ABSTRACT

UNDERSTANDING COGNITIVE DIFFERENCES IN PROCESSING COMPETING VISUALIZATIONS OF COMPLEX SYSTEMS

by
Madhavi Mukul Chakrabarty

Node-link diagrams are used represent systems having different elements and relationships among the elements. Representing the systems using visualizations like node-link diagrams provides cognitive aid to individuals in understanding the system and effectively managing these systems. Using appropriate visual tools aids in task completion by reducing the cognitive load of individuals in understanding the problems and solving them. However, the visualizations that are currently developed lack any cognitive processing based evaluation. Most of the evaluations (if any) are based on the result of tasks performed using these visualizations. Therefore, the evaluations do not provide any perspective from the point of the cognitive processing required in working with the visualization.

This research focuses on understanding the effect of different visualization types and complexities on problem understanding and performance using a visual problem solving task. Two informationally equivalent but visually different visualizations - geon diagrams based on structural object perception theory and UML diagrams based on object modeling - are investigated to understand the cognitive processes that underlie reasoning with different types of visualizations. Specifically, the two visualizations are used to represent interdependent critical infrastructures. Participants are asked to solve a problem using the different visualizations. The effectiveness of the task completion is measured in terms of the time taken to complete the task and the accuracy of the result

of the task. The differences in the cognitive processing while using the different visualizations are measured in terms of the search path and the search-steps of the individual.

The results from this research underscore the difference in the effectiveness of the different diagrams in solving the same problem. The time taken to complete the task is significantly lower in geon diagrams. The error rate is also significantly lower when using geon diagrams. The search path for UML diagrams is more node-dominant but for geon diagrams is a distribution of nodes, links and components (combinations of nodes and links). Evaluation dominates the search-steps in geon diagrams whereas locating steps dominate UML diagrams. The results also show that the differences in search path and search steps for different visualizations increase when the complexity of the diagrams increase.

This study helps to establish the importance of cognitive level understanding of the use of diagrammatic representation of information for visual problem solving. The results also highlight that measures of effectiveness of any visualization should include measuring the cognitive process of individuals while they are doing the visual task apart from the measures of time and accuracy of the result of a visual task.

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by
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To our little Anika – lovely and ever supportive of a mom trying to complete her PhD,
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TABLE OF CONTENTS

TABLE OF CONTENTS
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TABLE OF CONTENTS
(Continued)

TABLE OF CONTENTS
(Continued)

LIST OF TABLES

LIST OF TABLES
(Continued)

LIST OF FIGURES

LIST OF FIGURES
(Continued)

LIST OF FIGURES
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LIST OF FIGURES
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CHAPTER 1

INTRODUCTION

Information visualizations have been used in many domains to aid in the cognitive effort of individuals in problem understanding and problem-solving. The advantages of visualizations in solving complex problems have resulted in the implementation of visualizations in various planning and management areas of environmental systems, hydraulic systems, and transportation systems (Bartz et al. 2001; Card, Mackinlay and Shneiderman 1999; Treinish 2002; Yoo et al. 2000). Prior research has shown that for a large volume of information, visual models capitalize on a fundamental, native expertise of humans: the ability to solve complex problems by reasoning with visualizations (Bartz et al. 2001; Card, Mackinlay and Shneiderman 1999; Treinish 2002; Yoo et al. 2000). Visual models can offer advantages over purely lexical models by increasing interpretability and reducing cognitive load, thus enabling decision-makers to devote additional cognitive resources to problem-solving (Larkin and Simon 1987).

There has been substantial research in the field of visualization for model analysis (Brown and Afflum 2002; Dungan, Kao and Pang 2002; Mark et al. 1999; Sugumaran, Davis, Meyer and Prato 2000; Sui and Maggio 1999), manipulation (Aliaga 1996; Brisson 1989) and control (Elmqvist, Mattson and Otter 1999). These studies have shown the effectiveness of visualization models over existing tools and techniques in model understanding and usage. Advantages of using visual tools and widgets for manipulation and control of models have also been well established (Nielson 1995; Sutcliffe 2003). Other visualization studies have focused on developing simulation-based approaches for understanding and analyzing complex models (Peerenboom, Fischer and Whitfield 2001).

Applications and implementations of different information visualization techniques have been capitalized in many different domains of engineering, management and organizational systems and processes (Peuquet and Kraak 2002; Prichett 2002; Sui and Maggio 1999).

Investigating the history of the currently used visual tools shows that most of the existing visual tools, widgets and techniques are developed based on experience, availability of tools and intuition regarding the benefits of a certain representation. Few of the tools have evaluation studies to show their effectiveness. Even when evaluations are conducted, they are restricted to comparison of the performance of the visualization to an alternative approach including sentential representation where text is predominantly used. Therefore the problem is two fold. First, only a handful of visualizations have any evaluations to back up their effectiveness claims; second, there is very little known about the effectiveness of the different techniques used to evaluate visualizations. Also, since most of the evaluations/studies are focused on individual visualizations and isolated visual problems for a given scenario in a prescribed knowledge domain, the development of visualizations as well as the evaluations that have been carried out is isolated. This approach to evaluating visualizations limits the applicability of the results to the single visualization. Since there is no way to link the results to any theory of visualization, the results that are derived are non-extensible. This is another major gap with the current research related to developing adequate visualizations. This gap and the importance of bridging it is well recognized in the research community (Kerren, Stasko, Fekete and North 2008; Plaisant, Fekete and Grinstein 2007).

