Adjustable Properties of Visual Representations: Improving the Quality of Human-Information Interaction

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Complex cognitive activities, such as analytical reasoning, problem solving, and sense making, are often performed through the mediation of interactive computational tools. Examples include visual analytics, decision support, and educational tools. Through interaction with visual representations of information at the visual interface of these tools, a joint, coordinated cognitive system is formed. This partnership results in a number of relational properties—those depending on both humans and tools—that researchers and designers must be aware of if such tools are to effectively support the performance of complex cognitive activities. This paper presents 10 properties of interactive visual representations that are essential, relational, and whose values can be adjusted through interaction. By adjusting the values of these properties, better coordination between humans and tools can be effected, leading to higher-quality performance of complex cognitive activities. This paper examines how the values of these properties affect cognitive processing and visual reasoning, and demonstrates the necessity of making their values adjustable—all of which is situated within a broader theoretical framework concerned with human-information interaction in complex cognitive activities. This framework can facilitate systematic research, design, and evaluation in numerous fields including information visualization, health informatics, visual analytics, and educational technology.

Introduction

Scientists, analysts, decision makers, doctors, and other knowledge workers are constantly engaged in activities that involve complex cognition (Sternberg & Ben-Zeev, 2001). Such activities include, among others, decision making, problem solving, sense making, planning, analytical reasoning, and learning. To emphasize both the active and the complex nature of such activities, they can be referred to as complex cognitive activities (see, e.g., Baddeley, 2007; Sedig & Parsons, 2013). Two essential characteristics of complex cognitive activities can be identified: 1) the use of complex psychological processes—such activities rely on the combination and interaction of more elementary processes such as perception and memory; and 2) the presence of complex conditions—the environment may be dynamic, the outcome of actions may be uncertain, objects or states may be only partially observable, and/or many variables may exhibit a high level of interdependence (Knauff & Wolf, 2010; Schmid, Ragni, Gonzalez, & Funke, 2011). Complex cognitive activities can be contrasted with simple cognitive activities. Examples of simple cognitive activities include perceiving and recognizing colors and reading and understanding words in a book. Examples of complex cognitive activities, on the other hand, are making sense of global climate change patterns, analyzing genomic data to discover unknown patterns, and making decisions about resource allocation and organizational strategies.

The performance of complex cognitive activities involves active and goal-directed information processing by human beings (Funke, 2010). This information processing consists of humans using and working with some given information to derive new information (Knauff & Wolf, 2010). That is, humans interact with information to support their information-intensive thinking processes that are focused on solving problems, making decisions, and performing other complex cognitive activities. In this paper, we refer to humans

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who interact with information to perform complex cognitive activities as *actors*. Using this term has a number of benefits over using other terms that are often used such as users, clients, or patrons. Such benefits include placing emphasis on the activity aspect of human-information interaction; situating interaction with information in the context of the performance of activities; and shifting the focus from the system to the person or people that are using the system (Fidel, 2012).

Nowadays, actors typically use interactive computational tools to mediate their interaction with information and to support their complex cognitive activities. Examples of such tools include information visualization, personal information management, visual analytics, knowledge discovery, and educational tools. This paper is concerned with all such tools that mediate human-information interaction (HII) and support complex cognitive activities. As these tools have different meanings and connotations depending on the context and discipline in which they are used, we will use the umbrella term Cognitive Activity Support Tools (CASTs) to encompass all such tools and to emphasize their role in supporting the performance of complex cognitive activities. CASTs have many components, including displays, sensors, and other input and output devices, storage mechanisms, algorithms for processing and manipulating information, and interfaces that connect to humans or to other machines. The component that is of primary concern in this paper is their visually perceptible information interface that serves as a meeting point between information and the human visual system. Such interfaces communicate and provide access to information through visual representations (VRs). Research in cognitive science has repeatedly demonstrated the fundamental role that VRs play in the performance of complex cognitive activities (see Kirsh, 2010; Zhang & Patel, 2006). For instance, research has demonstrated that certain types of VRs are more appropriate for some tasks and activities than for others (Peterson, 1996; Stenning & Oberlander, 1995).

Although not yet a prevalent endeavor in most disciplines concerned with VRs, such as information visualization and visual analytics, researchers in related fields have long been concerned with ontological analysis of their domains of research—i.e., analysis of their nature and structure, which involves, among other things, identifying concepts, categories, and entities, as well as their properties and relationships; conceptual modeling; clarifying subtle distinctions in terminology; distinguishing between essential and non-essential, abstract and concrete, and other ontological dichotomies; and constructing taxonomies to organize such entities, properties, concepts, and so on. For instance, researchers concerned with designing, evaluating, and modeling information systems have been aware of the need to identify and characterize ontological properties, and to generally engage in ontological analysis of their domains, for at least two decades (see, e.g., Wand & Weber, 1990). Scholars concerned with artificial intelligence and knowledge representation have also engaged in such research (e.g., Guarino, 1995). In a similar manner, the information systems and information science communities have long recognized and emphasized the importance of metadata (i.e., an ontological aspect of the domain) in conceptualization, design, evaluation, and in scientific discovery and communication. For example, Hert, Denn, Gillman, Oh, Pattuelli, and Hernández (2007) stress the integral role of metadata in conceptualization and design of information systems. While examining the importance of metadata in scientific communication and discovery, Willis, Greenberg, and White (2012) argue that discipline-specific metadata schemes have contributed to establishing artificial barriers to data discovery and reuse across disciplines, and, furthermore, such schemes interfere with interdisciplinary scientific progress. Just as the development of metadata schemes and the process of ontological analysis are of vital importance for research, design, evaluation, and communication in some well-established disciplines, ontological analysis of the domain that encompasses the intersection of humans, information, VRs, interaction, computational tools, and complex cognitive activities is necessary if we are to develop a more scientific approach to this area of research—a need suggested by multiple researchers (e.g., Green & Fisher, 2011; Thomas & Cook, 2005; Meyer et al., 2010). Moreover, to design and evaluate CASTs in a systematic fashion, models and frameworks that are based on such analyses are needed. Such models and frameworks bring order and coherence to the landscape of relevant concepts, constructs, hypotheses, and research findings, scaffold thinking for design and evaluation, and can enable consistent communication for interdisciplinary research.

One aspect of ontological analysis is concerned with identifying entities and properties that exist within a domain and, furthermore, determining whether such properties are essential or non-essential, intrinsic or relational (i.e., extrinsic). In this paper, we are mostly concerned with actors and VRs, rather than with other components of CASTs. More specifically, we are concerned with a particular subset of VRs—interactive VRs. We analyze interactive VRs to identify their essential properties that influence cognitive processes and visual reasoning. By focusing on essential properties, we are concerned with properties of interactive VRs that are *present in all instances*. In other words, all interactive VRs, regardless of the context in which they are instantiated, have such properties. In addition, we are not concerned with all essential properties of interactive VRs, but only those that influence cognitive processes and visual reasoning and whose values can be adjusted by actors through interaction. While all instances of a category have the same essential properties, it is the values of such properties that are variable. For example, the category of ‘human’ has certain essential properties, one of which is height. All instances of this category (i.e., all humans) have this property; however, in each instance the value of the height property is variable (e.g., 5 feet, 6 feet, and so on). In a similar manner, the category of ‘interactive VR’ has certain essential properties, each of which has a value. These values do not have to be quantitative, but can be qualitative or categorical as well. In any instance of this category (i.e., any VR) these properties are existent, and their values influence cognitive processes and visual reasoning of the actor. In the case of interactive VRs, the values can be adjusted. Because the ideal values in any instance are dependent on the actor (e.g., his or her cognitive abilities, preferences, and prior knowledge and experience), the complexity of the activity, and other contextual factors, these essential properties are also relational. That is, their ideal values (i.e., those best suited to a task or activity) do not depend only on VRs, but depend on both VRs and actors. To summarize, we are concerned with properties of interactive VRs that influence cognitive processes and are present in all instances (they are essential); the ideal values of these properties are dependent on both the actor and CAST (they are relational); and the values of these properties can be adjusted by the actor through interaction. To provide an example, density is a property of interactive VRs that is present in all instances, whether in the context of decision support and visual analytics, analytical reasoning and intelligence analysis, or any other combination of actors, activities, and contexts. In any given VR, the value of the density property exists along a continuum from low to high (e.g., a VR may have a very high degree of density with thousands of encoded entities, or a low degree with only a few entities). This value influences an actor's cognitive processing and visual reasoning with the encoded information (e.g., too many entities can result in perceptual overload and errors in reasoning). The actors should thus be able to adjust the value (e.g., decrease it so a lower number of entities are encoded). This last aspect is what makes the focus of this paper human-centered. Such an approach is indeed the core of human-centered informatics—researching, designing, and evaluating according to human cognitive and perceptual characteristics, being flexible rather than rigid, being context-sensitive and adaptable to human needs, and measuring effectiveness in terms of human rather than system benefits (Kulik, Kosara, Urquiza, & Wassink, 2007; Zhang, Patel, Johnson, Smith, & Malin, 2002). In this paper, 10 of these previously described properties are identified, characterized, and examined in the context of their cognitive influences and adjustment possibilities.

Although interactive VRs have numerous advantages over static VRs, previous research has shown that simply making VRs interactive does not ensure that CASTs will effectively support the performance of complex cognitive activities; rather, an additional necessary concern is the *quality of interaction*—also referred to as *interactivity* (e.g., see Sedig, Klawe, & Westrom, 2001; Liang, Parsons, Wu, & Sedig, 2010). Sedig, Parsons, Dittmer, & Haworth (2013) have recently developed a framework that explicates many of the elements and factors that contribute to the quality of interaction between an actor and a visualization-based CAST, and which must be considered to ensure proper and optimal performance of complex cognitive activities. One of these identified factors is concerned with the range and availability of options that allow actors to adjust properties of the CAST to suit their needs and goals. In this paper we address this one aspect of interactivity partially (as we are concerned with only a subset of all such adjustable properties). This paper is part of a larger research plan aimed at establishing a comprehensive framework that can bring systematicity to research, design, and evaluation of CASTs. This comprehensive framework is named EDIFICE (Epistemology and Design of human-InFormation Interaction in complex Cognitive activitiEs). This paper presents a framework that complements other aspects of the EDIFICE framework, and can thus be considered a component of EDIFICE. We will henceforth refer to as EDIFICE-PVR, where PVR stands for Properties of Visual Representations. Although EDIFICE-PVR can be used as an independent framework, it is most useful when combined with other components of EDIFICE.

The rest of the paper is organized into five main sections as follows. The first two sections provide some conceptual and theoretical foundations by examining the concept of interactivity, the emergent nature of complex cognitive activities, the structure and process of CAST-mediated HII, and the role of interactive VRs in the performance of complex cognitive activities. The third section briefly examines some related work. The fourth section presents EDIFICE-PVR: its rationale and development, and a detailed treatment of each property in terms of its cognitive and perceptual influences. The fourth section provides an integrated scenario to demonstrate the utility of EDIFICE-PVR for systematic design and evaluation of CASTs. Finally, the fifth section provides a summary and discusses some potential future research directions.

Interactivity: Quality of Interaction

The concept of interactivity lacks a coherent and commonly agreed upon characterization (see Aigner, 2011; Sedig, Parsons, & Babanski, 2012; Sedig et al., 2013). One of the problems in discussing interactivity is that the terms 'interaction' and 'interactivity' are often used loosely and interchangeably. Although these two terms are similar, they are conceptually distinct. In this paper, interaction refers to the dialogue that takes place between an actor and information through the mediation of a CAST. Interactivity, however, by adding the suffix 'ity', denotes the *quality of the interaction*. This distinction is important—a tool may be interactive, but if the quality of interaction is not good, it will not effectively support complex cognitive activities. For example, an actor can interact with a VR of a chemical compound to make sense of a chemical reaction. As such a process involves a transformation from one state to another, it may take place in many different ways—it may be instantaneous or it may take place gradually; it may require one mouse click or may require a chain of events; it may or may not allow the actor to control certain parameters of the transformation; and so on. In each case, the interaction is the same: the actor is acting upon a VR to effect a transformation. The quality of the interaction, however, is what changes.

Another difficulty for discussing interactivity is that it is a complex and emergent construct. It is a construct in the sense that it is an abstraction for which there is no single, directly observable referent. It is complex in the sense that the factors that contribute to the construct are many, are dynamic, and are themselves complex (e.g., the human cognitive and perceptual system). Furthermore, it is emergent in the sense that it is the result of the interaction of multiple components and cannot be reduced to the properties of the components themselves. While performing complex cognitive activities, a connection is formed between an actor and a CAST that results in a joint, coordinated cognitive system (Brey, 2005; Kirsh, 2005; Parsons & Sedig, 2013b). Within this cognitive system, there is continuous and reciprocal causal influence between the actor and the CAST (Clark, 1998; Kirsh, 2005). Such a reciprocal causal influence gives rise to properties that are not reducible to its components in isolation. In other words, *interactivity is an emergent property of the cognitive system that is created by an interactive coupling between an actor and a CAST*.

The factors that contribute to the interactivity construct are many, and they can be examined at different levels of abstraction and granularity. At the micro-level, the manner in which the action and reaction components of a single interaction are operationalized affects the quality of interaction (see Liang et al., 2010; Sedig et al., 2013). At the macro-level, where multiple interactions are put together to perform tasks and activities, there are a number of factors that affect the quality of interaction. These include: the number and diversity of interactions that are available to the actor; the harmonious and reciprocal relationships among interactions; the appropriateness of interactions for given VRs, tasks and activities, and characteristics of actors; the types of interactions available to actors—whether interactions allow actors to access information, annotate information, modify existing information, insert new information, or any combination thereof; and, the range and availability of adjustability options that allow actors to adjust properties of the CAST to suit their needs and goals (see Sedig et al., 2013, for a more detailed examination of these micro- and macro-level considerations). The final consideration—regarding the range and availability of adjustability options—is the issue with which this paper is concerned.

