confusion when higher bars on a graph represented smaller numerical values[222]. Further supporting this point, eye-tracking evidence suggests that alignment between intuition and data presentation reduced the time needed to understand graphs and integrate graph elements[225]. Better spatial skills (mental rotation and paper folding) relate to the ability to match points on a graph, understand calculus equations and read kinematic graphs[226].

In sum, spatial thinking is central to diagram and graph comprehension in mathematics. Whether the spatial information in mathematical diagrams reflects iconic or relative relationships primarily relates to the mathematical concept that is represented.

Differences across STEM disciplines are reflected in the visualizations used. The same concepts have different instantiations across STEM disciplines[144] but similarities in how they are visualized. Different STEM fields are merely different approaches to quantifying the world. Any visualization more effectively communicates meaning if people know how to interpret it. Yet, interpreting visualizations is not always intuitive, particularly for unfamiliar concepts[85]. It remains an empirical question whether visualizations help students to make cross-disciplinary connections, particularly when the same or similar diagrams are used across disciplines.

Summary and future directions

Spatial thinking is a cross-cutting cognitive skill related to STEM success[25,37]. This spatial–STEM relationship applies across STEM disciplines[49]. Yet, spatial thinking differs across STEM domains, leaving open the challenge of identifying domain-general commonalities. The visuospatial nature of visualizations and their ubiquitous use in STEM suggests that they not only serve as a tool for STEM learning but also connect spatial thinking across STEM disciplines. Importantly, many of the cognitive processes recruited during spatial thinking are also used to understand visualizations. This overlap further suggests that training both spatial thinking and visualization interpretation can help people to understand the spatial relationships in visualizations[227–230] (Box 2). Both spatial thinking[8,228,231] and visualization comprehension benefit from training[230] and such training can transfer to STEM learning[4,30,213]. Although this connection between spatial thinking, visualization and STEM understanding has strong support, there are many open questions for future research.

One open question is whether focusing on spatial thinking might promote transfer of visualization competency across STEM domains. The ability to understand or produce different visualizations of a concept has been explored, often under the term metarepresentational competence[232]. A challenge with transferring visualization comprehension skills to another domain is that training metarepresentational competence requires specific examples from a particular domain. Concrete examples aid reasoning about concepts[233] but also inhibit

Box 2

Recommendations for educators

The connections between spatial thinking, visualization use and science, technology, engineering and mathematics (STEM) success suggest actionable ways to potentially improve STEM learning. Our recommendations broadly fall into three categories: train spatial thinking, train visualization use. and intentionally connect both spatial thinking and visualizations to STEM concepts. Note that our recommendations are based on existing research findings, some of which show mixed support. More research is needed to verify effectiveness and transferability to untrained skills, including to STEM learning.

Train spatial thinking

Spatial thinking can be successfully trained[8,231,259]. Spatial training has been implemented in various ways, including practising mental rotation or mental paper folding[259], drawing[252], playing video games[260] and engaging in origami and paper engineering[30,231]. For elementary grade children, spatial training has taken the form of using tangible manipulatives[261] or practising age-appropriate spatial tasks[228,262,263]. When training spatial thinking it is important to consider whether the type of spatial thinking will transfer to other spatial tasks and to STEM thinking. A 2013 meta-analysis of spatial training studies supported transfer to untrained spatial tasks across a wide range of spatial tasks[8]. We would also want to see that spatial training led to gains in STEM performance. Spatial training, including learning origami and spatial games, relates to improvements in mathematics performance in primary and secondary school aged children[30,263]. This finding is further supported by a 2022 meta-analysis[264]. Other work has demonstrated a causal link between spatial training through drawing and improved performance in various college-level STEM courses[10]. However, transferability of spatial training to other activities requires that the spatial training takes place consistently, which is challenging when the spatial tasks are considered boring[265]. Thus, we recommend that educators consider implementing engaging spatial thinking into classroom activities, even from a young age[266].

Train visualization use

Representational competence is the ability to use representations, such as visualizations, to understand and communicate ideas[267]. Concepts similar to representational competence, but more narrowly defined, include data visualization literacy[268,269] and graph reading competence[18]. Educators should not assume that students have representational competence[85,232]. Anecdotally, teachers implementing a primary-aged spatial training programme noted their own difficulty interpreting visual instructions and anxiety in their own spatial skills[47,231]. Further, challenges in decoding visual representations impact college students' STEM problem solving[191]. Several lines of research support the benefit of multiple types of visualization training[227,230,270]. Students show gains in interpreting literal and inferential visualization information when shown how to decode visualizations, particularly when the visualizations are accompanied by physical models and explanations[189,230]. Having students generate parts of visualizations that build towards a larger, more comprehensive visualization also improves visualization understanding[271]. Additionally, if students identify errors in diagrams, it improves their diagram interpretation and concept learning[272]. Once students understand basic visualization elements, linking hands-on, active learning activities[267] and data[273] to visualizations can help to promote representational competence. In general, training students in how to use space to represent a concept and promoting metacognitive reflection about a visualization improves visualization understanding.

Connect spatial thinking and visualizations

Our final recommendation is to recognize that spatial thinking and visualization use cut across STEM disciplines and reframe how to teach these skills. For instance, one reason students do not spontaneously use diagrams for problem solving is that they think of visualizations as props for teachers to demonstrate problem solving instead of as tools for problem solving[274]. Follow-up work demonstrated that when teachers both verbally encourage the use of visualizations and give students practice creating visualizations, spontaneous visualization use increases[275]. Helping students to realize that spatial thinking and visualization understanding and creation are skills that can help them to learn rather than additional skills they need to learn can help them to reframe these skills[37].

In summary, by conceptualizing spatial thinking and visualization understanding as core cognitive skills, educators can potentially improve STEM learning and outcomes by emphasizing both in the classroom. Our recommendations focus on incorporating spatial thinking activities into classrooms[266], instructing students on how to interpret visualizations[230] and making explicit links between the spatial aspects of STEM concepts and visualizations[227].

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transfer of understanding to other concepts[234]. Future research should examine whether first building strong metarepresentational competence with a specific visualization type aids comprehension of a new concept using that same visualization type. This question can be extended to examine the extent to which people need to be directed to use the visualization or spontaneously use it with the new concept. Another future research direction should examine how the order in which students interact with visualizations accompanied by text (multimedia learning materials) impacts learning. When given both text and a visualization, learners start with the text and spend more time on it[235,236]. Teaching students to first examine the visualization might facilitate learning and emphasize to students the value of the visualizations. These future directions might promote domain-general understanding of visualizations, a topic addressed by only a limited number of studies.

Another open research question is whether visualizations can help students to see connections between concepts that span STEM disciplines. Although related to the first question, this one focuses on connecting concepts rather than visualization interpretation. The same concept (such as the first law of thermodynamics) can be taught in different STEM disciplines (including chemistry, physics and engineering classes). Although the concept remains the same (heat is energy and therefore follows conservation of energy principles), the course domain determines the examples and accompanying visualizations used. For example, in engineering the example might involve the application of heat to coal in a coal-fired power plant; in chemistry the example might involve a chemical reaction initiated by applying heat. The example through which a student first learns about thermodynamics then serves as the base for understanding the concept. Few courses specifically draw cross-disciplinary connections[237]. Research to address this question could explore how similarities in visualizations used to teach the same concept in different domains impacts transfer of a learned concept to a new domain.

The connection between STEM success and spatial thinking has been established across the range of STEM disciplines. Less is known about what connects spatial thinking to STEM disciplines. Here, we make a case that visualizations serve as one such domain-general connection. With this connection in mind, we suggest that training spatial thinking and metarepresentational competence can support interdisciplinary STEM thinking. Innovation lies at the intersection of STEM fields, pointing to the need to train students who can work at this intersection.

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