This research is focused on techniques for evaluating different visualizations, which are currently evaluated primarily on how fast a task is completed or how error-free a solution is when using a given visualization for a given problem. These evaluation techniques limit the measures of effectiveness to the result derived out of the visual task. But the time-to-completion and error-rate do not provide the complete picture regarding the effectiveness of visualizations because they do not measure the process of completing the task using the visualization.

The research in this thesis provides a complementary view of the existing research for evaluating of visualizations of different systems. This view includes measuring the cognitive process of individuals using the visualizations. Previous studies have shown that visualizations can amplify cognition and aid in the problem-solving capabilities of an individual (Card, Mackinlay and Shneiderman 1999). The results of these studies show that suitable visualizations enable individuals to complete their intended work by increasing comprehensibility of the underlying information and enabling effective analysis and manipulation of the information. To understand the impact that visualization has on the representation and comprehension of information, it is necessary to understand how the information is viewed by individuals that makes one visual representation more effective than another. Therefore, understanding the cognitive processes that individuals use in solving a problem can provide insights into the characteristics of visualization that make them more effective. Hence the need arises to understand the cognitive processes that individuals use in visual problem-solving. Moreover, this understanding will enable better design of visualizations for a given task. Accordingly, the focus of the current research is on evaluating the cognitive processes of individuals when working with different visualizations.

To understand the effectiveness of different visualizations in terms of the cognitive processing associated with them, a specific set of visualizations called node-link diagrams is used. Node-link diagrams are usually represented as a set of nodes (circles or other geometric shapes) and connected with arcs or lines (straight or curved), which depict some relationship among the nodes. Node-link diagrams have been used to represent systems, with nodes depicting the entities of the system and links depicting the relationships among the different entities (Howard and Matheson 1981; Modell 1996; Sommerville 2001). The nodes and the links can be used to represent specific information about the entities and their relationships. This information is stored as attributes of the nodes and links. Different shapes, colors, boundary styles and highlighting features represent different types of nodes (Becker, Eick and Wills 1995). The links have symbols attached, and are dashed or dotted to represent different types of relationships (Irani and Ware 2003). Node-link diagrams are pervasive in situations where it is desirable to have an understanding of how elements relate to one another in a system. Examples of node-link diagrams include influence diagrams (for decision analysis), data flow diagrams (in computer software design), Gantt and PERT charts (in planning and management) and communication network diagrams (Howard and Matheson 1981; Modell 1996; Sommerville 2001). The wide applicability of node-link diagrams makes them suitable candidates for understanding individual cognitive processes in visual problem-solving.

The research investigates the impact of visualization using measures that go beyond speed and accuracy. It attempts to compare two visualizations by understanding the cognitive process of individuals navigating through the two visualizations and the information cues they use to complete a visual task. Class diagrams from Unified Modeling Language (UML) and Geon diagrams developed from Structural Object Perception Theory (SOPT) are used to develop hypothetical test scenarios of interdependent critical infrastructures for evaluating the difference that arises out of using different visualizations. Two parameters developed to measure this cognitive process of individuals are defined as *search path* and *search-steps.* Participants are asked to complete a problem-solving task using different visualizations types and complexity for the hypothetical scenarios. The process of completing the task and the results of the task together are used to draw the conclusions regarding the difference resulting from the two visualizations in completing the visual task.

The remaining part of the document is organized as follows. Chapter 2 outlines the theoretical background used to develop the research propositions leading to this proposed work. Chapter 3 provides the details of the design of an experiment that was set up for addressing the research propositions and the method of data analysis. Chapter 4 describes the results of the experiments conducted. Chapter 5 presents the discussion and Chapter 6 discusses the contribution of the research and future work.

CHAPTER 2

THEORETICAL BACKGROUND

Visualizations are used widely in different applications and different domains, and prior studies show that visualizations aid in cognitive processing of individuals during problem-solving (Kress and Leeuwen 1996; Larkin and Simon 1987). The differences in individual cognitive processing in visual problem-solving depend on the way information is encapsulated and presented in visualizations and the way this information is perceived by the individuals. For the most part, no theories are strictly followed to develop these visualizations. Despite considerable development in the field of information visualization (Card and Mackinlay 1997; Card, Mackinlay and Shneiderman 1999; Chi 2000; Shneiderman 2002) there is little guidance available on how to design or even select visualizations for a given purpose. Most visualizations that are developed and used have to meet the minimal requirements of adequacy, cost-effectiveness and adaptability (North and Shneiderman 2000; Spoerri 1999). Hence, these visualizations are developed based on experience, usability principles, availability of tools and intuition (Hartson and Hix 1989; Henninger, Haynes and Reith 1995; Nielson 1992). Less importance is given to understanding deeper aspects of which attributes of a visualization make them adequate and adaptable. The current research is an attempt to understand how different visualizations lead to differences in the way information is perceived. Since node-link diagrams are extensively used in different domains, two different node-link diagrams will be used for the study. A few key concepts used in the proposed study are discussed in the next section.