An analogy may facilitate thinking about how adjusting the values of properties can affect the quality of interaction. Two people may interact with one another through verbal communication. When one person speaks, information is being communicated through speech—an auditory representation of information. The auditory information representation has a number of properties—volume, speed, pitch, clarity, language, and so on. These properties have values: volume can be high, low, or in between; clarity can be good, bad, or in between; language can be English, French, or some other language; and so on. Additionally, in this context these properties should be conceptualized as relational, as their ideal values are dependent on the listener. Although interaction may occur between the participants, it is the quality of the interaction that is critically important in terms of the efficacy of communication. A speaker may be mumbling or speaking quietly, for example, which would negatively affect the comprehension of the listener. In other words, the values of the volume and clarity properties are not suitable. It is possible, through extended effort and concentration, for the listener to comprehend the speaker. However, if the listener is given the ability to adjust some of the values of the properties—by requesting that the speaker speak louder and more clearly—the quality of the interaction is affected, and the efficacy of the communication is increased. Thus the interaction stays the same, but the interactivity changes. By giving control to the listener she can adjust the values of the properties to suit her contextual needs and facilitate comprehension.

While using CASTs, there is also a dialogue that is taking place. As previously mentioned, the efficacy of tools in supporting cognitive activities depends in part on the quality of this dialogue. In the context of this paper, this dialogue takes place through visual, rather than auditory, representations of information. This paper identifies ten properties of VRs that affect the performance of complex cognitive activities: appearance, complexity, configuration, density, dynamism, fidelity, fragmentation, interiority, scope, and type. Each of these properties has a value: the value of complexity may be high, low, or in between; the value of dynamism may be high, low, or in between; the value of type may be a tree diagram, a plot, or some other representational form; and so on. Just as the context in the situation described above is important—whether the conversation is taking place in a noisy environment, for example—and has an effect on the ideal values of the properties, so too the context in which complex cognitive activities take place is important.

Human-Information Interaction in Complex Cognitive Activities

Researchers interested in HII investigate the relationships between humans and information, rather than those between humans and technology. HII is a broad area of research, and scholars are interested in many different aspects of HII, including those related to information retrieval, foraging, sharing, and seeking; information visualization; personal information management; medical, health, and bio informatics; human-computer interaction; and information systems. Therefore, the focus of HII research varies according to the dominant discipline in which researchers are situated, and their pertinent research challenges, domains of application, methodologies, and underlying theoretical frameworks.

Complex Cognitive Activities as Emergent Phenomena

One of the challenges for HII researchers is to develop models and frameworks that characterize and explicate complex cognitive activities and how they are performed through the mediation of CASTs. Considering the complexity of the human cognitive system, the complexity of the activities, as well as the sophistication of modern computational tools, addressing such a challenge is a formidable endeavor. Other components of the EDIFICE framework have begun to address aspects of this research challenge. For instance, Sedig and Parsons (2013) have identified and characterized a number of complex cognitive activities, developed a model of how such activities emerge over time through interaction that occurs at multiple levels of granularity, and have developed a model of the structure and process of HII during the performance of complex cognitive activities (see also Parsons & Sedig, 2013b). As was discussed in the previous section, Sedig et al., (2013) have further characterized the structure of HII and have identified a number of micro- and macro-level elements and factors that contribute to overall interactivity when using interactive tools to support complex cognitive activities. To situate EDIFICE-PVR, these other components of the EDIFICE framework can be briefly summarized as follows.

Complex cognitive activities are hierarchical, embedded, and emergent. Activities typically include sub-activities, which include tasks and sub-tasks, which include actions and micro-level physical events such as mouse clicks and gestures. Complex cognitive activities emerge over time from the performance of micro-level events, actions, tasks, and sub-activities. For example, consider the use of a CAST to support making sense of a large body of information regarding a terrorist attack. In order to make sense of the structure and features of the information, an actor may perform a number of tasks, such as scanning phone records for specific dates or locations; identifying prominent individuals and their relationships; browsing a collection of photographs; and categorizing emails and phone calls. Each task may involve the performance of any number of lower-level actions. For instance, to identify prominent individuals and their relationships, the actor might filter names based on dates or other criteria, annotate photographs or emails to add meta-information, rearrange a list of names and dates, or translate information from a table to a node-link diagram. To complete any one of these actions, a number of micro-level events such as mouse clicks, finger swipes, or keystrokes may be required. Thus, a sequence of events, actions, subtasks, tasks, and sub-activities results in a trajectory through the cognitive activity space that eventually leads to the accomplishment of an overall activity. During the performance of such activities, actors deploy general, high-level strategies that include the performance of many tasks and low-level actions that help actors alter their information environment, and, as a result, transform and support their cognitive processes to gradually achieve the ultimate goals of an activity (Sedig & Parsons, 2013).

Structure and Process of Human-Information Interaction in Complex Cognitive Activities

In the context of using CASTs that mediate human-information discourse, there are many components that require consideration. These include, among others, the information, the internal workings of the CAST, the representation of information at the interface of the CAST, characteristics of the actor, and the reciprocal action that takes place between the actor and the represented information. Moreover, if a CAST is to fulfill its intended function, the relationships between each of these aforementioned components must be considered carefully. To facilitate conceptualization for research and design, we have, in previous work (see Sedig, Parsons, & Babanski, 2012), proposed a categorization of this discourse into five broad spaces: 1) information space, 2) computing space, 3) representation space, 4) interaction space, and 5) mental space.

Information space refers to the body of information with which an actor is interacting to perform an activity. The types of complex activities in which actors engage often require access to information from multiple domains. For example, an analyst may require demographic, historic, financial, and geographic information to make decisions regarding the distribution of resources. As CASTs can maintain and provide access to all kinds of information, actors can interact with information that is combined and blended from multiple sources and environments. Thus, the term information space refers to a body of information that contains any combination of entities, properties, or relationships—whether concrete, abstract, large, small, visible, or invisible, and from any possible combination of domains—with which actors access and interact through the mediation of CASTs to perform cognitive activities. Henceforth, for the sake of simplicity, the term 'information item' will be used to refer to any constituent of an information space, such as an entity, component, structure, property, relationship, or process. Many researchers limit their scope to either concrete information sources (e.g., as in scientific visualization) or abstract information sources (e.g., as in information visualization). The high-level approach of EDIFICE-PVR, however, is applicable to all sources of information. Cognitive and perceptual processes that are influenced by the properties of VRs are consistent regardless of the source of information. Consequently, EDIFICE-PVR is applicable to a wide variety of domains, including business, medicine, mathematics, economics, biology, history, physics, sociology, and library science. *Computing space* refers to the internal portion of the CAST, where information items are digitally represented, stored, and operated upon. Data cleaning, filtering, normalization, and other pre-processing procedures take place in computing space. Moreover, data mining and knowledge discovery techniques allow CASTs to assume an active information-processing role and become active participants in information processing for complex cognitive activities (see Parsons & Sedig, 2013b for more on this issue). *Representation space* refers to the space in which information is represented in visual form at the interface of a CAST. This space is comprised of VRs of items from the information space, as well as representations of action possibilities, controls, labels, and other elements that are not part of the information space. As digital information is not directly visible to actors, it is only through the representation space that actors access, interact with, modify, or insert information into the underlying information space. Research and design of representation space is concerned with, among other things, how information can be organized and displayed in visual forms, how representation and encoding techniques influence the performance of tasks and activities, and how VRs affect actors' perceptual and cognitive processing of information. *Interaction space* refers to the space in which actions are performed and subsequent reactions occur. This space is where there is a back-and-forth flow of information between an actor and a CAST. Research and design of interaction space is concerned with what actions can and should be made available to actors to operate upon VRs, the utility of such actions in the context of performing complex cognitive activities, and how actions and their reactions should be operationalized. *Mental space* refers to the space in which internal mental events and operations take place (e.g., apprehension, induction, deduction, memory encoding, memory storage, memory retrieval, judgment, classification, and categorization).

These spaces do not exist or operate in isolation. When an actor performs complex cognitive activities, the actor and CAST form a joint, coordinated cognitive system across which cognitive processing is distributed (see Clark, 2008; Kirsh, 2005; Sedig & Parsons, 2013). That is, some of the processing takes place in mental space, some is offloaded onto VRs and computational processes, and some takes place through interactions with VRs. A principled understanding of how to best distribute the load of information processing for different activities and actors is still an open research problem (see Parsons & Sedig, 2013b for further discussion of this issue). Figure 1 depicts the structure and process of CAST-mediated human-information interaction. Interaction is depicted as a cyclical process in which an actor perceives VRs, performs some mental operations, acts upon VRs, a reaction occurs (visibly in representation space and/or hidden within computing space), and then the cycle repeats itself.

Role of Interactive VRs in Performing Complex Cognitive Activities

By organizing and giving form to information, VRs give perceptual access to an underlying information space in such a way that there is a unity of meaning between the VR and the information—in other words, *from the perspective of the actor, the VR is the information* (Cole & Derry, 2005; Peterson, 1996; Zhang & Norman, 1994). Consequently, the design and use of VRs in CASTs requires careful consideration. When using VRs to assist with cognitive activities, an actor's external cognition is engaged (Scaife & Rogers, 1996). The partnership that is formed between internal mental processes and external representations provides a number of benefits for performing complex cognitive activities (see Kirsh, 2010; Sedig et al., 2013 for a discussion of some of these benefits). However, when VRs are static, actors may be forced to exert a great deal of mental effort in order to reason and think about the information. Complex cognitive activities take place over a span of time, where internal mental processes (e.g., categorizations, abstractions, memory encodings, and comparisons) are dynamic and involve constant assimilation and reorganization of information. Static representations do not readily share in and distribute this temporal and dynamic processing of information, and thus force more of the processing load onto internal mental processes. This lack of operational harmony creates a distance between the mental space of an actor and representation space. With the addition of interaction, however, this distance can potentially be bridged. If interaction is operationalized properly, a strong coupling can be formed between an actor and a CAST that provides better support for performing cognitive activities (see Brey, 2005; Clark, 1998; Hoc, 2005; Kirsh, 1997, 2005, 2010; Sedig et al., 2013).

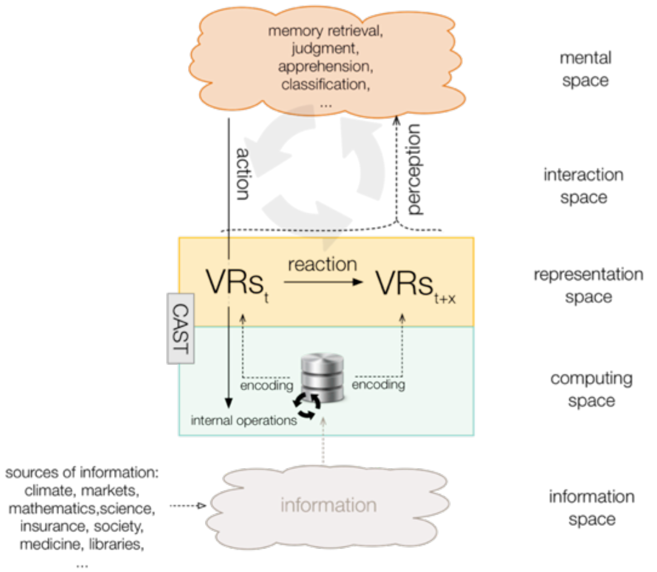


FIG. 1. The structure and process of CAST-mediated human-information interaction.

When CASTs are designed in a human-centered fashion, actors can dynamically adapt VRs to fit their cognitive and contextual needs. As a VR typically encodes only a subset of items from an information space, static VRs can force actors to make extrapolations regarding the items that are latent. In addition, with static VRs, the values of their properties are not adjustable, which can lead to an unnecessary burden being placed on actors' perceptual and cognitive faculties. When VRs are interactive, on the other hand, actors can fluidly and repeatedly act upon VRs to adjust them to best integrate them into their cognitive processing of the information. Consider Figure 2, which depicts a portion of an activity. The VRs at time t encode some items from the information space. The actor perceives the encoded information and performs an action (A_n). The reaction (R_n) results in the new state of the VRs (at time t+1), which encodes new items from the information space. The actor perceives the result (i.e., VR_{t+1}, as well as the process of transformation from VRs_t to VRs_{t+1}). Based on updated goals and strategies, the actor performs another action (A_{n+1}), and a reaction (R_{n+1}) ensues. The VRs at time t+2 now encode more items from the information space. In addition to accessing and working with items from the information space, such actions can adjust the values of the properties of the VRs. For instance, the appearance and density values of the VRs at time t+1 may not be appropriate for a task that an actor is trying to perform. By acting upon the VRs, the actor may adjust them to a more appropriate value, resulting in the VRs at time t+2. If a CAST is designed properly, this process of reciprocal action creates an operational harmony between mental space and the other spaces that increases interactivity and provides better support for the performance of complex cognitive activities.

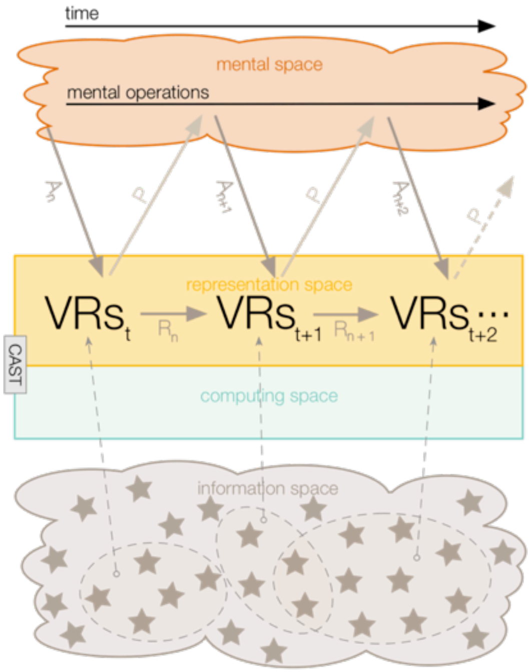


FIG. 2. The performance of a cognitive activity through information discourse that is mediated by a CAST

Related Work

Because of the inherently multidisciplinary nature of HII, researchers approach its study from different disciplines and areas of interest, such as those mentioned in the previous section. Only a small subset of such research, however, has taken a human-centered approach to HII at the intersection of complex cognition, human activities, and interactive technologies. Stasko and colleagues have been working on incorporating current theories and models from cognitive science research into information visualization research. For example, Liu, Nersessian, & Stasko (2008) have examined the use of distributed cognition as a theoretical framework for information visualization. Pike, Stasko, Chang, and O'Connell (2009) have strongly emphasized the importance of interaction in human insight and in the development of information systems. In addition, Liu & Stasko (2010) have developed a framework that combines research on mental models and reasoning with interaction and visualization, and have emphasized the primacy of the interplay between internal and external representations in the emergence of cognitive processes—an important area of research that requires much further examination. Sedig and colleagues have been investigating the role of interaction with VRs in supporting cognitive tasks and activities in the context of concept learning and distributed cognition (Sedig et al., 2001; Liang & Sedig, 2010a), visual and spatial reasoning (Sedig, Rowhani, Morey, & Liang, 2003; Liang & Sedig, 2010b), formation of cognitive maps (Sedig, Rowhani, & Liang, 2005), and other considerations for HII in complex cognitive activities (e.g., Fast & Sedig, 2005, 2011; Liang et al., 2010; Sedig & Liang, 2008; Sedig & Parsons, 2013; Sedig et al., 2013). Arias-Hernandez, Green, and Fisher (2012) have recently contributed a useful critique of the use of models of cognition in visual analytic research, and provide a loose framework for thinking about the material basis of cognition in visual analytics. Other contributions that have some general application to this area include Fidel's (2012) recent work on human-information interaction and cognitive work analysis, Kaptelinin and Nardi's (2012) recent work on activity theory in HCI, and Marchionini's (2008, 2010) work on information concepts and human-information interaction.

While more attention in general has been given to HII in recent years, existing work does not focus strongly on the particulars of how interactive VRs affect higher-order cognitive processes and complex cognitive activities. Although some existing research has examined how features of VRs influence human cognition, it has mostly been in the context of low-level perceptual and cognitive effects (e.g., Bertin, 1967; Tukey, 1977; Cleveland & McGill, 1984; Mackinlay, 1986; MacEachren, 1995; Nowell, 1997; Ware, 2008, 2012). Research that has examined some higher-level cognitive effects of VRs (e.g., Baker, Jones, & Burkman, 2009; Cheng, Lowe, & Scaife, 2001; Huang, Eades, & Hong, 2009; Shimojima, 1996; Zhang & Norman, 1994) has not attempted to systematically identify and characterize the essential properties of interactive VRs and describe how or why their values depend on both actors and CASTs. The need for such a research effort has been previously discussed and will not be repeated here. Following the next section, which presents the EDIFICE-PVR framework, there will be a more detailed comparison with some existing work in order to demonstrate the utility and unique contribution of EDIFICE-PVR.

The EDIFICE-PVR Framework

The presentation of EDIFICE-PVR in this section is divided into three subsections: 1) a discussion of the rationale for the development of EDIFICE-PVR; 2) a description of method of identification and development of the 10 properties; and 3) a detailed treatment of each property, including an examination of each one's cognitive and perceptual influences, and examples of CASTs that provide the ability to adjust the values of properties to support complex cognitive activities.

Rationale

In recent years, researchers have been emphasizing the need for more systematic development of theoretical frameworks (e.g., Chen, 2010; Fabrikant, 2011; Kaptelinin & Nardi, 2012; Keim, Kohlhammer, Ellis, & Mansmann, 2010). Kaptelinin and Nardi, for instance, state that "while understanding the structure and dynamics of purposeful human activities and identifying possibilities for their advanced technological support remain important issues, there is currently also *marked interest in frameworks that can provide an explanation of why and how certain subjective phenomena are taking place in situations surrounding the use of interactive technologies*." (2012, p. 47, italics added). One of the goals of EDIFICE is to develop a comprehensive framework that is applicable to all interactive tools that support the performance of complex cognitive activities through rich HII. In other words, the goal is to develop a general and comprehensive framework that can motivate research and design for a broad range of tools, tasks, actors, activities, platforms, techniques, and domains. As EDIFICE-PVR is one component of the EDIFICE framework, it adopts the same goal. Therefore, the properties of VRs that are presented as part of EDIFICE-PVR are generally applicable—whether to information visualization, visual analytics, or health informatics; whether using a laptop, desktop, tablet, or projection display; whether engaged in sense making, learning, problem solving, or decision making; whether in the context of biology, engineering, education, finance, or healthcare; whether the actor being young or old; and whether for a single actor or for multiple actors. Furthermore, as EDIFICE-PVR is concerned with human-information interaction, rather than human-technology interaction, it is not invalidated by technological change and is applicable across a wide variety of technologies and platforms.

Since EDIFICE-PVR is concerned with HII in the context of using CASTs, where cognitive activities are often complex and unstructured, to be most useful the properties must be embedded within a theoretical substrate that accounts for the complexities involved in the performance of such activities. In other words, simply identifying a number of properties—although potentially useful and welcome work—is of limited value if the properties are isolated from underlying theoretical frameworks and models that explain and describe how complex cognitive activities are performed. Thus, the initial task for developing EDIFICE-PVR was to situate it firmly within a broader theoretical framework, such that its conceptualization was consistent with other research concerned with HII, interactivity, and the performance of complex cognitive activities. Therefore, the theoretical foundations discussed above—which have been developed further in other components of the EDIFICE framework—were important in the conceptualization of the properties themselves, and in understanding how adjusting the values of properties fits into the overall performance of complex cognitive activities. Furthermore, the development of EDIFICE-PVR was guided by the conviction that syncretic and holistic research is much needed in this area, and by the assumption that there are indeed principles, features, processes, and relationships that are universal to all information spaces, domains, VRs, activities, and actors. As this domain is relatively young and underdeveloped, the explication and organization of fundamental concepts and their relationships that EDIFICE-PVR provides—e.g., VRs, information spaces, tasks, activities, and perceptual and cognitive influences of VRs—can stimulate further theoretical research and the development of frameworks that more fully describe, explain, and predict the performance of complex cognitive activities through CAST-mediated HII.

Identification and Development of Properties

Two processes shaped the identification and development of the properties of EDIFICE-PVR: 1) a broad survey of existing literature, and 2) a broad survey of existing CASTs. The survey of existing literature included research from the cognitive and learning sciences, perceptual psychology, information science, human-computer interaction, diagrammatic reasoning, interaction design, information design, and multiple visualization sciences. Based on numerous studies that have been done in these areas, it is well known that there are certain properties of VRs and visual information displays that affect perceptual processing of information, the speed with which decisions can be made, and other aspects of how humans process and think with information. Thus, in light of our goal to develop a general framework, our search was for properties of VRs that transcended particulars, and that, in the context of interactive VRs, could be adjusted to facilitate complex cognitive activities. We examined studies that had been conducted in the aforementioned areas to determine which of the findings were applicable to or could be generalized to interactive VRs. In addition to the aforementioned disciplines, we examined relevant literature from information graphics, communication design, information behavior, and other areas that are not necessarily concerned with interactive VRs and/or cognitive activities, but which could still provide valuable insights into the development of EDIFICE-PVR. During this process of literature review, we took note of the findings of studies that examined how features of VRs affected cognitive and perceptual processing, and examined existing established design and evaluation guidelines for VRs. We identified properties of VRs from literature that described the use, development, and evaluation of financial analytics tools, digital library interfaces, digital games, learning tools, visual analytic tools, and others.

The second process that shaped the identification and development of the properties was a systematic examination of 100 CASTs. To assure a wide sampling, we included tools from many domains. Although there is overlap, they can be roughly broken into 50 from visualization—information, data, geographic, scientific, medical and health visualization, and visual analytics; 25 from cognitive, educational, and learning technologies and digital cognitive games; 25 from personal information management, information retrieval, knowledge management, library science, and general productivity tools. A sampling of these is listed in Table A1 in the Appendix. While examining each tool, we identified the features of its VRs and kept a record of them. This process was similar to the process of pattern mining described by Dearden and Finlay (2006), in which invariant features of existing designs are identified and used to construct design patterns.

As these two mutually reinforcing processes were conducted in the context of developing a general framework, we categorized a number of features of VRs that were consistent across activities, domains, and actors. Eventually, these features were given a common label, and are now known by the properties that are presented in this paper. During the identification of properties of any phenomena, a desired level of abstraction must be determined. In the context of EDIFICE-PVR, the desired level of abstraction was based on three overlapping goals: 1) to provide a reasonable number of properties with which researchers and designers could work; 2) to ensure that the features of each property had a significant-enough effect on cognitive processes to warrant their own category; and 3) to maintain a consistent level of abstraction across all properties. Consider, for example, the *appearance* property (discussed in the following section). This property includes features such as hue, color, and opacity. Making each of these a separate property, however, would lead to a large, cumbersome list of properties that would likely be of limited value. In addition, these features alone do not seem to have a significant enough effect on cognitive processes to warrant a distinct property.

The two processes described above were intertwined and mutually beneficial. A continual identification of features, categorization of features, refinement of categorizations, and confirmation and testing between literature and CASTs eventually led to the properties that are now present. These are listed and briefly characterized below in Table 1. This systematic approach leads us to believe that the list of properties is fairly comprehensive; however, we do not claim that it is exhaustive, and, especially since this is an initial attempt at this particular area of research, it is possible that additions or refinements may occur in the future.

TABLE 1. Essential properties of interactive VRs, the values of which should be made adjustable to provide better support for the performance of complex cognitive activities

Property	Characterization
Appearance	aesthetic features (e.g., color and texture) by which information items are encoded in a VR
Complexity	degree to which encoded information items exhibit elaborateness and intricacy in terms of their quantity and interrelationships in a VR
Configuration	manner of arrangement, organization, and ordering of information items that are encoded in a VR
Density	degree to which information items are encoded compactly in a VR
Dynamism	degree to which encoded information items exhibit movement in a VR
Fidelity	degree to which information items are accurately encoded in a VR
Fragmentation	degree to which information items are broken up and discretized and encoded into non-continuous areas in a VR
Interiority	degree to which information items are latent and remain hidden below the surface of a VR, but are potentially accessible and encodable
Scope	degree to which the growth and development of information items are encoded in a VR
Type	form of a VR in which information items are encoded

A Note on the Justification and Validity of Particular Properties. It may appear, at a first glance, that some properties are simply different labels for the same phenomenon; after closer investigation, however, it should become evident that each property is distinct in its fundamental nature. Indeed, an attempt has been made here to demonstrate the intrinsic and distinct nature of each property. This distinctiveness does not preclude, however, situations in which there is a positive correlation between the values of two or more properties—situations in which increasing or decreasing the value of a property also increases or decreases the value of one or more other properties. In fact, it is often the case that adjusting the values of a property adjusts the values of other properties. As mentioned earlier, interactivity is an emergent property that results in part from the interaction between an actor and VRs—where such VRs, in practice, manifest the values of properties in a coalesced manner. While the values of each property in isolation may have an effect on cognitive processes, *the ultimate utility of this framework rests on a balance between analysis and synthesis of properties with respect to their influence on the performance of complex cognitive activities.*

In what follows, each property is accompanied by examples of CASTs that demonstrate and validate the existence of that particular property. The fact that a VR is dense, for instance, ontologically validates the density property; there is no need for experimenting to see whether or not the property exists. What is in need of experimentation, however, is the effect of the properties on the performance of cognitive activities. We have attempted below to validate these by referring to numerous empirical studies dealing with the perceptual and cognitive effects of VRs across a wide variety of activities, tasks, and domains.

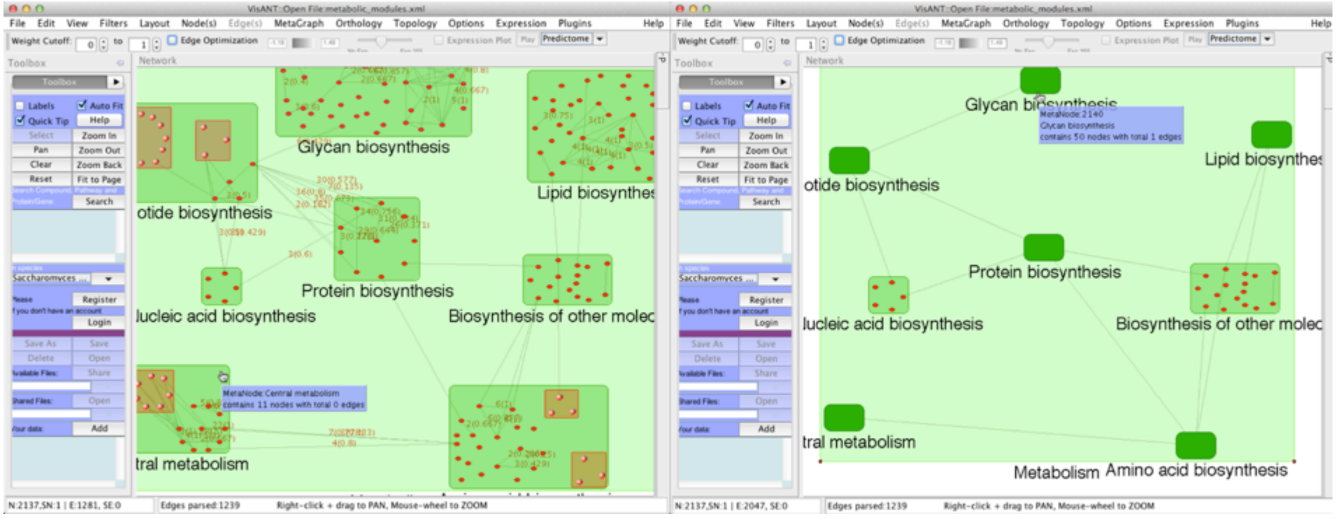
Appearance. Appearance refers to aesthetic features such as color, saturation, density, perspective, angle, orientation, and texture by which information items are encoded in a VR. Much research confirms that such features can significantly influence cognitive and perceptual processes (e.g., see Cleveland & McGill, 1984; Nowell, 1997; Ware, 2008, 2012). While performing visual search tasks, for instance, a distinct size or color can effectively make VRs stand out and thus increase speed of identification (see Wolfe, 1998). Additionally, actors often have their own appearance-related preferences that can help them perform tasks (Yi et al., 2007). For instance, actors may associate a particular shape or color with a particular meaning (see Sedig, Rowhani, Morey, & Liang, 2003). In addition, color can have very different semantics from one culture to the next (Ware, 2008). Not only do the values of appearance affect cognitive and perceptual processes, but the process of change between different appearance values can also have a significant effect (Ware, 2004).

Consider a sense-making activity in which an actor is trying to develop a mental model of a citation network. The appearance of a VR of the network could be adjusted in different ways depending on the task being performed. For instance, to identify all papers that share a common keyword or subject area, the actor could adjust the values such that the appropriate components of the VR are encoded with a particular color. To encode the relative strength of the connections between authors, the connections between them could be encoded with relative degrees of saturation. The most effective feature to adjust in any situation is dependent on the task. If actors are interested in tasks involving categorical properties of the information space, for example, color and texture are effective; for tasks involving ordinal properties, saturation and density are effective. Designers and evaluators must be aware of which of these features are best suited to which tasks (see, e.g., Cleveland & McGill, 1984; Nowell, 1997; Spence, 2007; Ware, 2008). However, as actors do not follow an algorithmic approach during the performance of complex cognitive activities, and strategies and goals are constantly revised and updated (see Sedig & Parsons, 2013), actors should be given the ability to adjust such values to best suit their task and mental state at any point during an activity.

Complexity. Complexity refers to the degree to which encoded information items exhibit elaborateness and intricacy in terms of their quantity and interrelationships in a VR. Complexity ranges in value from low (e.g., a single item with no encoded relationships) to high (e.g., thousands of items with many intricate pathways and connections among them). If complexity of VRs is not suitable for a task or an activity, a large burden can be placed on perceptual and cognitive faculties (Demetriadis & Cadoz, 2005; Moody, 2007). This burden can result in cognitive overload (Sweller, 2002) and has been shown to result in errors while performing tasks (e.g., see Huang, Eades, & Hong, 2009). Numerous studies have been performed confirming the negative effects of inappropriate values of complexity while performing tasks and activities. For example, Kumar & Benbasat (2004) found that as the complexity of graphs increased, the time taken to comprehend information also increased. Cruz-Lemus, Maes, Genero, Poels, & Piattini (2007) also found that as the complexity of a diagram increased, the length of time it took to understand the information also increased; in addition, they found that the efficiency with which the information was understood decreased. Huang et al. (2009) tested the effect of VR complexity on cognitive load. Their results similarly demonstrated that complexity had a significant effect on response time and on efficiency while performing tasks. However, they also measured the effect of complexity on the amount of mental effort required to complete a task, and found that more complex VRs required a significantly higher amount of mental effort to understand.

It may sometimes be the case that the increased perceptual and cognitive burden that high values of complexity place on actors is desirable. For instance, there is some evidence that high values of complexity can lead to increased planning (see Ainsworth and Peevers, 2003). It is possible that information is more likely to be committed to memory when VRs are more complex, whereas lower values of complexity allow actors to rely on visual search without engaging in deep mental processing of information. This type of forced deep engagement with information may be desirable for some types of CASTs, such as educational tools, but not others, such as tools for intelligence analysis (see also Parsons & Sedig, 2013b for more discussion of this topic).

Figure 3 shows a CAST, *VisANT* (http://visant.bu.edu), that supports visual data mining of multi-scale biological networks and pathways. One sub-activity that would be a likely component of any complex cognitive activity performed with this tool is sense making—an activity involving the development of a mental model of an information space about which one has insufficient knowledge (Klein, Moon, & Hoffman, 2006). Such an activity involves tasks such as identifying important items or pathways within the space, categorizing items based on similar features, and determining the hierarchical structure of the space. The complexity of the VR in Figure 3 (L), however, can make such tasks challenging. For instance, the number of items and the number of pathways among them can make the identification of important pathways very difficult due to cognitive and perceptual load. Figure 3 (R) shows how the actor can, through interaction, collapse a number of nodes into their metabolic modules to facilitate identification of high-level pathways within the network. As the actor progresses in the sense making activity, she can repeatedly collapse and expand VRs to dynamically adjust and develop her mental model of the information space.



MetaNode: Central metabolism
contains 11 nodes with total 0 edges

MetaNode:2140
Glycan biosynthesis
contains 50 nodes with total 1 edges

N:2137,SN:1 | E:1281, SE:0 Edges parsed:1239 Right-click + drag to PAN, Mouse-wheel to ZOOM

N:2137,SN:1 | E:2047, SE:0 Edges parsed:1239 Right-click + drag to PAN, Mouse-wheel to ZOOM

FIG. 3. Adjusting the value of complexity of a VR.

Configuration. Configuration refers to the manner of arrangement, organization, and ordering of information items that are encoded in a VR. Encoded items may be arranged according to certain data attributes (e.g., categorical, ordinal) or they may have a random arrangement. Different arrangements and orderings of encoded information items can affect cognitive activities in fundamentally different ways (Peng, Ward, Rundensteiner, 2004). For example, the ordering of encoded information items affects how easily actors detect underlying patterns, dependencies, trends, correlations, and relationships (Spence, 2007; Pirolli & Rao, 1996; Siirtola, 1999). Many CASTs are designed without much consideration for how encoded information items are arranged, and often do not provide mechanisms for adjusting the value of configuration (Peng et al. 2004). However, as mental space and representation space become coupled into a coordinated cognitive system through interaction, adjusting the ordering of information items in representation space can directly impact the ordering of information items in mental space (Kirsh, 1995a). Research in cognitive science has shown that it is easier to adjust the configuration of external representations of information while performing cognitive activities than to adjust one's internal mental representations without external support (Kirsh, 1995a). Indeed, studies have shown that adjusting the configuration of information representations has a significant positive effect on the performance of cognitive activities (e.g., see Kirsh, 1995b; Maglio, Matlock, Raphaely, Chernicky, & Kirsh, 1999). Providing mechanisms whereby actors can adjust the configuration of representations can facilitate cognitive activities by triggering mental associations that result from viewing new perspectives of information, and by simplifying the representation space from the perspective of the actor (Kirsh, 1995a).

Figure 13 shows a CAST, *Regional eXplorer* (stats.oecd.org/OECDregionalstatistics), that supports numerous activities involving regional statistics related to economic co-operation and development. The manner in which information items are organized in Figure 4 (L) does not make it easy to identify correlations within the encoded information. However, the actor can adjust the configuration value by sorting one column of the table (Figure 4R). Although no new information has been encoded, adjusting the value of configuration in this manner makes it very easy for the actor to identify a strong correlation between two columns.

Density. Density refers to the degree to which information items are encoded compactly in a VR. Density ranges in value from low (e.g., one or two dots that are spread out in a large display area) to high (e.g., thousands of information items encoded compactly in a small area). If the value of density of VRs is too high, perceptual tasks, such as locating and extracting relevant information, can be negatively affected (Pirolli, Card, & van Der Wege, 2001). In addition, such VRs can burden actors' mental faculties by placing a large informational load on working memory (Green & Petre, 1996). When engaged in decision making, for example, VRs that are too dense hinder quick extraction of information that is required to make decisions (Rosenholtz, Li, & Nakano, 2007). Indeed, numerous studies have shown decreased task performance when VRs have density values that are not appropriate for a task. For instance, Phillips and Noyes (1982) demonstrated that maps with low density values were associated with better performance on a number of visual tasks. Similarly, Springer (1987) showed quicker locating of targets when VRs were less dense. The results of these studies suggest that tasks—especially those requiring quick performance—are hindered if the value of density is too high. However, more compactness of information encoding can sometimes be desirable.

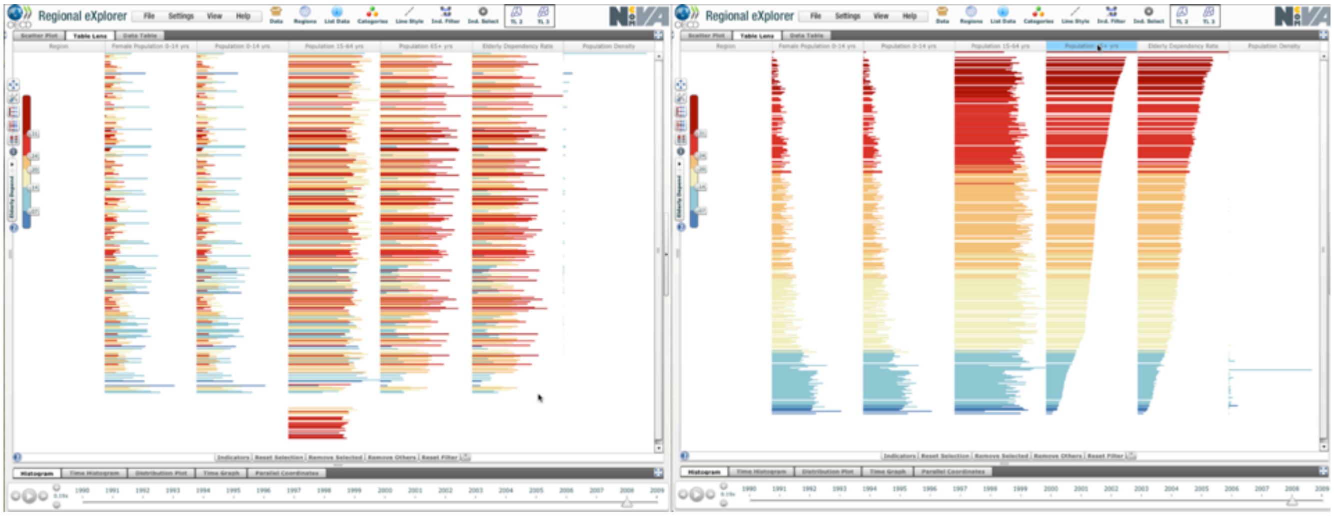


FIG. 4. Adjusting the value of configuration of a VR.

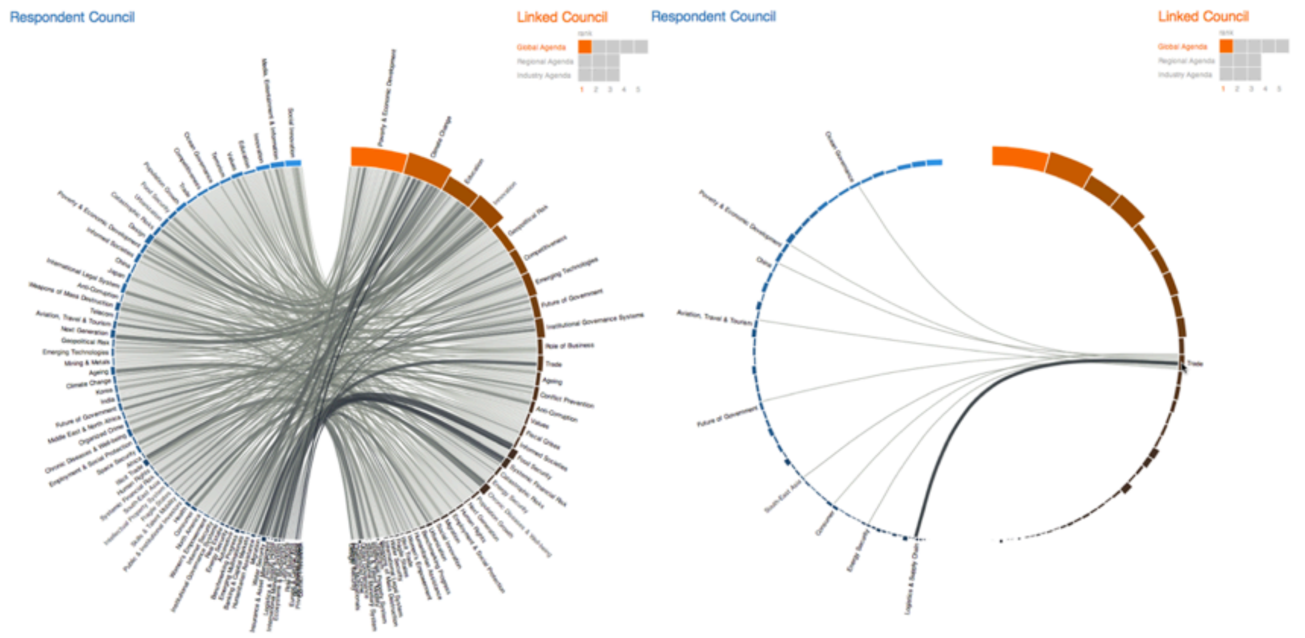


FIG. 5. Adjusting the value of density of a VR.

For example, representations that encode many information items and are very compact can provide a high-level overview of very large information spaces and can facilitate high-level comparisons (Tufte, 2001).

Many VRs are designed with the intention of encoding a large amount of information in an attempt to increase the cognitive information processing capabilities of actors (Pirolli et al., 2001). Long-standing prescriptions, however, often do not consider VRs with their interactive features at the forefront of consideration. For instance, according to Tufte (1990), “enriching the density of data displays [is one of] the essential tasks of information design” (p. 33), and, “visual displays rich with data are…frequently optimal…the more relevant information within eyespan, the better.” (ibid., 50). This may be true for many non-interactive, static representations. However, such propositions are not necessarily applicable to CASTs. Consider Figure 5, which shows a CAST, *Global Council Interlinkage* (janwillemtulp.com/worldeconomicforum/), that supports exploration of data derived from a survey of experts from 72 Global Agenda Councils of the World Economic Forum. The value of density of the VR shown on the left makes it difficult to perform tasks such as identifying connections between councils. Through interaction, an actor can select a particular council to show connections only to it and hide other connections, thereby facilitating such a task. Note that it is not the complexity of the VR that hinders such a task—that is, the hindrance is not due to the elaborate and intricate nature of the encoded items and their connections—but rather, it is due to the compactness with which the connections are encoded.

Dynamism. Dynamism refers to the degree of movement of encoded information items in a VR. Dynamism ranges in value from zero (i.e., all encoded information items are static) to high (i.e., all encoded information items are in motion). Actors can adjust the value of this property to increase or decrease the value of dynamism while performing cognitive activities. VRs that exhibit movement can effectively illustrate structural, functional, and procedural relationships among encoded information items (Jones & Scaife, 2000). Additionally, movement within a VR can make spatial information and depth order salient, reduce spatial ambiguities, and help overcome perceptual and cognitive biases that can be acquired from static VRs (Kaiser & Proffitt, 1987). It is often the case that cognitive activities involve information spaces that have a temporal nature, and motion in VRs can be an effective way to communicate temporal processes. However, although dynamism can facilitate cognitive activities, information items may be encoded in a transient fashion that does not facilitate sustained visual inspection (Tversky, Morrison, & Betrancourt, 2002). In other words, when a VR has no motion it is available for inspection without temporal constraints. This gives actors time to explore a VR at their own pace, which potentially avoids perceptual and cognitive overload (Cook, 2006). Schwan and Riempp (2004) compared performance of subjects who could adjust the dynamism values of VRs to those who could not. The results showed a significant decrease in time required to master the task in those who could adjust the values to suit their contextual and cognitive needs. As actors have different needs according to different tasks that are performed during an activity, no exact value of dynamism can be considered ideal for all contexts, and mechanisms should be provided to allow actors to adjust the value of dynamism to suit their particular tasks.

Fidelity. Fidelity refers to the degree to which information items are accurately encoded in a VR. Fidelity is a multifaceted property and can be with respect to structure, time, geometry, process, or function. Actors can adjust the value of one facet only or of multiple facets simultaneously. Fidelity ranges in value from low (i.e., very inaccurate) to high (i.e., completely accurate). The ideal value of fidelity for any given VR is very much context-dependent. Waller, Knapp, & Hunt (2001) suggest that tasks involving perceptual and motor training about particular information spaces benefit from high values of fidelity (see also Hunt & Waller, 1999). With tasks involving higher-level, conscious cognitive processing and the development of flexible mental models, however, a high value of fidelity is not necessarily best. In their study, Waller et al. found that differences in individual characteristics, such as gender, level of expertise, and cognitive ability, accounted for a significant variance in performance of the subjects, suggesting that even with a common task the ideal value of fidelity is actor-dependent. The ideal value of fidelity is also dependent on the tasks being performed during an activity. However, it may not always be obvious which aspects of an information space should be encoded with a high value of fidelity. For example, with the famous problem of the Seven Bridges of Königsberg, it was long thought that the geometry of the information space was important to represent with a high value of fidelity. By realizing that the geometry was irrelevant to the problem, however, Euler could represent the information space with a set of vertices and edges that were independent of the geometry of the information space, which allowed him to solve the problem. For the purpose of his problem solving activity, it was the network topology of the bridges that required a high value of fidelity. Another well-known example involves the famous London Underground map. When introduced, although the map had a low value of geometric fidelity, it encoded the topology of the subway network in a manner that facilitated pertinent tasks. It is reported that people found the map much more useful than the previous map that had a higher value of geometric fidelity, as they did not require a high value of geometric accuracy for the types of activities they were performing—namely, planning how to navigate from one location to another. Giving actors the ability to dynamically adjust fidelity values of a VR of the London Underground could potentially provide even stronger support for such planning and decision making activities. Consider the CAST, *Time Travel Tube Map* (www.tomcarden.co.uk/p5/tube_map_travel_times/applet/), shown in Figure 6 that supports planning and making decisions about travelling the London Underground. Actors are initially presented with a VR that encodes the geometry of the information space with a high value of fidelity (Figure 6 L). However, because their task is to identify travel times in order to plan and make decisions, such geometric fidelity is not helpful. This CAST allows actors to decrease the geometric fidelity to help identify travel times between stations (Figure 6 M and R). Although the resulting VRs have a lower value of geometric fidelity, allowing the actor to adjust this value can contribute to the overall planning activity. If the actor needs to perform another task, such as identifying the precise location of a station and its proximity to a particular part of the city, she could adjust the value of geometric fidelity to make it high again.

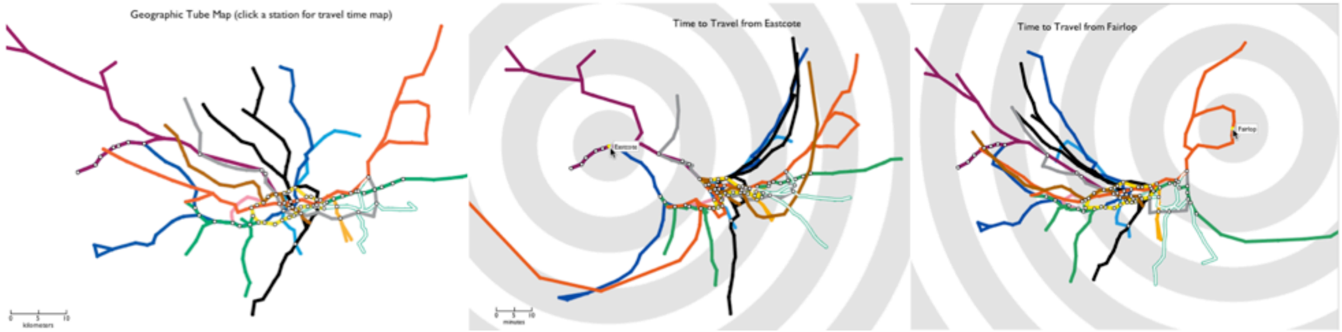


FIG. 6. Adjusting the value of geometric fidelity of a VR.

Fragmentation. Fragmentation refers to the degree to which information items are broken up and discretized when encoded in a VR. Information items may be encoded in a whole and continuous manner; alternatively, they may be encoded in a divided and discrete manner. Fragmentation ranges in value from zero (i.e., completely whole and continuous) to high (i.e., completely divided and discrete). Developing a mental model of an information space that includes an accurate model of discreteness and continuity and whole-part relationships is important in many complex cognitive activities. In the context of mathematical thinking and problem solving, for example, research suggests that to understand mathematical concepts (e.g., proportions, fractions, ratios) it is important to deeply understand discreteness and wholeness of an information space and the relations between wholes and parts (see Lesh & Harel, 2003). Olive (2000) suggests that allowing actors to interact with VRs of such concepts to adjust their values of fragmentation can facilitate such an understanding. Dörner & Wearing (1995) note that one of the essential elements of effective problem solving, planning, and decision making in complex situations is proper whole-part analysis during actors' goal formation. As goals are constantly revised and updated during the performance of complex cognitive activities while one explores and works with an information space, adjusting the value of fragmentation of VRs can help with whole-part analysis and the development of more sophisticated goals. Such thinking—often referred to as thinking both globally and locally—is important for reasoning, problem solving, and decision making in health professions (Higgs & Jones, 2008) and in business and management contexts (Proctor, 2010). Aside from understanding whole-part relationships, VRs with a low value of fragmentation can alleviate potential burden placed on working memory while carrying out tasks (Munyofu, Swain, Ausman, Lin, Kidwai, & Dwyer, 2007).

Figure 7 shows a CAST, *Panopticon* (www.panopticon.com), that supports analytical reasoning, decision making, and other activities concerned with financial information spaces. To perform such complex cognitive activities, an actor would likely need to develop an elaborate mental model of the information space, which would certainly involve tasks such as identifying whole-part relationships among industries and sectors, categorizing stocks according to their industries and sectors, and assessing the relative value of stocks. Figure 7 shows how the actor can adjust the value of fragmentation of the VR to show the relationships among and values of industries, and their division into supersectors and individual stocks.

Interiority. Interiority refers to the degree to which information items are latent and remain hidden below the surface of a VR, but are potentially accessible and encodable. Interiority ranges in value from zero (i.e., all information items are encoded at the visually perceptible surface of a VR) to high (i.e., most information items are latent and unencoded, but can be brought to the visually perceptible surface of a VR). Actors can act upon a VR (e.g., by drilling into it) to access deeper layers of information and bring latent information items to the surface. Historically, with static representations designers have had to make sacrifices and decide on trade-offs. As a result, information items that actors require for tasks may not be encoded and actors may be forced to make extrapolations, which may place a large burden on mental space. VRs that provide options for actors to adjust their value of interiority allow latent information to be probed and investigated when needed (Jern, 1997; Spence, 2007; Stone, Fishkin, & Brier, 1994). This can help to mitigate perceptual and cognitive overload and can also help create balance between overview and detail (Yi et al., 2007). When such interactive features are included in CASTs, actors can perceive the macrostructure of the encoded information, pose questions about it, and answer them by subsequently drilling them for latent information (Eick, 2000).

FIG. 7. Adjusting the value of fragmentation of a VR.

Huang et al. (2009) compared the effect of VRs that encoded only the information items required for a task to VRs that encoded extra items from the information space. They found that extraneous encodings had a significant negative effect on cognitive load and on task performance. Such studies suggest that actors should be given the ability to adjust the value of interiority to work with only the information that is needed for a particular task.

Figure 8 shows a CAST, *EdgeMaps* (mariandoerk.de/edgemaps/), that integrates the representation of explicit and implicit relations among items within an information space to support sense making and knowledge discovery. The VR in Figure 8 is depicting a timeline of well-known philosophers. To perform tasks such as identifying influences between philosophers and assessing the relative effect of their influences, actors can drill into the VR of each individual philosopher to bring such information to the surface and facilitate the performance of such tasks. As it would be unwieldy to encode such information all at once, control is given to actors to adjust the value of interiority and bring such information to the surface as needed.

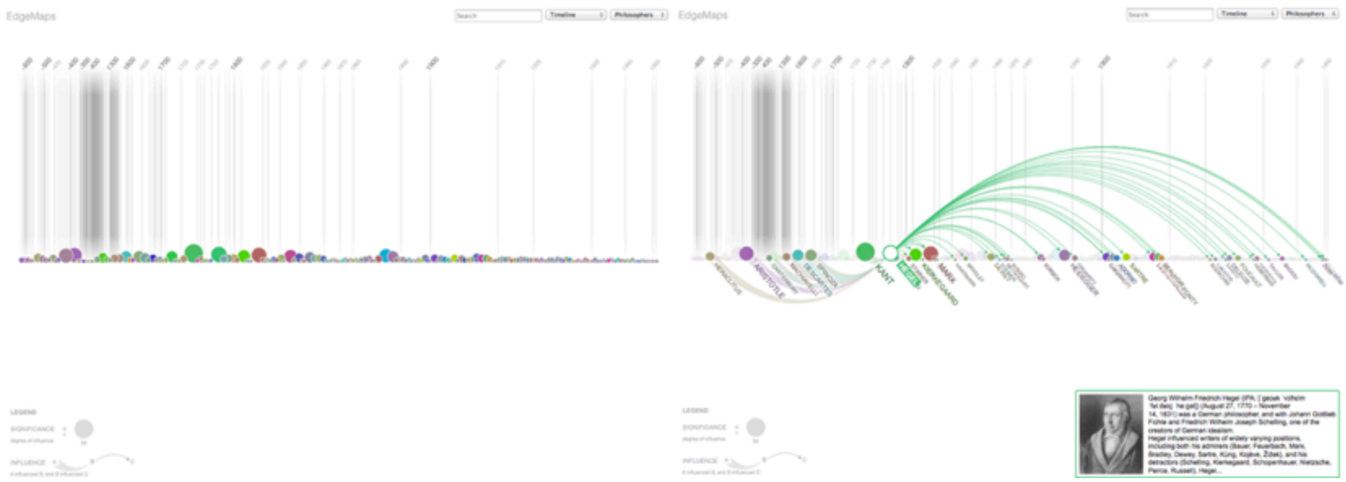


FIG. 8. Adjusting the value of interiority of a VR.

Scope. Scope refers to the degree to which the growth and development of information items are encoded in a VR. Actors can adjust the value of this property so that a VR encodes more or less of the growth of information items in a successive and sequential manner. Many information spaces contain information items that exhibit successive stages of growth through time and/or space. Being able to understand the prevalence of certain structures within such information spaces often depends upon tasks such as identifying the temporal order in which relationships are established (Moody, McFarland, & Bender-deMoll, 2005). Doing so can facilitate activities such as forecasting research trends and the life span of scientific communities (An, Jansen, & Milios, 2001). Gradually encoding the growth or development of an information space can be particularly useful for information spaces encompassing mathematical patterns, physical structures, as well as social, computer, disease, political, scientific, and co-citation networks (see Chen, 2004; Chen & Morris, 2003; Moody et al., 2005; Toyoda & Kitsuregawa, 2005), and can facilitate the detection of patterns and the understanding of how clusters are merged and split over time (Card, Suh, Pendleton, Heer, & Bodnar, 2006; Toyoda & Kitsuregawa, 2005). As actors develop mental models of such information spaces, static VRs can lead to erroneous interpretations, whereas interactive and/or dynamic VRs that show the growth of the information space can lead to more accurate interpretations (Moody et al., 2005). The ability to adjust the scope of VRs can play an important role in the performance of many complex cognitive activities, as the ability to analyze ideas by reasoning forward and backward and make sense of how information items are chained together is important in analytical thinking (Shrinivasan & Wijk, 2008).

Figure 9 shows a CAST, *NetLogo* (Wilensky, 1999, 2005), that supports numerous activities involving multi-agent modeling. In this particular example, an actor is making sense of the dynamics of preferential attachment networks. In this instance, the scope of the VR is being adjusted to increase it and encode more of the growth of the information space (Figure 9 from L to R). The CAST allows only for adjusting the scope value in this one direction. Often times, however, actors will want to adjust the scope in both directions. Designers should consider the nature of tasks and activities that will be performed to determine how the value of this property should be made adjustable.

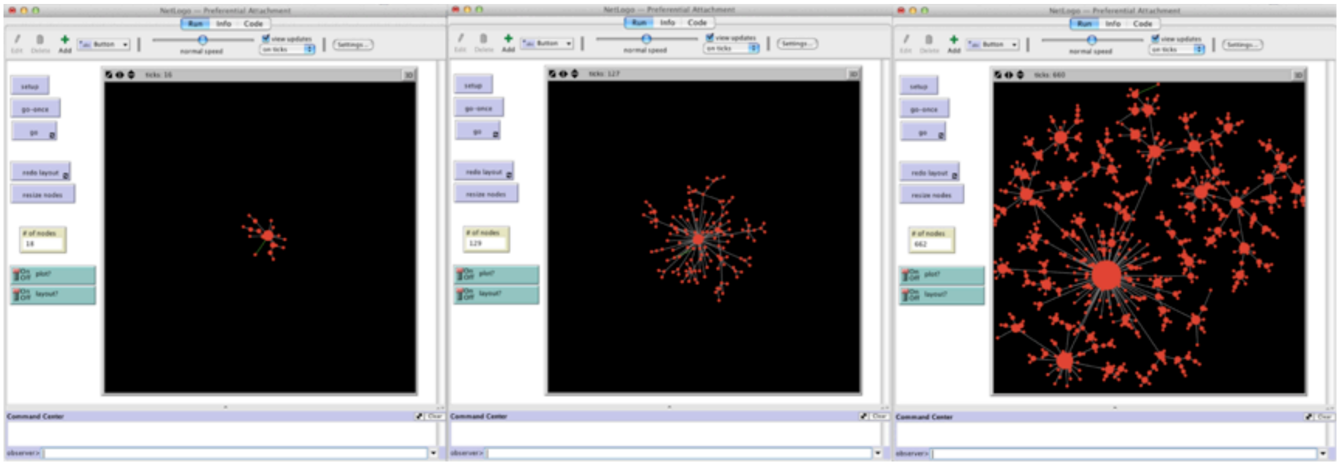
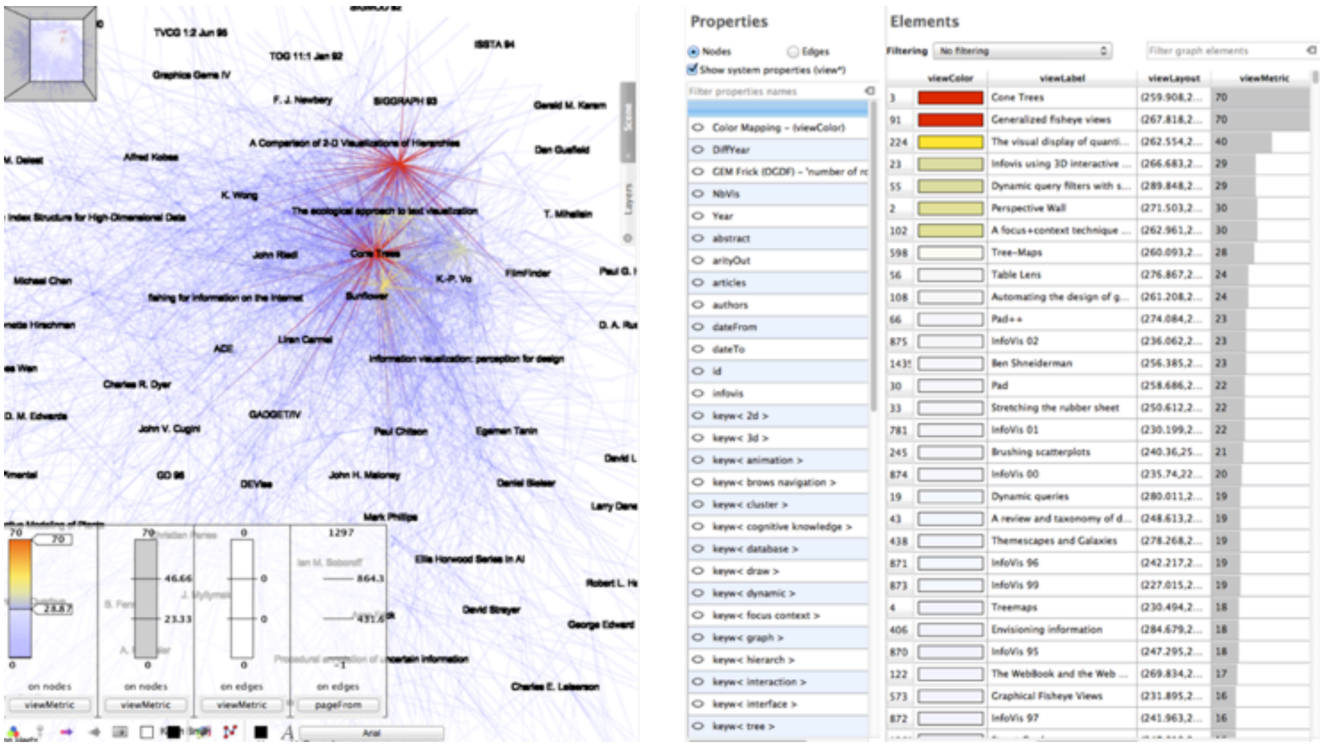


FIG. 9. Adjusting the value of scope of a VR.

Type. Type refers to the form of a VR in which information items are encoded. Different forms of VRs, such as plots, diagrams, images, symbols, and linguistic representations, have different benefits and trade-offs for communicating information (see Larkin & Simon, 1987; Novick, 2006; Stenning & Oberlander, 1995; Suwa & Tversky, 2002). Not only do different representational forms facilitate different tasks, but also the act of translating a representation from one type to another has been shown to facilitate the performance of complex cognitive activities (Tabachneck-Schijf & Simon, 1996). For example, when trying to solve a problem, changing the representational form of the information space can sometimes trigger apprehension of a solution (Robertson, 2001). Bodner and Domin (2000) investigated problem solving in the context of organic chemistry and concluded that "a significant difference between students who are successful in organic chemistry and those who are not is the students' ability to switch from one representation system [type] to another" (ibid., p.27).

To think about this property systematically, taxonomies and catalogs of types of VRs and their characterizations are needed. Although some work has been done in this area, there is no widely agreed upon typology of VRs. In the context of CAST-mediated HII, most designers and evaluators likely need a catalog of types that is manageable, accounts for common visualization techniques, and also identifies their utility in supporting complex cognitive activities. To contribute to this need, Parsons and Sedig (2013a) have recently categorized common VRs into six high-level types: 1) visual encodings and marks; 2) glyphs and multidimensional icons; 3) plots and charts; 4) maps; 5) graphs, trees, and networks; and 6) enclosure diagrams. In addition, they discuss the utility of each type for performing complex cognitive activities. They also identify a number of common techniques (e.g., treemaps, radial convergence diagrams, heatmaps, parallel coordinate plots) that fall under each category. With a manageable set of types, an examination of which types best suit particular tasks and activities, and a categorization of many common visualization techniques, such work can support methodical design and evaluation of this particular property of VRs. This work is far from complete, however, and future research is needed to develop more comprehensive categorizations of VRs at different levels of granularity.

Figure 33 show a CAST, *Tulip* (http://tulip.labri.fr), that supports numerous activities dealing with complex networks, such as scientific, social, or biological networks. Figure 10 (L) shows a VR of the relations among authors and papers within the information visualization community. This node-link VR type encodes relationships and facilitates tasks such as identifying highly connected nodes and major pathways. Other tasks, such as determining exact values and precise rankings, however, are not easily accomplished with such a VR. Figure 10 (R) shows the result of an actor translating or converting the node-link VR into a tabular form to facilitate such tasks.



	viewColor	viewLabel	viewLayout	viewMetric
3	🟥	Cone Trees	(259.908,2...	70
91	🟥	Generalized fisheye views	(267.818,2...	70
224	🟨	The visual display of quanti...	(262.554,2...	40
23	▨	Infovis using 3D interactive ...	(266.683,2...	29
55	▨	Dynamic query filters with s...	(289.848,2...	29
2	▨	Perspective Wall	(271.503,2...	30
102	▨	A focus+context technique ...	(262.961,2...	30
598	☐	Tree-Maps	(260.093,2...	28
56	☐	Table Lens	(276.867,2...	24
108	☐	Automating the design of g...	(261.208,2...	24
66	☐	Pad++	(274.084,2...	23
875	☐	InfoVis 02	(236.062,2...	23
143	☐	Ben Shneiderman	(256.385,2...	23
30	☐	Pad	(258.686,2...	22
33	☐	Stretching the rubber sheet	(250.612,2...	22
781	☐	InfoVis 01	(230.199,2...	22
245	☐	Brushing scatterplots	(240.36,25...	21
874	☐	InfoVis 00	(235.74,22...	20
19	☐	Dynamic queries	(280.011,2...	19
43	☐	A review and taxonomy of d...	(248.613,2...	19
438	☐	Themescapes and Galaxies	(278.268,2...	19
871	☐	InfoVis 96	(242.217,2...	19
873	☐	InfoVis 99	(227.015,2...	19
4	☐	Treemaps	(230.494,2...	18
406	☐	Envisioning information	(284.679,2...	18
870	☐	InfoVis 95	(247.295,2...	18
122	☐	The WebBook and the Web ...	(269.834,2...	17
573	☐	Graphical Fisheye Views	(231.895,2...	16
872	☐	InfoVis 97	(241.963,2...	16

FIG. 10. Adjusting the value of type of a VR.

Integrated Scenario: Epidemiological Analysis

In the previous section, CASTs from different domains that supported different complex cognitive activities were used to demonstrate the universality and general applicability of EDIFICE-PVR. In contrast, this section demonstrates how EDIFICE-PVR can be used in an integrated manner for systematic design and evaluation of a single CAST for a particular activity. This is demonstrated using a scenario in which an epidemiologist is engaged in an analytical reasoning activity regarding a disease outbreak. As the focus is on the interaction between the actor and VRs, for the sake of the scenario it is assumed that other considerations for proper design and use of CASTs are in place (e.g., data is accurate, complete, and consistent; the tool has built-in algorithmic behaviors; and so on).

To perform such an activity, the epidemiologist would need to perform other complex cognitive activities (i.e., subactivities) such as problem solving, sense making, and forecasting. Furthermore, as described previously, such activities involve the performance of goal-directed tasks and subtasks, as well as actions and low-level interface events. For example, to make sense of the current state and progression of the disease outbreak, the epidemiologist would likely need to perform tasks such as locating the origin of the disease, determining the rate and/or direction of its spread, navigating the disease network to discover pathways, and identifying individuals of importance. EDIFICE-PVR can support systematic thinking about design and evaluation of VRs from a human-centered perspective that accounts for the tasks and activities an actor will likely perform. Consider the

VR shown in Figure 11 (L), which encodes the existence and location of disease occurrences and known relationships among the infected individuals (e.g., friend, coworker, or relative). In the context of performing specific tasks, such as locating the origin of the disease and determining the rate and/or direction of its spread, a designer could infer which properties of the VR would likely need to have their values adjusted to help carry out the tasks. One strategy is to go through the properties methodically as follows. In terms of appearance, actors may wish to adjust colors to facilitate certain sub-tasks (e.g., to categorize diseases according to status, to identify and mark items of interest) while reasoning about how the disease is spreading and which areas are more seriously affected. Adjusting the value of density would not likely have a significant benefit for these particular tasks, as more diffuseness would not bring the actor any closer to locating the origin of the disease or determining its spread. Adjusting the value of complexity would not help to locate the origin of the disease, as it is not a matter of adjusting the elaborateness or intricacy of the VR. Adjusting the configuration value could help with similar tasks in other contexts; however, with this VR it would be detrimental, as the geographical locations of disease occurrences must be maintained to adequately complete the tasks. Adjusting the dynamism value would not likely be beneficial—increasing the value of motion would not facilitate such tasks. In terms of fidelity, in this case a high degree of structural and geometric fidelity must be maintained, as the tasks are fundamentally linked with geospatial accuracy. In terms of fragmentation, neither increasing or decreasing its value would help, as the epidemiologist needs to see the disease occurrences in a discrete manner to identify their geographical locations and connections between them. In terms of interiority, drilling into the VR to encode latent information may potentially be of some benefit, as it can provide information such as the date of infection. However, the most benefit would likely come from adjusting the value of the scope property of the VR. By adjusting the value of this property, the epidemiologist could increase and decrease the degree to which the growth and development of information items are encoded in the VR (see Figure 11 R). Doing so can help the epidemiologist perform other tasks, such as determining how certain areas grow and merge over time, where and when certain clusters are formed, and tasks concerned with the growth of the disease network and the connections among disease occurrences. Finally, adjusting the type value could help with these tasks, except that abandoning the map-based VR would hinder tasks in which geospatial accuracy is important.

FIG. 11. VR of disease occurrences and relationships (L). Adjusting the scope of the VR to locate the origin of the disease and determine its direction of spread (R).

As an alternative to the strategy examined above, designers and evaluators can first go through each property systematically to predict which tasks and activities would be facilitated by providing the ability to adjust its values. Such an endeavor could help to project what actions should be made available to adjust values of a VR's properties. For example, as the information space in this scenario is very large and complex, many of the information items are not encoded in the representation space and remain latent. It would be very likely that at some point during an activity, actors would need to access deeper layers of information from the information space. The epidemiologist may wish to browse or compare the relationships between individual disease occurrences and other known disease factors that may have causal links to the disease being investigated. Therefore, providing opportunities for actors to drill into the VR to bring latent information to the surface can be helpful. Designers can then use their creativity and design expertise to determine how to implement such a feature. For instance, Figure 12 shows the result of an actor drilling into a VR to access latent information items (i.e., individual disease occurrences and their relationships to known disease factors) and bring them to the surface. The prior state of the representation space encoded disease occurrences and their locations (as orange dots), but known information about each occurrence was latent. With the newly encoded information, disease occurrences are encoded (as orange lines) and their relations to known disease factors (i.e., genetic, nutritional, lifestyle, and psychological factors) are also encoded and brought to the surface of the VR. Designers can then determine which tasks would likely be performed, and provide options for adjusting values of different properties as they deem fit.

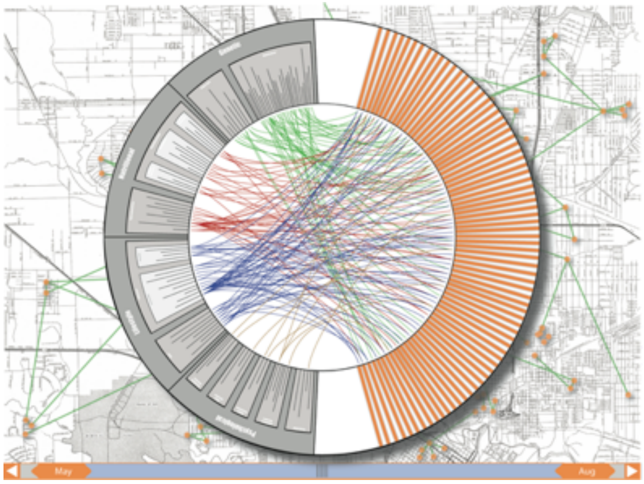


FIG. 12. Adjusting interiority value to encode latent information.

Although analyzing a CAST according to individual properties is useful, as mentioned previously, the ultimate utility of EDIFICE-PVR rests on a balance between analysis and synthesis of properties with respect to their influence on the performance of complex cognitive activities. This necessitates thinking about adjusting the values of a VR's properties in the context of the overall structure and process of HII in complex cognitive activities (see Figures 1 and 2). To do so, one must think about the hierarchical nature of complex cognitive activities, and how such activities emerge over time through the performance of multiple actions, tasks, and sub-activities. Figure 13 demonstrates how continually adjusting values of properties from the CAST above can be conceptualized within the context of an action, reaction, perception cycle that occurs over time while performing a complex cognitive activity. Figure 13 depicts the process of an actor decreasing the density of a VR to identify connections to one particular disease factor (e.g., obesity), perceiving the reaction, acting upon the new state of the VR to then increase the value of density and simultaneously decrease the value of fragmentation, perceive the reaction, and so on. As this process takes place, the actor performs numerous mental operations (e.g. induction, deduction, memory retrieval) as she attempts to develop an accurate mental model of the information space in order to plan and make decisions. Figure 14 suggests that designers and evaluators can ask themselves, with many different VRs and at different states during the performance of a complex cognitive activity, whether or not it is useful and possible for actors to adjust the values of certain properties to facilitate tasks.

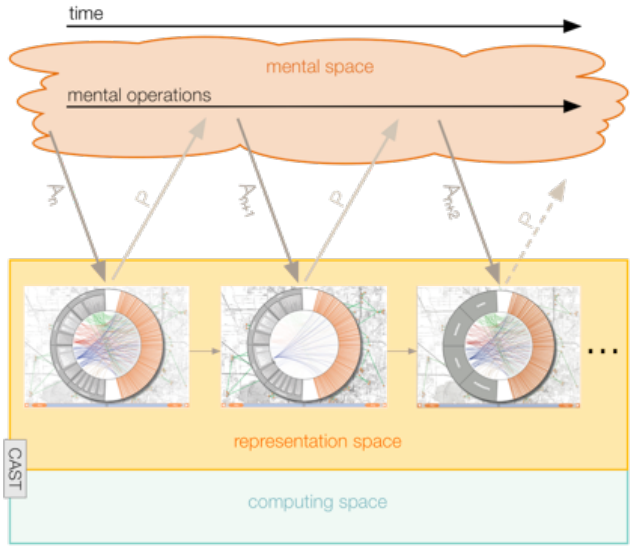


FIG. 13. Adjusting values of properties during the performance of an analytical reasoning activity.

Discussion

EDIFICE-PVR provides a high-level support structure for thinking about the quality of human-information interaction during the performance of complex cognitive activities. However, as this a young area of research, there is further work to be done to more fully understand the role of VRs in such activities. By laying some groundwork in this area, EDIFICE-PVR can contextualize and orient future research. Indeed, conceptual frameworks, such as EDIFICE-PVR,

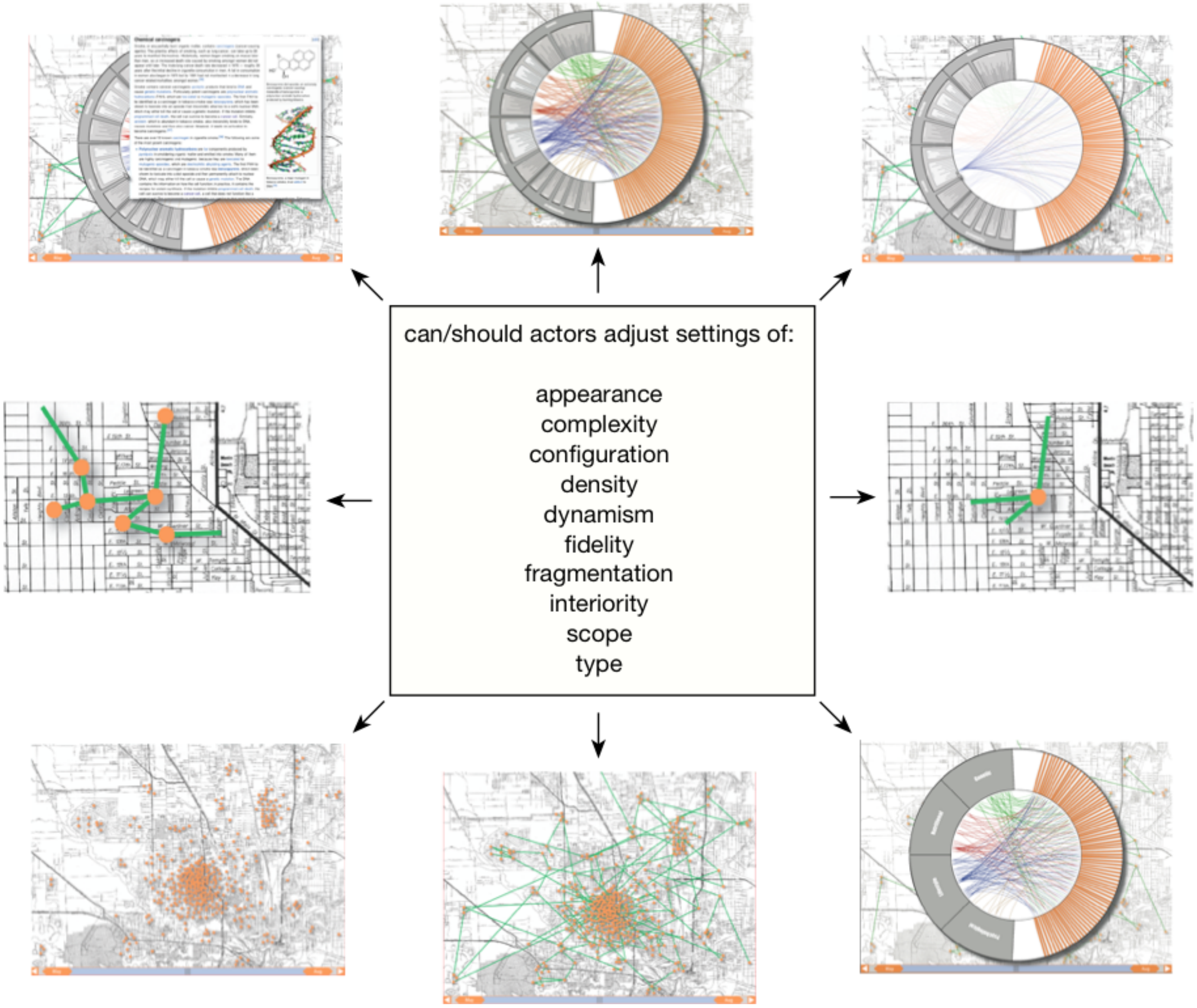


FIG. 14. Considering the properties of EDIFICE-PVR in an integrated manner for design and evaluation.

fundamentally influence research processes by determining what to look for, how phenomena are conceptualized, what their presumed relationships are, and how to make sense of observations and data (Becker, 1993). For instance, in the context of conducting empirical research, "the conceptual framework is both a guide and a ballast…" (Ravitch & Riggan, 2011, p. xiii). Researchers have suggested that such frameworks are needed for empirical studies. While discussing the state of research in the information visualization community, for example, Chen has noted that "the lack of theories becomes particularly prominent…when designing empirical and evaluative studies" (2010, p. 396). EDIFICE-PVR can provide a theoretical framework that facilitates the design of empirical studies, and determines what to look for and how results should be interpreted.

Not only does EDIFICE-PVR have utility for researchers, but it can also serve as a useful guide for designers and evaluators. One of the major hurdles confronting the effective design and evaluation of CASTs is a lack of comprehensive frameworks (see Chen, 2010; Sedig et al., 2013). While discussing the role and importance of theory in HCI, Kaptelinin and Nardi (2012) observe that both user studies and the design and evaluation of tools are rarely framed within a theoretical framework. Without such frameworks, design and evaluation of CASTs must be largely ad hoc and based on personal intuition. Bederson and Shneiderman (2003) note that theories can help not only to describe and explain, but also to predict performance, prescribe guidelines and best practices, and generate novel ideas to improve research and practice. Such frameworks can help designers and evaluators also by simply "stabilizing terminology and helping designers carry on meaningful discussions." (Bederson & Shneiderman, 2003, p. 350). Currently, there is no agreed upon terminology that designers can use to discuss VRs in a general manner. EDIFICE-PVR provides a set of terms and concepts that can be used consistently by designers in numerous different contexts.

In terms of evaluation, researchers have previously mentioned the need to move beyond traditional usability metrics and evaluation techniques to accurately analyze the interactivity of CASTs (e.g., Scholtz, 2006). Part of the problem with traditional approaches to evaluation is an overemphasis on quantification, which can place too much focus on quick and easy measurements, but may not give much indication as to the overall utility of a tool in supporting complex activities (Meyer et al., 2010; Albers, 2011). The EDIFICE-PVR framework provides a flexible and high-level support structure for thinking about the quality of human-information discourse, which is based on a manageable set of criteria (i.e., 10 properties). The EDIFICE-PVR framework can help evaluators think deeply and systematically about how the properties of VRs influence the performance of cognitive activities. Although outside the scope of this paper, future work may build on EDIFICE-PVR to construct evaluation heuristics and guidelines similar to others (e.g., Nielson's heuristics) that have been devised from earlier theoretical and empirical research.

As a final note on the utility of EDIFICE-PVR for design and evaluation, it must be emphasized that EDIFICE-PVR is not simply a list of properties. Rather, it provides a holistic framework that enables systematic conceptualization of the performance of complex cognitive activities—especially when combined with other components of the EDIFICE framework. Such research is much needed, and is not the same as isolated design principles or guidelines. As Fidel has appositely noted, what is required for the design of tools that support HII is research that is "conducive to the theoretical developments and relevant to the design of systems that support information interaction", and that "realizing this potential also necessitates a *conceptual basis that is continuous—rather than a fragmented puzzle of conceptual constructs*—and research strands that touch one another—rather than strands in isolation." (2012, p. 255, italics added). In other words, the design of CASTs cannot be optimally effective if based on fragmented—or nonexistent—underlying theoretical models and/or frameworks.

Comparison to Existing Work

As mentioned previously, much of the existing research has been concerned with static VRs and/or with only low-level perceptual and cognitive effects of VRs, and not explicitly with implications for complex cognitive activities (see related work section above). For instance, work by researchers such as Bertin (1967), Tukey (1977), Cleveland and McGill (1984), Mackinlay (1986), MacEachren (1995), Nowell (1997), and Ware (2008, 2012) has provided us with valuable insights into how VRs affect simple cognition—i.e., low-level perceptual and cognitive processes. Such research is certainly important and is necessary to consider for design and evaluation of any CAST. However, such work does not necessarily describe or explain the effects of VRs on high-level cognitive processes or even situate the low-level effects within the context of more complex activities, and thus cannot provide much guidance for design and evaluation of CASTs for complex cognitive activities. Although many of the references provided in the section above that presents the properties are concerned with only low-level effects, unlike much of the aforementioned work, such is not the extent of concern in this article. Rather, we contend that such effects must be contextualized within larger models and frameworks pertaining to HII in complex cognitive activities. Consequently, it is the emergent effects that result from the combination of such low-level effects that must be analyzed and studied in the context of human-information discourse during the performance of goal-directed tasks and overall complex cognitive activities.

One research endeavor worth comparing with EDIFICE-PVR is the Cognitive Dimensions of Notations framework (Green & Petre, 1996; Blackwell et al., 2001), which has examined some cognitive effects of notation systems and information artifacts. The framework is intended to help designers make choices where there are usability tradeoffs (Blackwell et al., 2001), and has been used for usability analysis for visual programming environments, calculators, spreadsheets, calendars, and other information artifacts (see Blackwell et al., 2001; Green & Blackwell, 1998; Green & Petre, 1996). While this framework is useful in certain contexts, it was not intended for design or evaluation of interactive VRs in the context of supporting complex cognitive activities. It does not include any model of human-information discourse, of the emergent nature of cognitive activities, of the complex structure and functioning of CASTs, or of the dynamic coupling that is formed between internal and external representations during the performance of cognitive activities. Certain of the cognitive dimensions identified in the framework (e.g., *premature-commitment, progressive evaluation, provisionality, consistency, secondary notation, error-proneness,* and *viscosity*) obviously deal with general usability rather than with complex cognitive activities. Other dimensions (e.g., *visibility, abstraction, closeness of mapping, diffuseness,* and *hard mental operations*) that may seem, on initial observation, to overlap the properties proposed by EDIFICE-PVR, are seen to be distinct after a quick examination. For instance, *diffuseness* may seem similar to our identified property of *density. Diffuseness* is characterized as "verbosity of language" (Blackwell et al., 2001, p. 328) and "how much or little can be said in a few word or symbols." (Blackwell, Green, & Nunn, 2000, p. 328). The property of *density* proposed by EDIFICE-PVR refers to how compactly a VR encodes information—this applies to interactive animations, plots, treemaps, and any other type of VR. As such, its concern is different from verbosity. A similar investigation of other dimensions will reveal the fundamental difference between the Cognitive Dimensions of Notations framework and EDIFICE-PVR. Furthermore, an understanding of how and why the values of properties should be adjusted, and how such interaction fits into an overall process of human-information discourse and cognitive processing, is not under the purview of the Cognitive Dimensions of Notations framework.

Although not constituting comprehensive models or frameworks, it is useful to briefly comment on two oft-cited mantras, the first being the Information Seeking Mantra: "overview first, zoom and filter, details-on-demand" (Shneiderman, 1996), and the second being the Visual Analytics Mantra: "analyze first, show the important, zoom, filter and analyze further, details on demand" (Keim, Mansmann, Schneidewind, & Ziegler, 2006). While these provide useful high-level guidance, and may be sufficient in some contexts, they are not entirely sufficient to guide design and evaluation of tools that provide all kinds of interactive possibilities and facilitate complex information-intensive tasks during the performance of complex cognitive activities (see Sedig & Parsons, 2013). Additionally, while they indirectly touch upon some of the properties identified in EDIFICE-PVR (e.g., complexity, density) they do not explicitly identify or characterize them, nor describe their cognitive and perceptual effects. Other properties (e.g., appearance, configuration, dynamism, fidelity, type), which have been shown above to have implications for the performance of complex cognitive activities, are not identified directly or indirectly by the mantras.

Researchers have recognized the lack of systematic and comprehensive research on VRs and their cognitive effects in general, and have suggested that much work is still required. For instance, in the context of geovisualization and visual analytics, Fabrikant has recently stated that "we still know little about the effectiveness of graphic displays for space-time problem solving and behavior, exploratory data analysis, knowledge exploration, learning, and decision-making" (2011, p. 2009). Green and Fisher (2011) have also recently observed that "there is still a lack of precedent on how to conduct research into visually enabled reasoning. It is not at all clear how one might evaluate interfaces with respect to their ability to scaffold higher-order cognitive tasks." In other words, we still know little about designing interactive VRs that effectively support complex cognitive activities. Research has hitherto provided us with a good idea of how features of VRs such as color and texture affect perceptual tasks and low-level cognitive processes; how humans perform simple, structured tasks; and how the usability of artifacts is affected by certain aspects of their design. What is not as clear, however, is how humans process and work with interactive VRs to solve complex problems, make sense of complex information spaces, and to perform other complex activities, and how the interactive features of VRs can and should be designed to best support such activities in the context of an overall human-information discourse. The EDIFICE-PVR framework attempts to provide more clarity to this matter by enabling a systematic approach to research, design, and evaluation of CASTs.

Summary and Future Work

This paper is concerned with interactive computational tools that mediate human-information interaction to support complex cognitive activities. Such tools have been referred to in this paper as cognitive activity support tools (CASTs). One of the important components of CASTs is their information interface, which is composed of visual representations (VRs). Actors perceive and work with VRs to facilitate their cognitive processes while engaged in sense making, problem solving, knowledge discovery, and other complex cognitive activities. In order to engage in systematic research, design, and/or evaluation of CASTs, and to facilitate consistent and accurate communication among researchers and designers, the essential properties of interactive VRs that influence the performance of complex cognitive activities must be identified and explicated. This paper has presented a framework that identifies and characterizes ten such properties, and discusses how their values influence cognitive and perceptual processes during the performance of complex cognitive activities. These properties are: appearance, complexity, configuration, density, dynamism, fidelity, fragmentation, interiority, scope, and type. Not only are these properties essential (i.e., present in every instance of a VR); they are also relational (i.e., depend on both actors and CASTs). The ideal values of these properties are dependent upon the characteristics of actors—their strategies, goals, needs, preferences, and prior knowledge and expertise—as well as the characteristics of CASTs and the context in which complex cognitive activities take place. The framework presented here provides a support structure to facilitate systematic thinking about how actors can and should be provided with options to adjust the values of these properties to provide better support for the performance of complex cognitive activities. This paper is part of a larger research plan aimed at establishing a comprehensive framework for human-information interaction in complex cognitive activities, named EDIFICE (Epistemology and Design of human-InFormation Interaction in complex Cognitive activitiEs), and has been referred to as EDIFICE-PVR, where PVR stands for Properties of Visual Representations.

EDIFICE-PVR provides opportunities for much future research. As discussed previously, such a high-level framework can encourage further theoretical research that more fully describes, explains, and predicts the performance of complex cognitive activities through CAST-mediated HII. For instance, the relationship among actions, tasks, and activities in the emergence of an overall complex cognitive activity requires further explication. In addition, the role of adjusting the values of properties in achieving goal-directed tasks through the performance of low-level actions is not completely understood. On another note, we still have a limited understanding of precisely how, when, and in what fashion adjustability options should be made available for particular activities, actors, and contexts.

EDIFICE-PVR can also stimulate empirical research, and can function as a lens through which studies are designed and interpreted. Although there is evidence to suggest how the values of properties affect some activities (e.g., problem solving), others are not as well understood (e.g., analytical reasoning). In addition, some properties have been more closely investigated than others, and by identifying these 10 essential properties of interactive VRs, EDIFICE-PVR can hopefully encourage research that results in a more balanced understanding. Moreover, many of the studies cited here were not conducted in the context of today's highly interactive computational tools. Thus, while their findings are relevant and applicable to the use of CASTs, further studies must be done to develop a better understanding of the role of these properties and their values in the context of performing complex cognitive activities with highly interactive tools. Furthermore, studies must be done to determine how the values of properties affect cognitive activities with particular types and characteristics of data and information, particular categories and techniques of VRs, particular actions and tasks, and actors with particular ages, skills, and levels of expertise. A future extension of such aforementioned research is the development of comprehensive *prescriptive* frameworks and design principles and guidelines that enable a systematic approach to the design of CASTs.

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Appendix

TABLE A1. List of examined CASTs

Domain	CASTs
(Information, Data, Geo, Scientific) Visualization, Visual Analytics	Action Science Explorer (Gove et al., 2011), Carbon Calculator (http://viz-carbontool.appspot.com), CGV (Tominski et al., 2009), ChronoZoom (www.chronozoomproject.org), City'O'Scope (Brodbeck & Girardin, 2003), CrimeSpotting (www.crimespotting.org), Cytoscape (Shannon et al., 2003), Datascape (www.daden.co.uk/solutions/datascape), Docuburst (Collins et al., 2009), Dust & Magnet (Yi et al., 2005), EdgeMaps (Dörk et al., 2011), EpiNome (Livnat et al., 2010), EpiScanGis (Reinhardt et al., 2008), Film Finder (Ahlbert & Shneiderman, 1994), Gapminder (www.gapminder.org), GeoTime (Eccles et al., 2008), GeoDa (Anselin et al., 2005), Gephi (Bastian et al., 2009), HARVEST (Gotz et al., 2010), Health Infoscape (visualization.geblogs.com/visualization/network), INSPIRE (in-spire.pnnl.gov), Jigaw (Stasko et al., 2008), Hierarchical Clustering Explorer (Seo & Shneiderman, 2005), Jellyfish (www.carohorn.de/jellyfish), Miner3D (www.miner3d.com), Mondrian (Theus, 2002), Multidatex (Wu et al., 2006), NetLens (Kang et al., 2010), Newsmap (newsmap.jp), NFlowVis (Mansmann et al., 2009), OECD eXplorer (stats.oecd.org/OECDregionalstatistics), Panopticon (www.panopticon.com), PanViz (Afzal et al., 2011), Polaris (Stolte et al., 2002), SeeSoft (Eick et al., 1992), SocialAction (Perer & Shneiderman, 2006), Spatio-Temporal Epidemiological Modeller (Ford et al., 2006), Spotfire (Ahlberg, 1996), Starlight (starlight.pnnl.gov), Table Lens (Rao & Card, 1994), Tableau (www.tableausoftware.com), time rime (timerime.com), Tulip (tulip.labri.fr), TNV (Goodall, 2011), TOPCAT (www.starlink.ac.uk/topcat/), VisANT (Hu et al., 2009), Visible Body (www.visiblebody.com), VisRa (Oelke et al., 2010), Vizster (Heer & Boyd, 2005), Well-Formed Eigenfactor (well-formed.eigenfactor.org)
Cognitive, Educational, and Learning Technologies and Digital Games	Archim (www.archimy.com), Archimedean Kaleidoscope (Morey & Sedig, 2004), Cabri (www.cabri.com), DEMIST (Ainsworth & van Labeke, 2001), Educational Virtual Anatomy (Petersson et al., 2009), GeoGebra (www.geogebra.org), Geometer's Sketchpad (www.dynamicgeometry.com), Hyperchem (www.hyperchem.com), Kalzium (edu.kde.org/applications/science/kalzium/), KAtomic (games.kde.org), Lattice Machine (Sedig et al., 2005), Living Liquid (Ma et al., 2012), Looking Glass (www.livinggraphs.com/enu/products/lg) ModellingSpace (Avouris et al., 2003), NCTM Illuminations (illuminations.nctm.org), NetLogo (Wilensky, 1999), PhET Simulations (phet.colorado.edu), PolygonR&D (Morey & Sedig, 2004b), Polyvise (Morey & Sedig, 2004a), SmartJigsaw3D (Ritter et al., 2000), Step (edu.kde.org/applications/science/step/), Stella (www.software3d.com/Stella.php), Sunaeon (www.sunaeon.com), Super Tangrams (Sedig & Klawe, 1996), TileLand (Sedig et al., 2002)
Personal Information Management, Information Retrieval, Knowledge Management, Digital Libraries, General Productivity	ActiveGraph (Marks et al., 2005), Butterfly (Mackinlay et al., 1995), Cat-a-Cone (Hearst & Karadi, 1997), Envision Digital Library Project (Fox et al., 1993), HotMap (Hoeber & Yang, 2006), Hunter Gatherer (Schraefel et al., 2002), Info Navigator (Carey et al., 2003), InfoSky (Andrews et al., 2002), LyberWorld (Hemmje et al., 1994), Mendeley (www.mendeley.com), MemoMail (Elsweiler et al., 2006), Microsoft Word, Microsoft Onenote, MindJet (www.mindjet.com), MindMaple (www.mindmaple.com), MyLifeBits (Gemmell et al., 2002), Phlat (Cutrell et al., 2006), PhotoMemory (Elsweiler et al., 2005), POLESTAR (Pioch & Everett, 2006), Stuff I've Seen (Dumais et al., 2003), TRIST (Jonker et al., 2005), VICOLEX (Buchel & Sedig, 2011), VisGets (Dörk et al., 2009), Visual Knowledge Builder (Shipman et al., 2004), xFIND (Andrews et al., 2001)