Chapter 7
Dynamic Visuospatial Ability and Learning from Dynamic Visualizations

Christopher A. Sanchez and Jennifer Wiley

7.1 Introduction

Developing understanding of many phenomena in STEM areas is a complex cognitive activity that theoretically requires not only the accumulation of rote knowledge of individual domain concepts, but also the creation of internal dynamic visuospatial representations that capture the interaction and integration between those concepts across space and time (Friedman & Miyake, 2000; Hegarty, 1992; Hegarty et al., 2010; Rinck, 2005; Wiley & Sanchez, 2010). These mental representations, or mental models of dynamic visuospatial systems, likely provide access to some of the same information as the actual experience, although often created in the absence of actual perceptual input. One marked benefit of this kind of mental simulation is that it offers knowledge-seekers the opportunity to better appreciate relationships that are not readily apparent in linguistic form, essentially permitting learners to see patterns or interactions that are otherwise 'invisible'. Indeed, some of the most critical advances in scientific thinking have occurred due to the ability of individuals to spatially recreate or imagine scientific content (e.g., DNA, benzene ring, etc.; National Research Council (NRC), 2006), allowing for insight that would otherwise not be possible. This suggests it may be critical to present information to potential learners in such a way that maximizes the likelihood that they will be able to form coherent and appropriate visuospatial representations of the material while learning. From a motivational perspective, the presence of animations might also positively affect levels of motivation within students, in addition to the learning benefits suggested above. For example, it has been demonstrated previously that the inclusion

C.A. Sanchez (✉)
Oregon State University, Corvallis, OR 97331, USA
e-mail: christopher.sanchez@oregonstate.edu

J. Wiley
University of Illinois at Chicago, Chicago, IL 60607, USA
e-mail: jwiley@uic.edu

© Springer International Publishing AG 2017

R. Lowe, R. Ploetzner (eds.), *Learning from Dynamic Visualization*,
DOI 10.1007/978-3-319-56204-9_7

of animations made it more likely that students would 'continue-on' with learning in a STEM content domain (Rieber, 1991). Based on intuitions such as these, it is common for instruction in STEM areas to include dynamic visualizations such as animations and videos in the hopes that they will help learners appreciate such dynamic relationships. Yet, some research on learning from dynamic visualizations has shown that they sometimes fail to produce this same facilitative benefit. Benefits of dynamic visualizations may depend to the nature of the material to be learned, as well as the way information is presented in the animations themselves. For example, a recent meta-analysis found that more 'decorational' animations (i.e., those that do not explicitly depict the representation to-be-learned) do not appear to demonstrate a benefit above static illustrations, and more importantly, also produce learning effects that are significantly smaller than animations that do explicitly demonstrate the target representation (Höffler & Leutner, 2007). Features of the learner are another factor that could determine whether benefits of dynamic visualization are seen (Wiley, Sanchez & Jaeger, 2014). The main purpose of this chapter is to explore a particular *aptitude-by-treatment interaction* that can help to explain when dynamic visualizations may be most likely to facilitate learning. The studies reported here assess *Multiple-Object Dynamic Spatial Ability (MODSA)*, a particular set of spatial skills involving integrating information from multiple objects over time and space, and discuss its relation to learning from dynamic visualizations.

7.2 Visualizations and Instructing STEM Topics

One common approach that has been taken to enhance learning of STEM topics, particularly topics that have a temporal or spatial component, has been to include explicit external visualizations to augment instruction. This approach involves the addition of visualizations to text to potentially provide a mechanism of external support to help the learner form their mental model of the STEM phenomena. For example, including appropriate static images has been shown to produce better learning of biology (Ainsworth & Th Loizou, 2003), physics (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Loftus & Harley, 2004), and mechanical devices (Hegarty, 1992; Mayer, 1989; Mayer & Gallini, 1990). Similarly, the addition of animations or videos has produced facilitation in learning meteorology, mechanical tasks, and computer programming tasks (Mayer & Moreno, 1998; Moreno & Mayer, 1999; Palmiter & Elkerton, 1993; Schnotz, Böckheler, & Grzondziel, 1999). The explanation given for such facilitative effects is quite simple: because these content areas all contain an explicit visuospatial component, providing relevant visuospatial information to learners in a pre-packaged form allows for the better development of understanding. Unfortunately, this assumption might prove to be overly simplistic.

Despite these successes, there are also numerous examples of failed attempts to enhance learning through the simple addition of visualizations, with some cases even leading to lower learning (Chanlin, 1998; Harp & Mayer, 1997; Rieber, Boyce, & Assad, 1990; Schnotz & Rasch, 2005; Westelinck, Valcke, Craene, & Kirschner, 2005; Wiley, 2003). Why is this the case, and how is the simple assumption described above flawed? While there are numerous potential explanations, there is some suggestion that the facilitative effects of visualizations is directly dependent on the interaction of such visual material with characteristics of the learner themselves (Geiger & Litwiller, 2005; Hannus & Hyönä, 1999; Sanchez & Wiley, 2006). In other words, an aptitude-by-treatment interaction, or individual differences in particular cognitive skills, might dictate the circumstances under which the use of visualizations is not only warranted, but also most effective. The general class of cognitive abilities that seem most relevant for understanding the 'how' and 'when' to use visualizations, and that are explored further in the following studies, are visuospatial aptitudes (see also Berney & Bétrancourt, 2017, this volume; Wagner & Schnotz, 2017, this volume).

7.3 Assessments of Visuospatial Aptitudes

A long history of psychometric research has established that the ability to represent and manipulate visuospatial relationships is directly tied to a set of discrete aptitudes that exist independent of such general cognitive factors as fluid intelligence or working memory capacity (WMC). Traditionally, these visuospatial abilities have been divided into two distinguishable but related sub-classes: those that evaluate the preservation of visuospatial relationships of an item, and those that examine how individuals can manipulate existing visuospatial relations to transform them into a set of novel new relations (Carroll, 1993; Cooper, 1975; Cooper & Shepard, 1973; Mumaw, Pellegrino, Kail, & Carter, 1984; Pellegrino & Hunt, 1991). The distinction between these sub-classes becomes more apparent when considering tasks that are frequently used to assess these different abilities. For example, visuospatial relations (VSR) are commonly evaluated with tasks that require the learner to mentally rotate or move the existing item in some way to make a subsequent judgment about whether a second item is the original item, or not. Prototypical VSR tasks are the Cube Comparisons task (French, Ekstrom, & Price, 1963) and Figure Rotation Task (Cooper & Shepard, 1973). On the other hand, visuospatial visualization (VSV) tasks instead require individuals to intake a given set of visuospatial relations, and then modify these relations in some constrained way into a new set of relations. The Paper Folding task (French et al., 1963) and Form-board task (French et al., 1963) are common examples of a VSV task. Example items of VSR and VSV tasks are available in Fig. 7.1.

Again, although distinguishable, there can be difficulties drawing strict boundaries between these different sub-classes of ability, and the tasks that measure them (Carroll, 1993; Just & Carpenter, 1985; Stumpf & Eliot, 1995). VSR and VSV tasks do tend to correlate at a moderate level (~.40), and also tend to cluster together in factor analytic solutions that also contain measures of verbal or reasoning ability (Kane et al., 2004). Perhaps a reason for the difficulty in fully segmenting these types of abilities from one another has to do with how the tasks that measure them

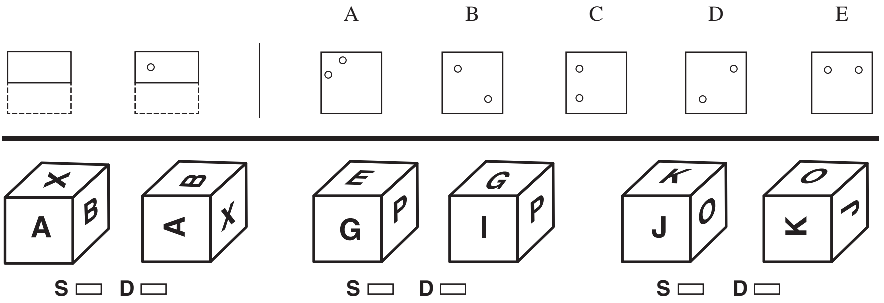

Fig. 7.1 Example items from the Paper Folding (*top*) and Cube Comparisons (*bottom*) tasks

are themselves constructed. For example, a common feature of nearly every VSR and VSV task is that they require the representation of relations within a single item, without the requirement to capture transitional changes over time, or relations outside of the referent itself. In other words, while these tasks require the manipulation and preservation of visuospatial relations, the nature of these relations is strictly self-referential. Thus, these tasks can be classified more broadly as measures of *<u>within-object manipulation spatial ability (WOMSA)</u>*, a description that is consistent with other frameworks of visuospatial processing that also emphasize the focus on intrinsic visuospatial processing required for these type of tasks (Newcombe & Shipley, 2012; Uttal et al., 2013).

Higher performance on WOMSA tasks has been shown to predict performance across a wide range of tasks that also contain a requirement to process visuospatial information. This includes tasks of mechanical reasoning (Boucheix & Schneider, 2009; Hegarty & Sims, 1994; Hegarty & Steinhoff, 1997), route learning (Sanchez & Branaghan, 2009), and even the comprehension of narrative texts about character movement in physical space (Bower & Morrow, 1990; De Beni, Pazzaglia, Gyselinck, & Meneghetti, 2005; Fincher-Kiefer, 2001; Fincher-Kiefer, & D'Agostino, 2004; Haenggi, Kintsch, & Gernsbacher, 1995; Meneghetti, De Beni, Pazzaglia, & Gyselinck, 2011). A recent meta-analysis also found that WOMSA tasks have been found to predict how well people learn from visualizations or illustrations, especially those that are non-dynamic in nature (Höffler, 2010). Related work has also suggested that the positive effect of learning from more *dynamic* visualizations or animations is also largest for lower WOMSA individuals (Höffler & Leutner, 2011; Mayer & Sims, 1994; Sanchez & Wiley, 2010). Thus, these WOMSAs appear critical not only for the formation of visuospatial knowledge derived from text, but also for the decomposition or understanding of explicit visuospatial referents that are used to instruct in these areas (i.e., visualizations and animations).

Given the above discussion, and the often visuospatial nature of STEM learning, it has been suggested that WOMSAs may also be critical for developing understanding of STEM topics (e.g., Halpern et al., 2007; Wu & Shah, 2004). However, studies exploring the relation between WOMSA and STEM learning have not provided a clear pattern of results. While a small number of studies have found that these WOMSAs do positively correlate with classroom performance in STEM topics such as organic chemistry and earth science (Black, 2005; Carter, LaRussa, & Bodner, 1987; Pribyl & Bodner, 1987; Sanchez, 2012; Sibley, 2005; Wu & Shah, 2004), there are also examples of WOMSAs failing to predict learning in other STEM domains like biology and physics (ChanLin, 2000; Koroghlanian & Klein, 2004). This lack of a consistent relationship between WOMSAs and STEM learning challenges the somewhat simple assumption that because many STEM topics have a visuospatial component, WOMSAs should also always be relevant for learning in STEM. An alternative explanation is that these WOMSAs, although likely relevant for STEM education, may not be *as relevant* for predicting learning dynamic concepts in dynamic STEM areas as visuospatial abilities that better capture the dynamic nature of most STEM topics.

7.4 Multiple Object Dynamic Spatial Ability

Tests of *Multiple-Object Dynamic Spatial Ability (MODSA)* focus on the change of spatial relations between multiple items, and also as they unfold over time. MODSAs (originally identified through the work of Hunt, Pellegrino and colleagues nearly two decades ago; Fischer, Hickey, Pellegrino, & Law, 1994; Hunt, Pellegrino, Frick, Farr, & Alderton, 1988; Law, Pellegrino, & Hunt, 1993), were proposed as distinguishable from traditional measures of WOMSA, and have been shown to be separable from not only typical assessments of WOMSA (Contreras, Colom, Hernandez, & Santacreu, 2003; D'Oliveira, 2004), but also measures of visuospatial perspective taking like the Guilford-Zimmerman task (Hunt et al., 1988). MODSA has also been shown to be independent of verbal intelligence (Jackson, Vernon, & Jackson, 1993) and education level (Contreras, Colom, Shih, Alava, & Santacreu, 2001), further confirming its validity as a novel and independent indicator of visuospatial processing.

As MODSA theoretically focuses on the processing of visuospatial relationships across multiple items, over time, it is natural for assessments of MODSA to exhibit this kind of dynamic focus. A typical example of a MODSA task is the Intercept task. In this task (described in more detail below), a target item moves across the screen, and participants must intercept this item with a second moving item (a missile) which they control the timing of release from the launchpad (cf. Fig. 7.2). To successfully achieve an interception, the learner must first represent visuospatial movement over time; effectively computing a relative velocity for both the target *and* the interceptor. It is this information that can then be used to calculate an intersection between the visuospatial items, and subsequently produce a valid release point for the interceptor (missile). While other measures of MODSA do exist, such as the Race task (Hunt et al., 1988), appropriate measures of MODSA all share this focus on relative velocity between multiple visuospatial items. Importantly, tasks which measure these factors in isolation (e.g., time/velocity or visuospatial change

Fig. 7.2 Three progressive screenshots of the Intercept task. Labels in parenthesis do not appear in the actual task display

alone) often fail to correlate with validated measures of MODSA (Fischer et al., 1994). Thus, it appears that the integration of visuospatial and temporal information is the key element of effective MODSA assessments, and an effective measurement of MODSA must focus on both.

While the use of MODSA assessments to predict real-world performance has been less frequent than work on their WOMSA counterparts, there has been some demonstration that these dynamic abilities predict performance in tasks that require participants to integrate visuospatial and temporal information together. For example, there was found to be a positive relationship between MODSA and performance in an air-traffic controller task; a task that overtly involves representing multiple spatial objects that are moving and changing over time (Contreras et al., 2003; D'Oliveira, 2004). Importantly, MODSAs were also recently found to predict STEM learning about plate tectonics, and revealed an aptitude-by-treatment interaction between MODSA and the use of dynamic visualizations in instruction (Sanchez & Wiley, 2014). The details of this pivotal study are discussed next.

7.5 An ATI for MODSA and Science Learning

To evaluate the possible role of MODSAs in learning from dynamic visualizations, first it was necessary to select a topic that required the construction of a visuospatial mental model in order to represent key systemic and dynamic interactions. Plate tectonics was selected as the topic for the lesson as a fundamental tenet of understanding the theory of plate tectonics is the idea that the entire process is cyclical in nature, and progresses across multiple components, in multiple locations, and across time. This is consistent with research on learning plate tectonics that suggests that the main struggle of most learners in this area is to integrate the conceptual units into a coherent cyclical process (Smith & Bermea, 2012). Quite simply, the Earth is composed of a dense molten core, on top of which floats a hard rock crust, which is the surface we live on. Critically, this crust is not uniform. In areas that are unbroken, the crust is usually flat and free of deformation. However, there are also several breaks in the crust which lead to the topography (i.e., mountains, volcanoes, etc.) that make up the more interesting features on the Earth's crust. These breaks represent the intersection of different tectonic plates, and the subsequent deformations at these plate boundaries are a result of the different types of collisions at these points.

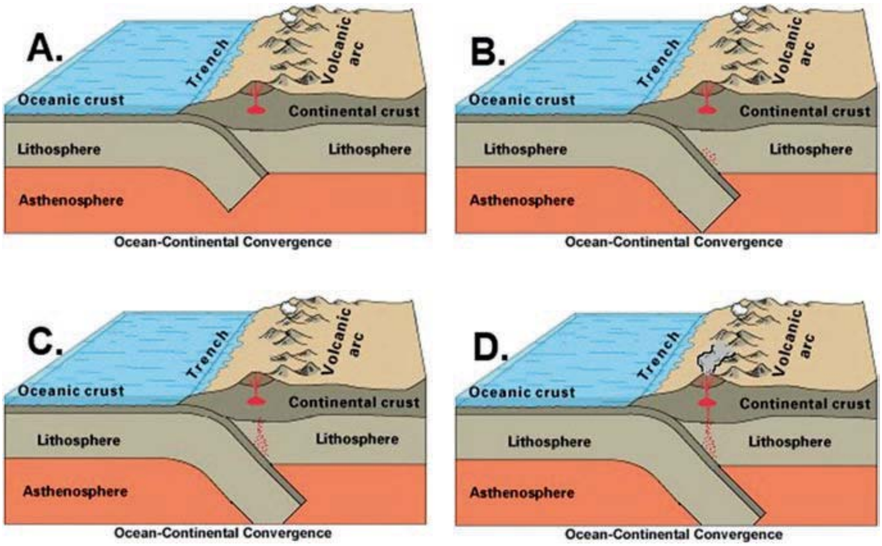

Fig. 7.3 Example visualizations used to instruct the process of subduction

For example, convergent boundaries can produce mountains or volcanoes, whereas divergent boundaries produce more slowly erupting volcanoes that underlie the formation of some islands (e.g., Hawaii) and sea-floor spreading. These plates interact at all because they are floating on top of the sea of liquid rock that makes up the core of the planet, which itself moves and circulates in convection currents within the innermost areas of the Earth.

As such, if a learner is presented with a purely textual description of the above phenomenon (i.e., not supplemented with any kind of visualizations), to successfully develop an understanding of plate tectonics, the learner would be required to not only mentally represent the spatial units themselves (e.g., plates), but also the interactive processes between these spatial units. Such a situation would likely place a very high demand on visuospatial resources given the concurrent need to both represent and integrate the conceptual material in the text. Further, misconceptions are not only possible at the level of basic representation of the concepts themselves, but also regarding how these units interact. In other words, learners may not only misunderstand the conceptual units themselves, but potentially compound this issue with further misunderstanding of the interaction between said units. Contrast this now with at text that is given a basic level of visuospatial support, in the form of static visualizations. A typical static visualization that might illustrate a portion of the above overall interaction is visible in Fig. 7.3d. This figure demonstrates the process of subduction, a specific type of plate collision where the ocean plate collides with (and is forced underneath) the continental plate. This process causes the ocean plate to not only grind apart against the continental plate, but in so doing produces a thick and viscous magma that traps gases, eventually leading to an explosive eruption from a volcano located at the plate boundary. While all of these discrete concepts are captured in the visualization in Fig. 7.3d, the interaction between these concepts is not necessarily prominently highlighted. Instead, as the change of relationships is not explicitly demonstrated, the independent concepts themselves take the forefront, forcing the learner to mentally 'fill-in-the-blanks' regarding how they interact. This 'filling-in' process is expected to be an effortful process, not only requiring preservation of spatial relations, but also integrating these changes over the event.

Now contrast this with a simple dynamic visualization, which would consist of an animated sequence of 4 frames (Fig. 7.3a–d). Note that the end frame is identical to the static visualization discussed above. Thus, while the visuospatial relations and concepts are ultimately consistent between these two genres of illustrations, what is fundamentally different is the conveyance of the process leading up to the final presented state. As is visible throughout Fig. 7.3a–d, the change across frames would receive the primary emphasis. The ocean plate is shown to move and subduct, while the magma slowly rises, fills magma chambers and eventually leads to an eruption. Again, the spatial concepts (e.g., ocean plate, subduction, etc.) are all present in both static and dynamic visualizations, however the dynamic visualization places a greater emphasis on the relationships between concepts, rather than just the concepts alone.

As is visible in Fig. 7.3, and is also hopefully apparent in the above discussion of the topic of plate tectonics, forming a well-developed and complete model of tectonic theory requires learners to not only understand visuospatial concepts in isolation, but also appreciate the interaction of these units over time, and any subsequent changes these interactions produce in the system. Thus, there appears to be a basic requirement in this domain to represent these conceptual relationships as the process unfolds, and this requirement should rely heavily on visuospatial abilities that deal with the representation and understanding of multiple relationships over time (e.g., MODSA). Further, as developing understanding in tectonic theory is an inherently dynamic process, one might also predict that MODSAs should predict unique variance in learning over and above any contributions of WOMSA or basic cognitive abilities such as working memory capacity.

To test for a possible ATI between MODSA and illustration condition, low-knowledge undergraduates ($N = 162$) from a large public university read a text about plate tectonics that contained either no visualizations, static visualizations or dynamic visualizations, and were then tested on their understanding of the content. The text itself was approximately 3500 words long (adapted from the Classrooms of the Future 'Exploring the Environment – Volcanoes & the Earth' module (Center for Educational Technologies, 1997; http://www.cotf.edu/ete/modules/volcanoes/volcano.html). Eight critical concepts underlying volcanic eruptions were identified within the text (Fig. 7.4). Given the nature of the material, it was expected that in order to truly understand the content area, learners would need to integrate these concepts with one another, and understand how they might fit together into a dynamic causal model of volcanic eruptions. For example, they must not only understand that plates move, but also that these collisions can lead to plate subduction, which in turn leads to the formation of magma. This magma then rises and

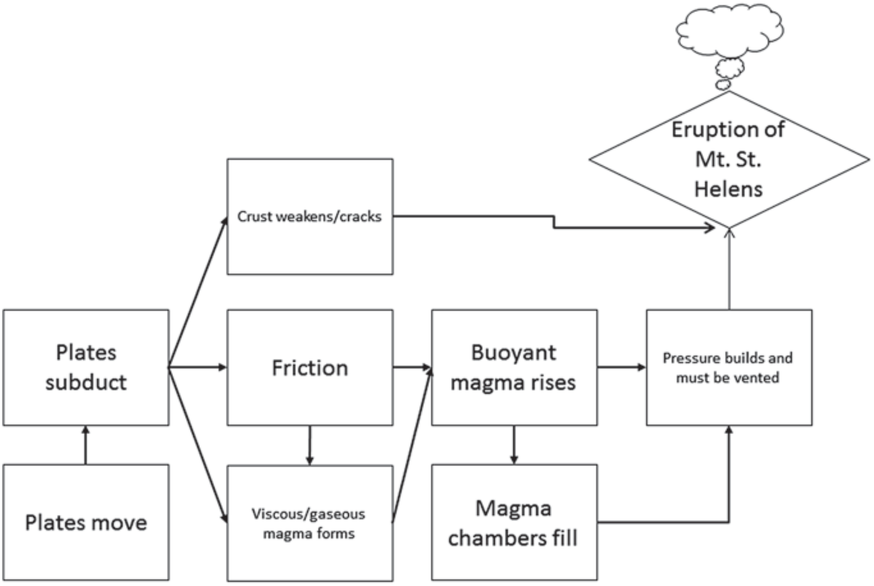

Fig. 7.4 Critical causal concepts within a model of plate tectonics

builds pressure within the crust, eventually culminating in an explosive volcanic eruption. Thus, this text does contain information of a very temporally dynamic and visuospatial cyclical nature, made up of the interaction of multiple visuospatial objects, rather than single items which only reference where understanding is localized within the object itself. As such, to form a more complete understanding of the content domain itself, there is an explicit demand to internally generate a dynamic representation between objects that is consistent with the actual external phenomenon.

Based on experimental condition, this lesson was further modified to contain different levels of external support for the need to mentally simulate visuospatial interactions. The first group was not given any diagrams or illustrations, while the second group read the same text instead illustrated with relevant static diagrams. Finally, the third group was given the same text as the first two groups, however their lesson contained animated versions of the static illustrations seen by the second group. All visualizations in the static and dynamic condition provided a visual analogue of the textual presentation, consistent with general interactions described in the text. These different visualizations do provide differing levels of explicit support for the representation of the visuospatial interaction between relevant concepts. For example, the non-illustrated condition offers no external support, while the static illustrated condition provides at least a visual representation of the operators and how they might be structured within a system. However, the interaction of these operators is not emphasized in these static illustrations. Dynamic illustrations (i.e., animations), on the other hand, not only highlight the visuospatial concepts themselves, but also provide an external representation of the interaction between these concepts. Thus, these animated visualizations provide maximal external support for learning the topic, highlighting not only 'what' but also the 'how' these various visuospatial components come together and interact.

To evaluate how well individuals learned in the different conditions, participants were asked to generate a written response to the question 'What caused Mt. St. Helen's to erupt?' Importantly, the instance of Mt. St. Helens was not explicitly mentioned in the text, so in order to answer this question participants would have to transfer the knowledge they learned from the lesson to this specific application. These essay responses were then evaluated for the presence of the eight critical concepts identified in the target text (cf. Fig. 7.4).

All participants were also assessed for their WOMSA and MODSA. MODSA was assessed using a version of the Intercept task (Hunt et al., 1988), with adjustments based on Law et al. (1993; Fig. 7.2). The appearance of the Intercept task is very similar to a simple video game. In this task, a small target moves across the screen (from left to right) at one of three potential preset speeds. Participants are required to release a second item that travels at a constant speed vertically, in an effort to intercept the horizontally moving target. In order to successfully hit the target, and subsequently earn a higher score in the task, the participant must launch their vertically traveling 'missile' so it reaches the point of intersection at the same time as the target. Thus, successful performance on this task involves representing not only where items are on the screen, but also where they will be after a certain amount of time, which can then be used to decide when to release the 'missile'. The Intercept task lasts approximately 15 minutes from start to finish, and previous iterations of this task have been shown to be not only reliable measures of MODSA (Spearman-Brown $r > .87$; Law et al., 1993), but also correlate positively with other valid measures of MODSA (e.g., Race task; Hunt et al., 1988).

WOMSA was measured with the Paper Folding task (VZ-2; French et al., 1963). In this task, participants were shown a series of 20 diagrams of an irregularly folded piece of paper, and asked to imagine a single hole being punched through the paper at an indicated point. Participants were then required to mentally unfold this piece of paper to decide between a set of alternatives. This task has been shown to be a reliable and valid indicator of WOMSA (Kane et al., 2004), and is traditionally considered a measure of VSV.

Participants were also evaluated for their working memory capacity (WMC; Kane et al., 2004) using two standard complex span tasks: Operation Span (OSpan), and Reading Span (RSpan). In each trial on these tasks, participants are first required to verify a given piece of information (i.e., the sum for a simple math equation in OSpan, or the grammaticality of a simple sentence in RSpan), then remember an unrelated target item (word for OSpan, and letter for RSpan) for a later test at the end of each set of trials. Set size is generally manipulated between two and five trials, and proactive interference increases throughout the tasks. Points are awarded for correct recall of the target items (words or letters). The scores for these two tasks were averaged together to form a composite working memory score, thereby reducing any variance unique to each corresponding WMC task (Conway et al., 2005).

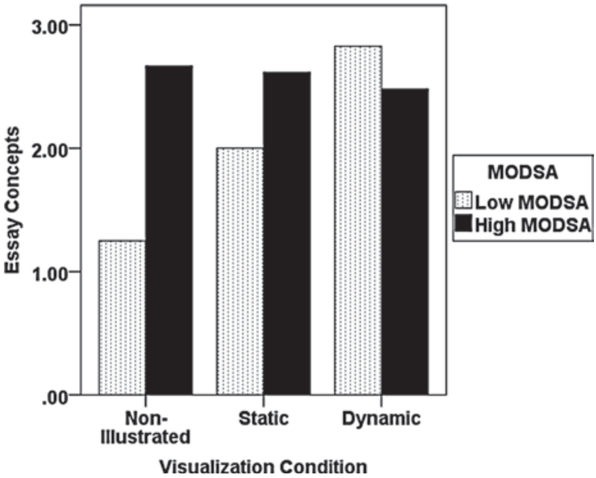

Fig. 7.5 Interaction between MODSA and illustration condition

Although the main purpose for including these assessments was to explore aptitude-by-treatment interactions with these individual differences, it is important to note that the three experimental conditions did not differ in WMC, WOMSA or MODSA scores. There were also no differences in the number of science courses taken across conditions. To examine the influences of ability and visualizations on learning, a set of hierarchical linear regressions was conducted on essay performance. The cognitive ability measures and prior coursework (number of classes taken) were entered into the first block of the analysis, followed by illustration condition in the second block. Illustration condition was decomposed into two dummy coded variables: the first capturing the presence of illustrations or not (illustrated dummy variable), and the second capturing whether the illustrations were dynamic or not (dynamic dummy variable). Finally, interaction terms between the illustration dummy variables and each ability variable were entered into the subsequent blocks of the analysis.

Results from the first block of this analysis showed that WMC and MODSA both predicted unique variance in learning about plate tectonics, but WOMSA, and number of previous science courses did not predict unique variance. Results from the second block showed that the visualization condition failed to explain any variance in essay performance. However, MODSA was found to significantly interact with the visualization condition, but only with the dynamic dummy variable (and not the illustrated dummy variable). These results suggest that MODSA is *less* related to learning content when a lesson contains dynamic visualizations, and the influence of MODSA does not depend on whether the lesson contains any visualizations or not. In other words, dynamic visualizations appear to compensate for lower MODSAs, leading to overall higher performance. But, when dynamic visualizations are not provided, then MODSA strongly predicted learning about plate tectonics. This pattern of results is evident in Fig. 7.5. Finally, both WMC and WOMSA

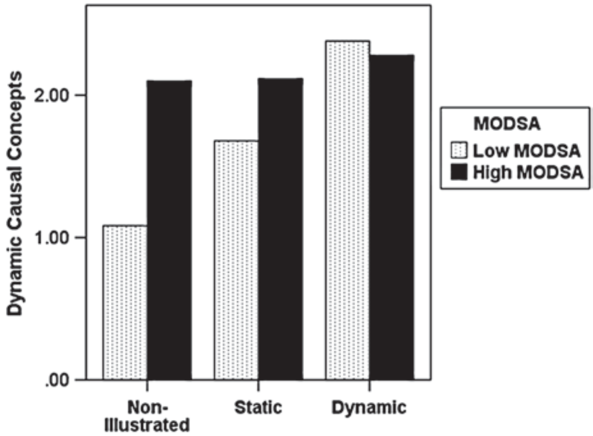

Fig. 7.6 Learning of dynamic concepts across different visualizations by MODSA

did not appear to interact with the visualization condition at any level. These results raise two interesting issues: first, WMC does not appear to influence the ability to use visualizations, dynamic or not, and second, WOMSAs did not account for any unique variance either in the ability to use visualizations, or in learning in the content domain (as evidenced by the lack of an initial significant main effect above).

A second follow-up analysis examined a subset of concepts from Fig. 7.6 that are more explicitly dynamic in nature. These five concepts were: (1) plates move, (2) plates converge, (3) heated magma rises, (4) magma chambers fill, and (5) pressure builds and is released. In contrast with the remaining three concepts that lack dynamic aspects, these five dynamic concepts represent changes in the conceptual system over time. The three non-dynamic concepts appear to be more connected to outcomes of these dynamic processes (e.g., magma forms because plates converge), than being processes in and of themselves. Learning of these dynamic concepts was then compared across the different visualization conditions, for high and low MODSA learners (defined by a median split on MODSA performance), and is visible in Fig. 7.6. Here main effects for visualization condition, MODSA, and a significant interaction were found. As is visible in Fig. 7.6, dynamic visualizations provided the greatest opportunity for learning these dynamic concepts ($F(2, 156) = 7.50$, $p < .01$), significantly more so than both the non-illustrated and static illustration conditions as evidenced by post-hoc comparisons ($p < .05$). Higher MODSA also again predicted better learning of dynamic concepts ($F(1, 156) = 8.35$, $p < .01$). Most importantly, there was also a significant interaction between MODSA group and visualization condition ($F(2, 156) = 4.25$, $p < .05$), just as was observed in the overall analysis. While there was little change in performance in the different visualization conditions for high MODSA learners, low MODSA learners learned the dynamic concepts best in the dynamic visualization condition. This further supports the suggestion that dynamic visualizations make the learning of these dynamic concepts more accessible to all individuals, and not solely for those that are high in MODSA.

Taken together with the above regression results, this final analysis provides a more complete picture on the role of MODSA in learning, and the interaction between MODSA and providing dynamic visualizations. To begin, it appears that MODSA generally facilitates learning about plate tectonics, especially for those concepts that themselves are dynamic in nature. This facilitation was observed over and above measures of general ability and WOMSA. Second, and directly relevant for the focus of this chapter, this study demonstrated a significant aptitude-by-treatment interaction between MODSA and visualization type, suggesting that dynamic visualizations can compensate for lower MODSA scores, and essentially eliminate the observed difference between low and high MODSA individuals on learning. By making the implicit requirements for comprehension of the domain explicit through dynamic visualizations, learning was improved specifically among individuals who might be less likely or able to engage in dynamic mental simulation on their own. Dynamic visualizations were most useful for those individuals who were lower in a particular spatial aptitude (MODSA) and were neither beneficial (nor detrimental) for those individuals who were already high on this ability. The benefit of dynamic visualizations was therefore localized to a specific group of individuals who were most likely to benefit from this kind of external support. This result is consistent with the 'ability-as-compensator' hypothesis originally proposed by Mayer and Sims (1994).

7.6 Specificity of Benefits for Dynamic Visualizations and MODSA

A parallel study using a different subject matter helps to highlight when MODSA and dynamic visualizations will specifically benefit learning. As in the plate tectonics study, a second group of undergraduates ($N = 119$) read a similar length text (~3500 words) about the Irish Potato Famine (adapted from Wiley, 2001) in order to understand the causes of the drastic change in population that occurred between 1841 and 1851. Again, this text was either not illustrated ($n = 40$), or instead illustrated with static ($n = 40$) or dynamic ($n = 39$) visualizations that portrayed changes in agricultural products and their diversity, death rates, and other economic indicators such as rent costs by county (cf. Fig. 7.7). Like the plate tectonics text, eight *a priori* concepts were identified in this text that represented a thorough understanding of population changes in Ireland. Critically, although this Irish Potato Famine text does reference visuospatial locations (e.g., towns or counties on a map), the causal concepts themselves are not inherently based in dynamic spatial relations between entities. Thus, while the content does contain a small discrete component of visuospatial information, this topic seems less likely to require the construction of a runnable visuospatial mental model in order to represent key systemic and

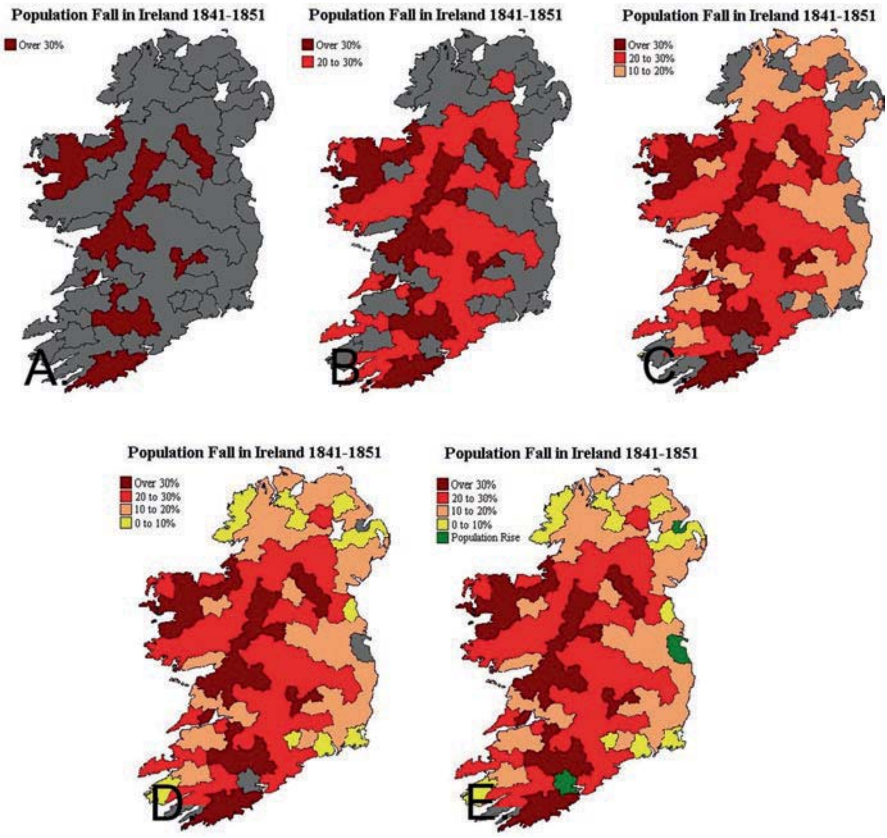

Fig. 7.7 Sample visualization from Irish Potato Famine text

dynamic interactions compared to a topic such as plate tectonics. Participants were again assessed for their WMC, WOMSA and MODSA. Of interest was whether the same pattern of relationships would be observed here as demonstrated previously with the plate tectonic content, or whether the interaction between DSA and visualizations on learning might depend on the subject matter.

To examine the influences of ability and visualizations on learning about the Potato Famine, a set of hierarchical linear regressions was again conducted on essay performance. Results from the first block of analysis ($R^2 = .10$, $F(3, 116) = 4.10$, $p < .01$) indicated that the only significant predictor of learning was WOMSA ($\beta = .30$, $p < .01$). WMC ($\beta = .02$, $p > .05$) and MODSA ($\beta = -.01$, $p > .05$) did not contribute unique variance for learning about the Irish Potato Famine. In the second block, no differences were seen in learning due to visualization condition ($R^2\Delta = .01$, $p > .05$). Both visualization condition dummy variables also failed to significantly predict performance (both p-values > .05), and failed to interact with any of the cognitive ability variables in the later blocks (all $R^2\Delta < .025$, $p > .05$). Thus, no interaction between MODSA and visualization condition was seen for this content.

As a whole, the results of this follow-up experiment allow for a number of important observations. First, advantages due to individual differences in MODSA were not found on a topic that did not seem to require the creation of a runnable visuospatial mental model. Because there is no inherently dynamic component to be understood from this text, there was little need to invoke MODSA to form understanding. This helps to rule out alternative explanations for MODSA effects on learning as being due to more general differences in ability, since it does not always relate to superior learning. Second, dynamic visualizations also do not always lead to improved understanding. This helps to rule out alternative explanations for dynamic visualizations as being necessarily more interesting or engaging to students.

Third, the only ability measure that was uniquely related to learning for this topic was WOMSA. Although the reasons for this observed relation are less clear than the observed relation between MODSA and learning about plate tectonics, one speculative interpretation is that as the information in the potato famine text does reference several spatial locations (i.e., different counties/towns of Ireland), it is possible that the processing of these simple spatial orientations was required to contextualize the rest of the factual information contained with the text. This is somewhat consistent with previous findings regarding WOMSA abilities being related to following character movements within narrative texts (Bower & Morrow, 1990; De Beni et al., 2005; Fincher-Kiefer, 2001; Fincher-Kiefer, & D'Agostino, 2004; Haenggi et al., 1995; Meneghetti et al., 2011). Further, because learners were also presented with visualizations in two of the conditions, it is possible that WOMSA might have been needed to help readers to decode these diagrams, and therefore it resulted in an overall relationship with learning. As a simple test of this potential explanation, a final hierarchical regression was conducted that examined only WOMSA and the visualization dummy variable that evaluated whether the text was illustrated or not. Results indicated that while there was still only a main effect of WOMSA ($\beta = .30$, $p < .01$) and not the presence of visualizations ($\beta = -.11$, $p > .05$) in the first block ($R^2 = .11$, $F(2, 117) = 7.14$, $p < .01$), WOMSA did interact with the presence of illustrations in the second block ($R^2\Delta = .03$, $p < .05$; $\beta = .74$). Again, this suggests that WOMSA was necessary for the decoding of the visualizations, both dynamic and not, and this relationship could underlie the main effect found in the overall analysis. This effect should be interpreted cautiously, however, because when explored in the full model, with all variables, this pattern did not reach statistical reliability. The failure to observe this interaction in the overall model is likely a result of intercorrelations between WOMSA and the other ability measures in this study. For example, when considering WOMSA alone, a portion of general ability variance that is usually shared with WMC (evidenced by the typically observed intercorrelation between WOMSA and WMC in this study, $r = .45$, $p < .01$) could be attributed inappropriately to WOMSA; thus producing an overestimate of the connection to learning, based on variance that is not specific to WOMSA (Jaeger, Jarosz, & Wiley, 2014). Obviously, when both WMC and WOMSA are present in the model, such overlapping variance would not be attributed to either factor, which although has the positive side effect of providing a more clear estimation of the effect, also potentially obscures smaller effects. Regardless of this WOMSA explanation, the observed patterns portrayed here at the very least provide an additional perspective on when MODSA and the use of dynamic visualizations are likely to impact learning.

7.7 Conclusions, Caveats, and Future Directions

The current chapter sought to explore the relationship between MODSAs and learning dynamic STEM topics through dynamic visualizations, and the potential for an aptitude-by-treatment interaction. Results from a study investigating the influence of MODSA on learning about plate tectonics showed not only that MODSA is relevant for predicting learning in dynamic domains, but also that MODSA significantly predicted the utility of dynamic visualizations used for instruction. While dynamic visualizations failed to lead to significant improvements in performance over non-illustrated or statically illustrated text when considered alone, an aptitude-by-treatment interaction revealed that the presence of dynamic visualizations specifically benefitted lower MODSA individuals. Further, these dynamic visualizations helped facilitate the learning of dynamic domain concepts more-so than the other visualization conditions, and specifically for lower MODSA individuals. This suggests that such visualizations allowed these lower ability individuals to better encode and learn such dynamic information; information that might have otherwise not been accessible to them. Essentially, these dynamic visualizations were most beneficial for those that likely struggle to mentally visualize such information themselves. This finding is consistent with other results suggesting that dynamic visualizations differentially impact high and low ability individuals (Höffler & Leutner, 2011; Mayer & Sims, 1994; Schnotz & Rasch, 2005), and help to clarify when facilitation may be found by adding relevant visualizations to learning environments (ChanLin, 2000; Craig, Gholson, & Driscoll, 2002; Mayer & Moreno, 2002; Rieber, 1990).

Importantly, the influence of MODSA on learning was also observed above and beyond the influence of WMC and WOMSA. This suggests that high MODSA enabled understanding independent of higher general ability or other less relevant visuospatial abilities, further validating its consideration as an independent factor worth assessing when designing visualizations for learning (cf. Lowe & Boucheix, 2017, this volume). The results of a second study further support the distinction made above that this set of dynamic abilities is only invoked when there is an explicit demand for such processing made by the content area, and not invoked in situations that are less dynamically visuospatial (e.g., Irish Potato Famine). Encouragingly, the results of the plate tectonic study also suggest that this explicit demand can also be alleviated through the use of quality dynamic visualizations, thus allowing all learners to better access this kind of dynamic content information. It must be noted, however, that the caliber of dynamic visualizations does vary significantly across educational settings and applications. Note that a given visualization could be considered less-than-ideal for numerous reasons such as: being awkwardly constructed thus causing a focus on less relevant relationships (Fischer, Lowe & Schwan, 2008; Lowe, 2003), unrelated to the instructional content (e.g., decorational; Höffler & Leutner, 2007), or even being too complex despite being relevant (Lowe, 2004), to name a few. In these situations, MODSA might also play an additional role, namely the ability to decipher and extract information that is contained within a less-than-ideal visualization. For example, learners sometimes segment complex visualizations into smaller meaningful units when attempting to learn (Lowe, 2004). The unfortunate by-product of this type of segmentation is a reduced ability to integrate across segments. Higher MODSA might permit learners to maintain and integrate these isolated units, due to their enhanced ability to integrate temporal and visuospatial elements. Thus, it is possible that MODSA is not only useful for building internal dynamic mental representations, but also breaking down external dynamic representations (cf. Lowe & Boucheix, 2017, this volume). Future work is necessary to validate whether this is in fact the case.

Given that the relationship between WOMSA and learning through visualizations has been somewhat well established by previous research (Hays, 1996; Hegarty & Sims, 1994; Hegarty & Steinhoff, 1997; Höffler & Leutner, 2011; Koroghlanian & Klein, 2004; Mayer & Sims, 1994), it may seem curious that no role was seen for WOMSA in the plate tectonic study. When MODSA and WMC were taken into account, WOMSA failed to predict any unique variance in learning, and also failed to interact with visualizations in any way to predict how well learners understood plate tectonics. A tentative explanation is that by assessing all three aptitudes (WOMSA, MODSA and WMC) in this work, the independent role of each could be seen more clearly. Because MODSA and WOMSA are generally correlated, it is entirely possible that overlapping variance usually attributed to WOMSA was instead attributed to MODSA here, as it is again most relevant for learning within a dynamic domain, and also from dynamic visualizations, thus leaving little unique variance to be accounted for by WOMSA. When this content domain demand is removed, however, as was the case in the Irish Potato Famine study, MODSA then appears to take a back seat to WOMSA, and the relationship between WOMSA and learning from visualizations returns consistent with other research.

These results thus offer some insight from an individual differences perspective into why dynamic visualizations may sometimes fail to benefit learning. The results suggest that dynamic visualizations are most likely to facilitate learning under a specific set of conditions: when the topic and subject matter requires dynamic simulation for comprehension, and when the reader lacks MODSA. Although in these studies no harm was seen from providing dynamic visualizations in other conditions, there is some evidence from other work that suggests that there may be cases where animations can cause detriments in performance (Tversky, Morrison, & Bétrancourt, 2002). One class of concerns comes from studies on *seductive details* in which interesting illustrations or animations could cause readers to devote less attention to processing the ideas from the text (Harp & Mayer, 1997; Sanchez & Wiley, 2006; Wiley, Ash, Sanchez, & Jaeger, 2011). Another class of concerns arises from the subjective sense of fluency that readers may perceive after viewing a diagram or animation. Although visualizations can be a powerful tool for conveying a system of relations, they have also been shown to cause *illusions of comprehension* in which readers report having understood concepts better than they actually have (Jaeger & Wiley, 2014; Serra & Dunlosky, 2010; Wiley, 2003). For both of these reasons, further research that can help delineate the specific conditions under which dynamic visualizations are actually effective at improving learning is critical.

In conclusion, these studies have highlighted the benefits of assessing individual differences in learner characteristics when instructing in a visuospatial domain, and more specifically, while using dynamic visualizations. By incorporating an assessment of MODSA, educators will be able to more accurately tailor or scaffold the presentation of visual information so that it best meets the needs of the target population of learners. This research suggests that dynamic visualizations are most useful under constrained circumstances, such as when required by both the content domain *and* the needs of the learner themselves.

Acknowledgements Portions of this work were supported by the APA dissertation research award to the first author.

References

Ainsworth, S., & Th Loizou, A. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science, 27*, 669–681.

Berney, S., & Bétrancourt, M. (2017). Learning three-dimensional anatomical structures with animation: Effects of orientation references and learners' spatial ability. In R. Lowe & R. Ploetzner (Eds.), *Learning from dynamic visualization – Innovations in research and application*. Berlin: Springer (this volume).

Black, A. A. (2005). Spatial ability and earth science conceptual understanding. *Journal of Geoscience Education, 53*, 402–414.

Boucheix, J. M., & Schneider, E. (2009). Static and animated presentations in learning dynamic mechanical systems. *Learning and Instruction, 19*, 112–127.

Bower, G. H., & Morrow, D. G. (1990). Mental models in narrative comprehension. *Science, 247*, 44–49.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor analytic studies*. New York: Cambridge University Press.

Carter, C. S., LaRussa, M. A., & Bodner, G. M. (1987). A study of two measures of spatial ability as predictors of success in different levels of general chemistry. *Journal of Research in Science Teaching, 24*, 645–657.

Center for Educational Technologies. (1997). Volcanoes and the Earth. In Exploring the environment. Retrieved from http://www.cotf.edu/ete/modules/volcanoes/volcano.html.

ChanLin, L. J. (1998). Animation to teach students of different knowledge levels. *Journal of Instructional Psychology, 25*, 166–175.

ChanLin, L. J. (2000). Attributes of animation for learning scientific knowledge. *Journal of Instructional Psychology, 27*, 228–238.

Chi, M. T., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science, 13*, 145–182.

Contreras, M. J., Colom, R., Hernandez, J. M., & Santacreu, J. (2003). Is static spatial performance distinguishable from dynamic spatial performance? A latent-variable analysis. *The Journal of General Psychology, 130*, 277–288.

Contreras, M. J., Colom, R., Shih, P. C., Alava, M. J., & Santacreu, J. (2001). Dynamic spatial performance: Sex and educational differences. *Personality and Individual Differences, 30*, 117–126.

Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin and Review, 12*, 769–786.

Cooper, L. A. (1975). Mental rotation of random two-dimensional shapes. *Cognitive Psychology, 7*, 20–43.

Cooper, L. A., & Shepard, R. N. (1973). Chronometric studies of the rotation of mental images. In W. G. Chase (Ed.), *Visual information processing* (pp. 75–176). New York: Academic Press.

Craig, S. D., Gholson, B., & Driscoll, D. M. (2002). Animated pedagogical agents in multimedia educational environments: Effects of agent properties, picture features and redundancy. *Journal of Educational Psychology, 94*, 428–434.

De Beni, R., Pazzaglia, F., Gyselinck, V., & Meneghetti, C. (2005). Visuospatial working memory and mental representation of spatial descriptions. *European Journal of Cognitive Psychology, 17*, 77–95.

D'Oliveira, T. C. (2004). Dynamic spatial ability: An exploratory analysis and a confirmatory study. *International Journal of Aviation Psychology, 14*, 19–38.

Fincher-Kiefer, R. (2001). Perceptual components of situation models. *Memory and Cognition, 29*, 336–343.

Fincher-Kiefer, R., & D'Agostino, P. R. (2004). The role of visuospatial resources in generating predictive and bridging inferences. *Discourse Processes, 37*, 205–224.

Fischer, S. C., Hickey, D. T., Pellegrino, J. W., & Law, D. J. (1994). Strategic processing in dynamic spatial reasoning tasks. *Learning and Individual Differences, 6*, 65–105.

Fischer, S., Lowe, R. K., & Schwan, S. (2008). Effects of presentation speed of a dynamic visualization on the understanding of a mechanical system. *Applied Cognitive Psychology, 22*, 1126–1141.

French, J. W., Ekstrom, R. B., & Price, L. A. (1963). *Kit of reference tests for cognitive factors*. Princeton, NJ: Educational Testing Service.

Friedman, N. P., & Miyake, A. (2000). Differential roles for spatial and verbal working memory in the comprehension of spatial descriptions. *Journal of Experimental Psychology: General, 129*, 61–83.

Geiger, J. F., & Litwiller, R. M. (2005). Spatial working memory and gender differences in science. *Journal of Instructional Psychology, 32*, 49–58.

Haenggi, D., Kintsch, W., & Gernsbacher, M. A. (1995). Spatial situation models and text comprehension. *Discourse Processes, 19*, 173–199.

Halpern, D. F., Benbow, C. P., Geary, D. C., Gur, R. C., Hyde, J. S., & Gernsbacher, M. A. (2007). The science of sex differences in mathematics. *Psychological Science in the Public Interest, 8*, 1–51.

Hannus, M., & Hyönä, J. (1999). Utilization of illustrations during learning of science textbook passages among low-and high-ability children. *Contemporary Educational Psychology, 24*, 95–123.

Harp, S. F., & Mayer, R. E. (1997). The role of interest in learning from scientific text and illustrations: On the distinction between emotional interest and cognitive interest. *Journal of Educational Psychology, 89*, 92–102.

Hays, T. A. (1996). Spatial abilities and the effects of computer animation on short-term and long-term comprehension. *Journal of Educational Computing Research, 14*, 139–155.

Hegarty, M. (1992). Mental animation: Inferring motion from static diagrams of mechanical systems. *Journal of Experimental Psychology: Learning, Memory and Cognition, 18*, 1084–1102.

Hegarty, M., & Sims, V. K. (1994). Individual differences in mental animation during mechanical reasoning. *Memory & Cognition, 22*, 411–430.

Hegarty, M., & Steinhoff, K. (1997). Individual differences in use of diagrams as memory in mechanical reasoning. *Learning and Individual Differences, 9*, 19–44.

Hegarty, M., Crookes, R. D., Dara-Abrams, D., & Shipley, T. F. (2010). Do all science disciplines rely on spatial abilities? Preliminary evidence from self-report questionnaires. In *Spatial Cognition VII* (pp. 85–94). Berlin: Springer.

Höffler, T. N. (2010). Spatial ability: Its influence on learning with visualizations – A meta-analytic review. *Educational Psychology Review, 22*, 245–269.

Höffler, T. N., & Leutner, D. (2007). Instructional animation versus static pictures: A meta-analysis. *Learning and Instruction, 17*, 722–738.

Höffler, T. N., & Leutner, D. (2011). The role of spatial ability in learning from instructional animations – Evidence for an ability-as-compensator hypothesis. *Computers in Human Behavior, 27*, 209–216.

Hunt, E., Pellegrino, J. W., Frick, R. W., Farr, S. A., & Alderton, D. L. (1988). The ability to reason about movement in the visual field. *Intelligence, 12*, 77–100.

Jackson, D. N., Vernon, P. A., & Jackson, D. N. (1993). Dynamic spatial performance and general intelligence. *Intelligence, 17*, 451–460.

Jaeger, A. J., & Wiley, J. (2014). Do illustrations help or harm metacomprehension accuracy? *Learning and Instruction, 34*, 58–73.

Jaeger, A. J., Jarosz, A.F., & Wiley, J. (2014, November). Know when to hold em, know when to fold em: WMC and spatial reasoning. Poster presented at the 2014 Annual Meeting of the Psychonomic Society, Long Beach.

Just, M. A., & Carpenter, P. A. (1985). Cognitive coordinate systems: Accounts of mental rotation and individual differences in spatial ability. *Psychological Review, 92*, 137–172.

Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The generality of working memory capacity: A latent variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology: General, 133*, 189–217.

Koroghlanian, C., & Klein, J. D. (2004). The effect of audio and animation in multimedia instruction. *Journal of Educational Multimedia and Hypermedia, 13*, 23–45.

Law, D. J., Pellegrino, J. W., & Hunt, E. B. (1993). Comparing the tortoise and the hare: Gender difference and experience in dynamic spatial reasoning tasks. *Psychological Science, 4*, 35–40.

Loftus, G. R., & Harley, E. M. (2004). How different spatial-frequency components contribute to visual information acquisition. *Journal of Experimental Psychology. Human Perception and Performance, 30*, 104–118.

Lowe, R. K. (2003). Animation and learning: Selective processing of information in dynamic graphics. *Learning and Instruction, 13*, 157–176.

Lowe, R. (2004). Interrogation of a dynamic visualization during learning. *Learning and Instruction, 14*, 257–274.

Lowe, R., & Boucheix, J.-M. (2017). A composition approach to design of educational animations. In R. Lowe & R. Ploetzner (Eds.), *Learning from dynamic visualization – Innovations in research and application*. Berlin: Springer (this volume).

Mayer, R. E. (1989). Systematic thinking fostered by illustrations in scientific text. *Journal of Educational Psychology, 81*, 240–246.

Mayer, R. E., & Gallini, J. K. (1990). When is an illustration worth ten thousand words? *Journal of Educational Psychology, 82*, 715–726.

Mayer, R. E., & Moreno, R. (1998). A split-attention effect in multimedia learning: Evidence for dual processing systems in working memory. *Journal of Educational Psychology, 90*, 312–320.

Mayer, R. E., & Moreno, R. (2002). Aids to computer-based multimedia learning. *Learning and Instruction, 12*, 107–119.

Mayer, R. E., & Sims, V. K. (1994). For whom is a picture worth a thousand words? Extension of a dual-coding theory of multimedia learning. *Journal of Educational Psychology, 86*, 389–401.

Meneghetti, C., De Beni, R., Pazzaglia, F., & Gyselinck, V. (2011). The role of visuo-spatial abilities in recall of spatial descriptions: A mediation model. *Learning and Individual Differences, 21*, 719–723.

Moreno, R., & Mayer, R. E. (1999). Cognitive principles of multimedia learning: The role of modality and contiguity. *Journal of Educational Psychology, 91*, 358–368.

Mumaw, R. J., Pellegrino, J. W., Kail, R. V., & Carter, P. (1984). Different slopes for different folks: Process analysis of spatial aptitude. *Memory and Cognition, 12*, 515–521.

National Research Council. (2006). *Learning to think spatially*. Washington, DC: The National Academies Press.

Newcombe, N. S., & Shipley, T. F. (2012). Thinking about spatial thinking: New typology, new assessments. In J. S. Gero (Ed.), *Studying visual and spatial reasoning for design creativity* (pp. 1–18). New York: Springer.

Palmiter, S., & Elkerton, J. (1993). Animated demonstrations for learning procedural computer-based tasks. *Human-Computer Interaction, 8*, 193–216.

Pellegrino, J. W., & Hunt, E. B. (1991). Cognitive models for understanding and assessing spatial abilities. In H. A. H. Rowe (Ed.), *Intelligence: Reconceptualization and measurement* (pp. 203–225). Mahwah, NJ: Lawrence Erlbaum Associates.

Pribyl, J. R., & Bodner, G. M. (1987). Spatial ability and its role in organic chemistry: A study of four organic courses. *Journal of Research in Science Teaching, 24*, 229–240.

Rieber, L. P. (1990). Using computer animated graphics with science instruction in children. *Journal of Educational Psychology, 82*, 135–140.

Rieber, L. P. (1991). Animation, incidental learning, and continuing motivation. *Journal of Educational Psychology, 83*, 318–328.

Rieber, L. P., Boyce, M. J., & Assad, C. (1990). The effects of computer animation on adult learning and retrieval tasks. *Journal of Computer-Based Instruction, 17*, 46–52.

Rinck, M. (2005). Spatial situation models. In P. Shah & A. Miyake (Eds.), *The Cambridge handbook of visuospatial thinking* (pp. 334–382). New York: Cambridge University Press.

Sanchez, C. A. (2012). Enhancing visuospatial performance through video game training to increase learning in visuospatial science domains. *Psychonomic Bulletin and Review, 19*, 58–65.

Sanchez, C. A., & Branaghan, R. J. (2009). The interaction of map resolution and spatial abilities on map learning. *International Journal of Human-Computer Studies, 67*, 475–481.

Sanchez, C. A., & Wiley, J. (2006). An examination of the seductive details effect in terms of working memory capacity. *Memory & Cognition, 34*, 344–355.

Sanchez, C. A., & Wiley, J. (2010). Sex differences in science learning: Closing the gap through animations. *Learning and Individual Differences, 20*, 271–275.

Sanchez, C. A., & Wiley, J. (2014). The role of dynamic spatial ability in geoscience text comprehension. *Learning and Instruction, 31*, 33–45.

Schnotz, W., & Rasch, T. (2005). Enabling, facilitating, and inhibiting effects of animation in multimedia learning: Why reduction of cognitive load can have negative results on learning. *Educational Technology Research and Development, 53*, 1042–1629.

Schnotz, W., Böckheler, J., & Grzondziel, H. (1999). Individual and co-operative learning with interactive animated pictures. *European Journal of Psychology of Education, 14*, 245–265.

Serra, M. J., & Dunlosky, J. (2010). Metacomprehension judgments reflect the belief that diagrams improve learning from text. *Memory, 18*, 698–711.

Sibley, D. F. (2005). Visual abilities and misconceptions about plate tectonics. *Journal of Geoscience Education, 53*, 471–477.

Smith, G. A., & Bermea, S. B. (2012). Using students' sketches to recognize alternative conceptions about plate tectonics persisting from prior instruction. *Journal of Geoscience Education, 60*, 350–359.

Stumpf, H., & Eliot, J. (1995). Gender-related differences in spatial ability and the k factor of general spatial ability in a population of academically talented students. *Personality and Individual Differences, 19*, 33–45.

Tversky, B., Morrison, J. B., & Bétrancourt, M. (2002). Animation: Can it facilitate? *International Journal of Human-Computer Studies, 57*, 247–262.

Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., et al. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin, 139*, 352–402.

Wagner, I., & Schnotz, W. (2017). Learning from static and dynamic visualizations: What kind of questions should we ask? In R. Lowe & R. Ploetzner (Eds.), *Learning from dynamic visualization – Innovations in research and application*. Berlin: Springer (this volume).

Westelinck, K., Valcke, M., De Craene, B., & Kirschner, P. (2005). Multimedia learning in social sciences: Limitations of external graphical representations. *Computers in Human Behavior, 21*, 555–573.

Wiley, J. (2001). Supporting understanding through task and browser design. In L. R. Gleitman & A. K. Joshi (Eds.), *Proceedings of the twenty-third annual conference of the Cognitive Science Society* (pp. 1136–1143). Hillsdale, NJ: Erlbaum.

Wiley, J. (2003). Cognitive and educational implications of visually-rich media: Images and imagination. In M. Hocks & M. Kendrick (Eds.), *Eloquent images: Word and image in the age of new media* (pp. 201–218). Cambridge, MA: MIT Press.

Wiley, J., Ash, I. K., Sanchez, C. A., & Jaeger, A. (2011). Clarifying readers' goals for learning from expository science texts. In M. McCrudden, J. Magliano, & G. Schraw (Eds.), *Text relevance and learning from text* (pp. 353–374). Greenwich, CT: Information Age Publishing.

Wiley, J., & Sanchez, C. A. (2010). Constraints on learning from expository science texts. In N. L. Stein & S. Raudenbush (Eds.), *Developmental cognitive science goes to school* (pp. 45–58). New York: Routledge.

Wiley, J., Sanchez, C. A., & Jaeger, A. J. (2014). The individual differences in working memory capacity principle for multimedia learning. In R. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (2nd ed., pp. 598–619). New York: Cambridge University Press.

Wu, H., & Shah, P. (2004). Exploring visuospatial thinking in chemistry learning. *Science Education, 88*, 465–492.