2.1 Key Concepts

This section introduces the main concepts, the literature review of related research and the research framework for the proposed work. Visual tools can be defined as a collection of symbols graphically linked by mental associations to create a pattern of information and a form of knowledge representation about an idea (Hartley 1996). Visual tools reduce the cognitive load associated with information presentation and processing, and have been used in various applications (Card, Mackinlay and Shneiderman 1999; Ware 2000). Visualization widgets or visual tools used to control or process a visual model enable individuals to interact with models (Lo and Yueng 2002). Examples of widgets include menus, control buttons, sliders for navigating through a computer interface (Gahegan 1998). The emphasis in the current work on visualization is on the representation aspect and not on the control aspect. The research draws upon visualization and modeling sciences and tries to integrate system development perspectives to help design and develop a visualization appropriate for a visual task in a given application domain.

Individuals use a three-step process of analyzing, refining, and expanding to reason with visualizations in problem-solving tasks. These steps help them to extract information from a visualization that is otherwise not obvious to them (Stylianou 2002). The process of reasoning with visualizations depends on the problem-solving task to be accomplished and the type of visualization used to represent the problem (Halverson and Hornof 2004; Shneiderman 2002). To develop the right visualization, there is a need to understand the characteristics of the visualizations that lead to the differences in cognitive processing techniques of individuals. This leads to the question of how different visualizations are developed and what makes these visualizations different from each other. Because understanding visualizations depends on the perceptual abilities of individuals (Gershon 1994; Gordon 1989; Gregory 1990; Ware 2000), investigating different visualizations will be limited to the attributes that lead to their perceptual properties. Two types of visualizations and their perceptual properties are discussed below.

2.1.1 Types of Visualization

Literature on object perception talks about how individuals understand objects based on their visual representations (Bruce 1996; Gordon 1989; Johnston 1996). Regardless of the method of developing visualizations, there are syntactic principles, rules and heuristics that underlie the visual language used to represent information (Kress and Leeuwen 1996). Different features or characteristics of the object representation help an individual form a mental image of the object and its function (Bruce 1996; Johnston 1996). These characteristics of the object representation are dictated by the underlying visual language. This may lead to amplifying certain characteristics of an object in the visualization and reduction of other characteristics. Based on the way the objects are visualized, certain features of the objects provide cues to their use and functionality (Bruce 1996). For example, an object perceived to be a hollow container may provide the impression that it can be used to store a liquid. Following are two types of visualizations and their implementation details.

2.1.2 UML Diagrams

UML (Unified Modeling Language 2001) is a modeling language from the Object Management Group (OMG) (Booch, Rumbaugh and Jacobson 1999). It is the result of combining many design methodologies for describing object-oriented systems developed in the late 1980s (Koch and Kraus 2002). It standardizes several diagramming methods, including Grady Booch's work at Rational Software, Rumbaugh's Object Modeling Technique and Ivar Jacobson's work on use cases (Booch, Rumbaugh and Jacobson 1999). The rich vocabulary of UML consists of twelve diagrams including four structural, five behavioral and three model management diagrams (Booch, Rumbaugh and Jacobson 1999). UML diagrams are an example of an elaborate graph diagram where nodes represent objects and links represent relationships or associations between the objects. The large set of UML diagrammatic views has made it possible to view and understand software system requirements for system design. It has become a *de facto* standard in user interface design (Kovacevic 1998). UML diagrams are one of the more widely accepted and commercially available tools for building diagrams based on Object-Oriented Design (OOD) (Booch, Rumbaugh and Jacobson 1999).

In object-oriented design methodology, designers abstract all OOD components (objects, attributes, methods, and messages) to emphasize the important points and to suppress immaterial or diversionary details (Kim and Lerch 1992). OOD helps to simplify problem interpretation by focusing on individual objects of interest rather than on functions, and by transforming the general operators and constraints into functionalities of individual objects. Therefore, OOD representation reduces memory overloading of designers, which leads to fewer errors and interrupts and leading better understanding of the information behind the representation (Burton-Jones and Meso 2006). Also, designers spend less time in absolute and relative terms in the task domain and develop a better understanding of the underlying problem structure that is the emphasis in object modeling (Bodart and Vanderdonckt 1996). In modeling software systems with complex interactions, abstracting the concepts and relationships between the concepts as objects in the physical world allows the developer to think on a higher level of detail than is possible with structured code (Collins 1995; Gamma, Helm, Johnson and Vlissides 1995; