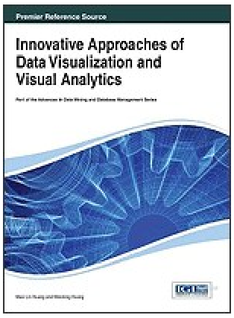

Innovative Approaches of Data Visualization and Visual Analytics

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Chapter 5: Cognitive Processes and Traits Related to Graphic Comprehension

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ABSTRACT

The subject of how visualizations and graphics in general can be understood by their viewers draws on theories from many fields of research. Such theories might address the formal structure of the visualization, the style and graphic design skills of the creator, the task driving the viewer's interaction with the visualization, the type of data being represented, or the skills and experiences of viewer. This chapter focuses on this last question and presents a set of interrelated constructs and viewer traits that contribute to (or interfere with) a viewer's ability to analyze a particular data visualization. The review covers spatial thinking skills, cognitive styles, mental models, and cognitive load in its discussion of theoretical constructs related to graphic comprehension. The review also addresses how these cognitive processes vary by age, sex, and disciplinary background–the most common demographic characteristics studied in relation to graphic comprehension. Together, the constructs and traits contribute to a diverse and nuanced understanding of the viewers of data visualizations.

INTRODUCTION

With the rise of big data initiatives in academia, industry, and the public sector, the need for rapid and reliable pattern and trend analysis that can be easily communicated to a broad audience has created a growing demand for data visualization. Data visualization as a practice is thus becoming increasingly global, being conducted by and distributed to increasingly diverse stakeholder groups. Users of visualizations may engage in a variety of tasks related to the visualization, including both low-level tasks like data foraging and high-level tasks like problem-solving and composing (Card, Mackinlay, & Shneiderman, 1999), but the success of user interactions with visualizations is dependent on a variety of factors.

Small-scale studies of individual visualizations or common visualization types have established user success at interpreting specific structural devices or artifacts (see work by Fabrikant and colleagues–e.g., [Fabrikant, Montello, Ruocco, & Middleton, 2004]) or selecting appropriate interaction strategies (Molitor, Ballstaedt, & Mandl, 1989), commonly using response rate and accuracy as evaluation metrics (Lam, Bertini, Isenberg, Plaisant, & Carpendale, 2012). These studies, however, are often designed to evaluate a specific graphic or a limited set of visualization properties. With the rise of visual analytics and the broadening of the audiences for visualizations, a detailed examination of the interaction between an individual's skills and success at a full complement of visualization interpretation tasks is crucial to the development of appropriate and successful data visualizations and visual analytics systems.

This chapter will synthesize theoretical work that focuses on the viewer and the cognitive processes and traits that have been found to be relevant to the comprehension and interpretation of visualizations or, more broadly, graphics. We focus on the user/viewer of data visualizations and visual analytic systems to the exclusion of the visualizations and systems themselves; this focus allows us to identify research outside of the fields of data visualization and visual analytics that nonetheless have bearing on the interpretation process.

THEORIES OF COGNITION RELATED TO GRAPHIC COMPREHENSION

Graphic comprehension is at its heart a process of sense making. Low-level perceptual processes interact with higher-level attentional, associative, and interpretational processes to influence what people see and understand. The following section omits the cognitive processes with broader applicability and focuses instead on a series of specific constructs developed and tested to explain some component of graphic comprehension. Research on spatial thinking skills helps to categorize independent sets of skills necessary for different types of graphic comprehension tasks, from mental rotation of objects to maintaining vivid imagery. Mental models research applies across those spatial skills to describe how individuals interacting with an expectable external system gain experience and expertise, which they use to guide future interactions. Finally, cognitive load theory addresses the context surrounding the visualization system, building of the individual's experiences to predict what sorts of modes of communication are likely to be helpful or confusing.

Categories of Spatial Thinking Skills

A major theoretical area related to graphic comprehension is that of spatial thinking. Research within the field of spatial thinking forms a foundation upon which graphic perception can be structured. The visual encodings and reference systems used by graphics and diagrams to represent data in a manner that can be interpreted depends heavily on the skills developed during interactions with the visible world around us. Spatial thinking as a construct incorporates many other, related concepts, including spatial literacy, spatial intelligence, mental maps, and so forth. Research on spatial thinking describes the general types of spatial reasoning competencies people can acquire as they develop (e.g., spatial perception, mental rotation) and provides a broader framework within which more specified theories of graphic perception can be placed.

Spatial thinking, though foundational to a variety of interpretive tasks, is not an undifferentiated pool of tasks and abilities. Linn and Petersen (1985) conducted a meta-analysis of spatial ability research and identified the following three categories of spatial ability: spatial perception, mental rotation, and spatial visualization. Spatial perception relates to the orientation of an individual's body in physical space. Mental rotation is the ability to manipulate two- or three-dimensional objects in mental space, correctly associating one view of the object with a view of the object after it has been rotated along one or more axes. Spatial visualization is a name for a variety of spatial ability tasks that require "multistep manipulations of spatially presented information" (Linn & Petersen, 1985). Spatial visualization can be thought of as a form of problem solving, and as is typical of problem solving, a correct solution can often be found via multiple methods (Downs & DeSouza, 2006); in the case of spatial visualization, tasks may incorporate spatial perception or mental rotation processes, among others.

Skills in the various types of spatial thinking have been found vary across individuals, however, helping us to further explore the relative independence of these skills. One attempt to identify independent spatial thinking skills comes from the literature on intellectual and cognitive styles. Though empirical evidence in its support is sparse, there is a commonly-held belief that learners have differing *intellectual styles* and that matching a learner's intellectual style to different teaching strategies will improve learning outcomes (Mayer, 2011a; Newcombe & Stieff, 2012). Within the umbrella term of intellectual styles there are the related terms of *cognitive*, *learning*, and *thinking* styles (Evans & Cools, 2011). Of particular interest to the study of graphic comprehension is the body of research on cognitive styles, which are often seen as more fixed and stable modes of processing within an individual than learning and thinking styles (ibid).

Within the cognitive styles literature is a long-standing discussion of visuospatial processing. Factor analysis of tests of both general intelligence and specific types of intelligences has identified powerful visual components to intelligence that emerge in response to visuospatial questions included in those tests (Blazhenkova & Kozhevnikov, 2010). Early acknowledgments of spatial intelligence and a visuospatial cognitive style postulated a bipolar interaction between verbal abilities and visual abilities (Blazhenkova & Kozhevnikov, 2009; Blazhenkova, Becker, & Kozhevnikov, 2011), but further elucidation of the nature of spatial intelligence and its relation to identified cognitive processes suggests that there are actually three, largely-independent dimensions to this cognitive style: verbal, visual-object, and visual-spatial (Blajenkova, Kozhevnikov, & Motes, 2006; Blazhenkova & Kozhevnikov, 2009, 2010; Blazhenkova et al., 2011; Kozhevnikov, Blazhenkova, & Becker, 2010; Kozhevnikov, Hegarty, & Mayer, 2002; Kozhevnikov, Kosslyn, & Shephard, 2005). This three-dimension model is known as the Object-Spatial-Verbal (OSV) cognitive style model.

Many of the tasks and tests related to spatial thinking (e.g., mental rotation, paper folding tests) have been strongly associated with the visual-spatial dimension of the Object-Spatial-Verbal (OSV) cognitive style model. Skills that are specifically visual-spatial include processing images sequentially and representing images schematically and in terms of object locations and spatial relationships (Blazhenkova & Kozhevnikov, 2009). Visual-object skills, however, had largely been ignored by intelligence tests and cognitive style researchers until the recent body of work by Kozhevnikov, Blazhenkova, and colleagues (Blazhenkova & Kozhevnikov, 2010). Visual-object skills include processing images holistically and maintaining vivid imagery with little conscious effort (ibid). Evidence suggests that visual-object tasks and functions are processed by a separate cognitive system than those associated with visual-spatial tasks (Kozhevnikov et al., 2010).

The independence of visual-object and visual-spatial skills, however, may not be the only notable distinction in spatial thinking skills. Another proposed independence separates visual-spatial skills like mental rotation and other "intraobject" skills from navigation, perspective taking, and other "interobject" skills (Newcombe, Uttal, & Sauter, in press). This additional division is supported by behavioral, linguistic, functional, and neurological evidence (ibid). While navigation has been largely absent from studies of individual differences, extensive theory in the development of navigation skills may soon lead to appropriate measures of these skills, enabling the further differentiation of visual-object, intraobject, and interobject components of spatial thinking.

Relevant for the study of graphic comprehension is an understanding of the tradeoff between the various spatial thinking systems. In the earlier bipolar verbal-visual model, it was assumed that increasing skills on the visual dimension of the cognitive style would diminish skills on the verbal dimension. The structure of the OSV cognitive style model presented verbal, visual-object, and visual-spatial skills as largely independent, allowing for the possibility that individuals can, in fact, have high (or low) achievement in all three types of intelligence at the same time. During the development of the self-report instrument that measures OSV cognitive style abilities–the *Object-Spatial Imagery and Verbal Questionnaire* (OSIVQ)–the researchers found that, among a sample of 625 college students and professionals, about 11% scored above average on all three dimensions and about 10% scored below average on all three dimensions (Blazhenkova & Kozhevnikov, 2009). The independence of these dimensions is consistent with findings that, just as mental rotation has been seen to improve with practice among those with initially low performance on this task (Lohman & Nichols, 1990), performance on one or more of the spatial thinking dimensions may be improved with training and experience (Newcombe & Stieff, 2012).

Gaining Domain Expertise

The development of this expertise in a particular spatial thinking task represents another potential focus area for research on graphic comprehension. As is true for other cognitive processes, the primary mechanism by which individuals gain expertise in graphic comprehension is by repeated practice of the skills. This expertise results in several differences between novice users of data visualizations and expert user. One suggested difference is that the overlearning of particular tasks or stimuli will reduce cognitive load in those or related tasks by allowing automatic process of portions of the task or stimuli (Downs & DeSouza, 2006). (Cognitive load will be addressed more specifically in the following section.) Experts also gain knowledge of meaningful (domain-specific) patterns in stimuli, allowing them to chunk perceptual information and solve problems more effectively. Finally, experts more easily interpret functional information in visual representations, beyond the simple spatial structures that are identified by novices. "While a novice can understand the spatial structure of a bicycle pump or heart from a diagram, only those with some expertise can grasp the functional and causal relations among the parts" (Downs & DeSouza, 2006).

One proposed description of the process of gaining domain expertise is the development of mental models. As a theoretical construct describing cognitive processes related to the simulation or prediction of external mechanisms (Howard, 1995; Hutchins, 2002; Johnson-Laird, 1983; Mantovani, 1996; Norman, 1983; Payne, 2003; Rumelhart, 1984), mental models are widely studied by researchers in many fields, including psychology, cognitive science, human-computer interaction, and information visualization. As such, the mental models construct has undergone redefinition and reification for many decades by these various communities. Recent literature commonly identifies two camps of mental models researchers: those who approach mental models "literally" and those who approach them "figuratively" (Rips, 1986).

A literal approach to mental models uses the term to refer to the structure of the mental model, or how representations are actually constructed and stored, and is epitomized by the early work of Johnson-Laird (1983). "A mental model is the representation of a limited area of reality in a format which permits the internal simulation of external processes, so that conclusions can be drawn and predictions made" (Molitor, Ballstaedt, & Mandl, 1989). This literal mental model might also be called an internal representation (Liu & Stasko, 2010) and is hypothesized to be a detailed representation, analogous to some real-world system or object, held in working memory and serving as an input to mental operations or simulations.

The construct of mental models has been adapted from this foundational psychology literature to the Human-Computer Interaction (HCI) and visualization domains in an attempt better to understand how individuals structure interactions with systems that have semantic organization and, often, dynamic components (Payne, 2003). A secondary, more "figurative" definition of mental models thus emerged and took hold in HCI and similar fields. The alternative use of mental models is a more simplified theory of how a system (whether it be mechanical, behavioral, social, etc.) is organized or will react to perturbations. This definition is less concerned with the structure of mental representations but instead focuses on the content of the representations, emphasizing "the role that world knowledge or domain-specific knowledge plays in cognitive activities like problem solving or comprehension" (Rips, 1986).

Instead of presuming the existence of detailed mental representations, figurative mental models research tends to treat mental models as a set of assumptions about the components and organization of a system that guide the strategies a user uses to approach interactions with the system. The construct presumes that users, rather than being able to store and operate on a detailed representation of a specific system, have a sort of sketch of how the system is organized that is based both on interactions with previous systems and on feedback from the current system. This sketch influences (but does not necessarily solely determines) the strategies a user adopts when working with or interpreting the system.

This transition from literal to figurative mirrors a similar transition in the history of Artificial Intelligence research, where early assumptions about literal representation, or "image-like replicas" (Ekbia, 2008) also gave way to logicist approaches assuming figurative, "word-like" (ibid) representations. The transition also responds to criticisms of the literal approach, which suffers from empirical studies that suggest that individuals find it very difficult to run mental simulations that accurately predict the outcome of external mechanistic processes (Rips, 1986). Because of the tight coupling between HCI and visualization research, the remainder of this discussion will focus on the figurative approach to mental models.

Norman's (1983) summary of the figurative mental models research in HCI introduces helpful terms for the ensuing discussion. Norman describes users' mental models as often inaccurate, and he relates how these inaccuracies can prompt either inefficient or at times incorrect responses to an interactive system. He also defines conceptual model, which is an expert's mental model that can be used as a benchmark for how the user's mental model should be structured, and system image, which encapsulates the interface, feedback, and documentation available to guide the user toward an appropriate mental model.

Mental models research is compelling for interaction and visualization researchers for a variety of reasons, including the need to explain and predict problematic interactions and the goal of improving system design to better reflect the needs and expectations of users. It has intuitive strength in that researchers are able to see patterns of interaction strategies across systems and can associate erroneous strategies with erroneous assumptions about the system. Because the construct can be summarized as the expectations people hold for interactions, mental models also have logical connections to empirical findings showing that expectations based on prior experience affect not only conscious decision-making behavior but also low-level perceptual processes (Mantovani, 1996; Rumelhart, 1984).

Researchers take two predominant approaches to operationalizing mental models. One category of empirical research uses open-ended questions to elicit from users verbal or pictorial representations of thought processes, which are then coded by experts as associated with a particular mental model. Another category of empirical research uses expert assessments of possible mental models as the inspiration for closed-ended questions, and user performance in terms of accuracy, response time, or recall is interpreted as indicative of a particular mental model.

The operationalizations developed and adopted in an attempt to capture the user's mental models themselves typically involve open-ended questions that ask users to describe either their problem-solving strategies for particular tasks or their organizational schemes for tasks or conceptual areas. Interview-based or talk aloud procedures are often employed to gather these data (e.g., Tullio, Dey, Chalecki, & Fogarty, 2007), but verbal representations may also be collected in written form (e.g., Greene & Azevedo, 2007). A recent trend toward graphical representations (Carpenter, Fortune, Delugach, Etzkorn, Utley, Farrington, & Virani, 2008) and sketches (e.g., Denham, 1993; Kerr, 1990; Rieh, Yang, Yakel, & Markey, 2010; Qian, Yang, & Gong, 2011; Zhang, 2008) attempts to address concerns that users may have difficulty verbalizing their own problem-solving strategies. After either verbal or graphical representations are collected from users, domain experts can code the representations as indicative of different mental models that may be more or less appropriate for the task.

The other major approach to mental models research involves instruments with closed-ended questions that have been designed to differentiate between different mental models in a particular domain. An example of a domain that has been very active in mental models research is the study of computer programming, and the mental models of novice programmers are frequently tested using accuracy/success rate on closed-ended questions (e.g., Dehnadi, Bornat, & Adams, 2009; Götschi, Sanders, & Galpin, 2003; Kahney, 1983; Ma, Ferguson, Roper, & Wood, 2007). A related technique involves the logging of a user's actions (including timing and errors or inefficiencies) while using an interactive system (e.g., Waern, 1990). In addition to typical measures of accuracy and reaction time, closed-ended questions can be used after a delay to measure recall of model-related information (Coulson, Shayo, Olfman, & Rohm, 2003).

Either open- or closed-ended instruments that measure mental models can be incorporated into larger research design to test different phenomena. For example, measures can be employed in a within-subjects, pre-test/post-test research design to measure changes in mental models over time. Another technique designed to improve mental models is to test the interaction between different types of instructional or priming materials and measures of mental models (e.g., Fein, Olson, & Olson, 1993; Ziemkiewicz & Kosara, 2008). A final manipulation that can be made to the research design to extend mental models research is to test both a learned task and a slight variation of that task to measure the transfer of a learned mental model to new domain (e.g., Clegg, Gardner, Williams, & Kolodner, 2006).

As powerfully intuitive as the construct is, however, there are two criticisms of mental models that bear review for visualization research. The first addresses flaws in the operationalizations described above. The second relates to the goal of applying mental models research to the design of interactive systems.

The first criticism of mental models questions whether the construct is actually being tested by current studies or if, instead, other theoretical constructs might better explain the results of these studies. For example, there are alternative theories of cognition, including propositions, networks, and production rules, that have been proposed and studied by psychologists for many decades and that each offer explanations of the empirical findings of (especially "literal") mental models research (Nardi & Zarmer, 1990; Rips, 1986). Many of the criticisms levied at literal mental models are doubly true for the figurative approach to mental models, however. The HCI community addressing mental models is even more likely to conflate success of performance with the existence of an identified mental model and not take into account propositional or production-rule explanations. Other similar criticisms relate to specific methodologies, such as the need to take into account differences of skill in verbalizing (Zhang, 2008).

The second relevant criticism of mental models has to do with the application of mental models research to the design of interfaces or visualizations. A common motivation for mental models research is the idea that knowing the users' existing mental models (particularly for a work task) allows a designer to correctly construct a system or visualization to best suit the user's needs. As Young (1981) suggests, "the appropriateness of a design is to be judged in terms of the match (i.e. mapping) between the Task and the Actions needed to perform it," a sentiment which focuses the work of designing an interface on identifying the users' primary tasks and then matching those tasks to actions that need to be taken in such a way as to optimize the interaction for those primary tasks. Norman (1983) despairs for perfect mental models, but he does nonetheless admonish designers to "develop systems and instructional materials that aid users to develop more coherent, useable mental models," highlighting the role of the system image in the development and activation of an appropriate mental model.

A criticism of this approach appears in Nardi and Zarmer (1990):

> To see the interface as a mechanism for translating thoughts is to completely miss the interaction between the user and the user interface, and the way in which the user interface itself can stimulate and initiate cognitive activity. Like other cognitive artifacts…a good user interface helps to organize and direct cognition - it is not a passive receptacle for thoughts emanating from an internal model, but plays an active role in the problem solving process. (Nardi & Zarmer, 1990)

This reminder from Nardi and Zarmer of the co-construction of activity urges designers of systems to avoid expecting "noiseless" transmission of information, perfect comprehension of interfaces. The data visualization is only one component of a larger problem solving process. Espousing a design agenda that presumes that noiseless transmission of information is possible risks trivializing both the role of the artifact and the agency of the user, which may prevent designers from benefiting from what is understood about the complexity of the socio-technical environment.

The construct of mental models, as a description of how a user stores information about and interprets environmental stimuli, has been studied in relation to both information visualization and interaction (e.g., Liu & Stasko, 2010; Nardi & Zarmer, 1990). The full system of graphic comprehension, however, includes not only the skills and expertise of the user as they relate to a particular graphic, but also the context in which the user encounters the graphic.

Graphics in Context

Certain temporary states–the context in which individuals attempt to make sense of graphics–may also have an impact on the ability to comprehend graphics. Many studies use the concept of cognitive load to identify conditions under which users will experience impairments to their ability to effectively process stimuli or complete operations. Cognitive load becomes particularly relevant to graphic perception when dealing with graphics in multimodal environments (Huang, Eades, & Hong, 2009; Mayer, 2002, 2011b; Mayer & Moreno, 1998, 2003; Mayer, Heiser, & Lonn, 2001; Moreno & Mayer, 1999; Pastore, 2009). Research on cognitive load addresses the cognitive mechanisms that regulate executive function and working memory.

Cognitive load theory is often applied to multimodal instructional environments in an attempt to understand how additional modes of communication (e.g., adding visuals to text) improve or impede comprehension of the instructional content (Mayer, 2002; Mayer & Moreno, 1998, 2003; Mayer, Heiser, & Lonn, 2001; Moreno & Mayer, 1999; Pastore, 2009). Cognitive load can affect three types of cognitive processing in multimodal instructional environments (Mayer & Moreno, 2003). Cognitive load during *essential processing* happens when the load is caused by making sense of the presented material. Cognitive load can also occur during *incidental processing*, when a cognitive process that is not essential but is primed by the learning task increases the load on the learner. Finally, cognitive load can be the result of *representational holding*, or "cognitive processes aimed at holding a mental representation in working memory over a period of time" (Mayer & Moreno, 2003).

Mayer and colleagues have identified many situations that increased cognitive load and have proposed solutions to situations that may result in the various categories of cognitive load (Mayer & Moreno, 2003). For example, essential processing demands have been hypothesized to result in increased cognitive load if a learner is being asked to process both text and visual information, which both employ visuospatial working memory during the organization phase of cognition (ibid). The proposed method of reducing cognitive load for this situation is to transfer verbal information to the audio channel–with or without moderate time compression (Pastore, 2009)–resulting in improved performance on the instructional task (Mayer, 2002; Mayer & Moreno, 1998, 2003; Moreno & Mayer, 1999). Other situations of increased cognitive load include: situations where the pace of instructional content exceeds the learner's pace for selecting, organizing, and integrating the content fully (i.e., essential processing demands in both visual and audio channels exceed capacity); situations where instructional material includes superfluous, high-arousal information (i.e., incidental processing competes with essential processing to exceed capacity); situations where instructional materials are designed in a confusing way, either by including redundant information or by misaligning visual content (where, again, incidental processing is competing with essential processing); and situations where working memory in one or both channels is being used to maintain some mental representation and is unable to meet the essential processing demands of the instructional task (Mayer & Moreno, 2003). For many of these types of cognitive load, suggested solutions involve redesigning the instructional materials, but several are also reduced when learners gain additional experience in certain types of processing (ibid).

Regardless of the presence of multiple modes of communication, users have more generally been found to have less success completing spatial tasks in situations of low automaticity (Downs & DeSouza, 2006). Automaticity is a response to overlearning; when a stimulus is encountered repeatedly, associated materials are recalled more automatically than those of novel stimuli. In terms of spatial thinking, an automatically-processed spatial visualization type (e.g., a bar chart) may successfully accompany the learning of new content because it does not increase cognitive load (i.e., it does not tax working memory). On the other hand, "[i]f the content and form of the map or graph are relatively unfamiliar, then too much working memory capacity is required to process both the unfamiliar form and the intended content of the representation" (Downs & DeSouza, 2006), and the visualization type may inhibit learning.

INDIVIDUAL TRAITS THAT INTERACT WITH GRAPHIC COMPREHENSION

Each of the constructs described above can be explored in connected with additional traits of individuals. Empirical evidence of systematic–but not intractable–differences allow us to make some predictions about how different groups of viewers may vary on comprehension measures. More than that, however, the study of the relationships between traits and cognitive processes provides us with additional resources for overcoming these differences and improving graphic comprehension for all groups of viewers.

Age

Age is one of the most frequently studied traits that interact with graphic perception (Blazhenkova et al., 2011; Downs & DeSouza, 2006; Kirsch & Jungeblut, 1986; Kozhevnikov et al., 2010; Lohman & Nichols, 1990). Research on several cognition theories highlight the ways that (particularly childhood) development relates to graphic perception. This section highlights how experience in spatial and spatialized environments and the transitions from child to adult and novice to expert relate to changes in perceptual strategies.

The interaction between age and cognitive process related to graphic comprehension is somewhat conflated with specific experiences in particular domains. The section on disciplinary background below focuses more directly on differences that have been observed across individuals with specific training in different disciplinary traditions, for example. As individuals age, they experience different types of stimuli and training situations at varying times and in varying contexts, but some generalities and regularities can be described to summarize the types of expertise individuals typically develop over time.

Basic skills related to spatial thinking are acquired gradually over the course of development. Early developmental theories ranging from a Piagetian assumption of a "blank slate" to later "nativist" proposals of core knowledge areas available from birth have been tempered and blended in a neoconstructivist perspective called *adaptive combination* (Newcombe, Uttal, & Sauter, in press). This perspective asserts that infants have a strong starting point for spatial development but continue to progress over time in response to interactions with the environment and symbolic systems, though at a pace more rapid than originally theorized by Piaget.

Preschool-aged children typically acquire skills in topological differentiation (*in*, *on*, *next to*, *between*, *open*, and *closed*; e.g., distinguishing a U from a circle) (Downs &DeSouza, 2006). During this developmental phase, however, children can make location-based judgments based on both relative, categorical information (e.g., relation to a landmark, containment within a region) and also more precise, metric information (measurable distances) in a manner similar to that used by adults. Additionally, "well before they enter preschool, children have mastered basic spatial relations in physical space, understanding…how to effect skilled movements in space" (Downs & DeSouza, 2006).

The onset of visual-spatial skills like mental rotation likely happens as early as the age of 4 to 5 years, and with appropriate training and testing may be undertaken by much younger infants (Newcombe, Uttal, & Sauter, in press). Such skills have been shown to increase rapidly from ages 10 to 14 (Blazhenkova et al., 2011)–though the increase is perhaps limited to students interested in science (Kozhevnikov et al., 2010)–and to improve rapidly with practice (Lohman & Nichols, 1990). Visual-object and verbal abilities have been found to increase sharply in early childhood and either remain stable or continue to increase slightly with age (Blazhenkova et al., 2011). Skills that are learned at one point in development, however, may decline without maintenance. Performance on visual-spatial tasks begins to decline around age 16 (Blazhenkova et al., 2011).

Over the early elementary school years, individuals continue to acquire additional spatial skills and strategies. Two categories of skills frequently studied are those involving projective and Euclidean concepts (Downs & DeSouza, 2006). Projective concepts include the ability to use point of view to predict the shape of the shadows cast by rotating objects or of cross-sections of 3D objects, as well as the successful use of alternate frames of reference to resolve such conflicts as misaligned "you-are-here" maps. Euclidean concepts are those that utilize concepts like Cartesian coordinate systems to represent spatial problems. Students also gradually develop skills in distinguishing shapes that differ in characteristics other than the topological relations mentioned earlier (e.g., a square from a trapezoid).

Related to the effects of age are the effects of education, regardless of any disciplinary specialization. An early attempt by the National Assessment of Education Progress to catalog literacy skills of young adults from ages 21 to 25 (Kirsch & Jungeblut, 1986) includes a type of literacy called "document literacy" – "the knowledge and skills required to locate and use information contained in job applications or payroll forms, bus schedules, maps, tables, indexes, and so forth." The document literacy tasks from the assessment instrument exhibit varying levels of difficulty, based on the number of features or categories of information required by the task or included as distractors in the document.

While at least 96% of all groups–varied by number of years of education–achieve document literacy at the lowest level (involving tasks like signing one's name on the social security card), proficiency drops rapidly for shorter-duration education groups as complexity increases. For tasks like locating data in a table and on a street map using two features, only 84% of all participants achieved proficiency, including only 31.5% of participants with zero to eight years of education and 83.4% of high school graduates. Increasing the number of features and the differences between question and document phrases, only 50% of high school graduates achieve proficiency at the next level of complexity. Less than 11% of high school graduates successfully completed the most complex task involving a match of six features to a bus schedule.

Skills in reading documents of all kinds, including those with spatial information displays, tend to increase over the course of aging and education to early adulthood, at least, but proficiency levels can vary dramatically depending on task complexity or other individual factors. As discussed in the earlier section on categories of spatial thinking skills, disparities in performance across individuals at different ages can often be reduced with appropriate training and testing (Newcombe & Stieff, 2012). Knowing the typical skill levels for particular age groups, however, may lead to improved design of visualizations, assessment materials, or instructional texts.

Sex

Differences across sexes have been identified in studies relating to many spatial thinking tasks. Though discussion of the mechanisms behind sex differences is outside the scope of this review, it has often been shown that these differences may be reduced to insignificance with training and practice in the skills of concern, suggesting that the differences are not biological in nature (Newcombe & Stieff, 2012). Without additional training, however, the following skills are regularly found to interact with the sex of the participant. Male participants tend to perform better on spatial perception and visual-spatial tasks–especially those involving mental rotation (Vandenberg & Kuse, 1978). Female participants, however, have been found to perform better on visual-object tasks and tasks that involve memory for spatial location (Blajenkova et al., 2006; Blazhenkova & Kozhevnikov, 2009, 2010; Blazhenkova et al., 2011; Downs & DeSouza, 2006). Different strategies may also exist without affecting performance. For example, women more frequently make reference to landmarks, whereas men more frequently use cardinal directions (Downs & DeSouza, 2006). Studies typically do not find an interaction between sex and verbal abilities (Blazhenkova & Kozhevnikov, 2009, 2010; Blazhenkova et al., 2011).

Disciplinary Background

Many studies of graphic perception have used disciplinary background to explore variation across individuals (Blazhenkova & Kozhevnikov, 2010; Burnett & Lane, 1980; Isaac & Marks, 1994). Training in sciences, arts, and even physiological fields relates to differences in graphic perception skills and has been used to identify experts in certain tasks related to data visualization and visual analytics. The causality of the relationship between visual skills and training in certain disciplines is not yet clear; it may be that early development of certain skills influences the pursuit of related disciplines, that the choice of discipline puts an individual through training that improves certain skills, or that some more complicated interaction between skills and training occurs. The early onset of both visual skills and individual differences in performance suggests that success with certain spatial skills may precede a related interest in Science, Technology, Engineering, and Mathematics (STEM) careers (Newcombe, Uttal, & Sauter, in press).

Traditional mental rotation studies identified a link between that spatial reasoning task and individuals with training in mathematics and sciences. Less attention, however, has been paid to the visual skills that are well developed by individuals with training in visual arts and design (i.e., visual-object skills). These two groups of disciplines with known relations to visual abilities were thus used for ecological validity testing for the OSV model (Blazhenkova & Kozhevnikov, 2010). As expected, visual-spatial abilities were shown to be highly developed in individuals with training in sciences and mathematics. Additionally, after two years of college instruction, these abilities also improved to a greater degree among this population than among students with other specializations (Burnett & Lane, 1980). Visual-object abilities have conversely been shown to be highly developed in individuals pursuing visual arts and design (Blajenkova et al., 2006; Blazhenkova & Kozhevnikov, 2009, 2010). High vividness of imagery has likewise been found in physical education students, elite athletes, air traffic controllers, and pilots (Isaac & Marks, 1994). Furthermore, disciplinary specializations are found to exhibit stronger interactions with visual-object and visual-spatial abilities than gender (Blajenkova et al., 2006; Blazhenkova & Kozhevnikov, 2009, 2010).

Other Related Traits and States

Though the research is often done with a different purpose in mind or in a limited capacity, the following studies provide evidence of other traits and skills that interact with graphic comprehension and suggest additional avenues of research that would help form a more complete understanding of individual differences in this area.

Handedness, both of study participants and of their immediate family members, has been suggested as an indication of brain organization, and in some studies, presence of Familial Sinistrality (FS) interacts with sex, spatial experience, or specialization to improve performance on mental rotation tasks (Casey, Winner, Brabeck, & Sullivan, 1990).

Another trait of note may be trait curiosity. One study (Risko, Anderson, Lanthier, & Kingstone, 2012) found that for users viewing images while using an eye tracking system, trait curiosity was correlated to one eye movement measure (number of regions visited). If trait curiosity is related to the number of regions the eyes attend to in an image, there may be implications for how viewers explore novel graphics, particularly in a "free-viewing" setting where no task has been assigned.

Insofar as poor movement control (clumsiness) might be considered a trait (or, perhaps, a condition), clumsy children have been found in one study to have weaker abilities in imagery and movement vividness, perhaps owing to the need for accurate images for negotiation of spatial environments (Isaac & Marks, 1994).

Finally, in terms of state factors for graphic comprehension, mood (slight positive or negative affect) may well play a role in visual processing. Two studies by (Gasper & Clore, 2002) examined how affect related to visual memory and global-local processing of visual stimuli. In each study, positive affect was shown to correlate with global (holistic) processing of visual stimuli, including more accurate reproduction of an image from memory and attentional focus on global (composite) structures within an image. Negative affect had the reverse effect, reducing ability to reproduce an image from memory and focusing attention on component parts of an image. While the authors refer to these results using a "global vs. local frame" context, the nature of the tasks used to measure global and local processing make the results comparable to those of visual abilities studies. The implication would be that positive affect has some relationship to visual-object ability and negative affect to visual-spatial ability, a sentiment that may be echoed by the findings of Blazhenkova and Kozhevnikov (2010) that associate visual-object ability with emotion. Further research on emotion and the OSV model and a comparison between global-local measures and standard object-spatial measures would help to clarify the relationships between these areas of study.

CONCLUSION

Individuals employ many skills and strategies that influence how graph comprehension processes are carried out. This chapter has provided a review of several theories of cognition and individual traits that have been shown to be relevant for individuals engaged in the perception of graphics. Many of the constructs and traits presented, however, are still in their early stages of empirical study. The precise nature of the relationship between visual-object, visual-spatial, and navigation skills has not yet been identified. Likewise, the types of training necessary to reduce differences across age, sex, and disciplinary groups will need extensive investigation and, perhaps, customization for different data visualization forms and visual analytics systems.

Because of the rapidly widening audience for relatively new and specialized visualization types, the common practice of designing visualizations based on the understanding of expert users or the limited scope of a single task environment may contribute to a suboptimal interpretation environment for users. The processes related to graphic comprehension range from the most fundamental perceptual processes to the most complex sociotechnical evaluations, and viewers not only interact with the constructed image but also operate within a broader task context. A particularly complicated focus for research, graphic comprehension is also a high stakes topic, potentially influencing both the growth of interest in STEM careers and also the ability of STEM research to reach a broad, public audience. Evidence confirms that it is unwise to be complacent about graphic comprehension; significant differences do exists between different groups of viewers, and those differences can cascade through many layers of cognitive processing. The design of data visualization and visual analytics systems must reflect our growing understanding of both the skills of users and also their capacity for improvement in those skills, given well-designed training and systems.

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KEY TERMS AND DEFINITIONS

(Data) Visualization: The term visualization can refer both to the process by which data are visualized and to the graphic that results from that process. In this literature review, the latter use is predominant. Though often used interchangeably with graphic as described above, visualization is used when a more constrained concept is appropriate and when the theories or methodologies involved are strongly tied to the Data Visualization field.

Comprehension: For the purposes of this review, comprehension refers to the process by which an individual makes sense of a graphic. Individuals may bring many experiences, skills, and strategies to bear in the process of comprehension, including the individual's exposure to prior images or related systems of analysis or notation, the individual's assumptions about the image's designer and his/her intentions, the individual's understanding of the content area related to the image, the individual's cultural background, etc. Comprehension is acknowledged to be an active co-construction of meaning between an individual, an image, a social context, and a task environment.

Graphic: Typically used in noun form (e.g., "graphic comprehension"), this term refers to a constructed image or visual representation in general. It is used somewhat interchangeably with visualization throughout this literature review because the review often covers literature that extends to graphics in general. The adjective form is typically graphical (e.g., "graphical devices").

Trait: In the context of psychology processes, traits are persistent characteristics of individuals (e.g., sex, handedness), rather than transient or malleable states (e.g., fatigue, inexperience).

Viewer: The viewer is an individual who is interacting with a particular visualization or graphic.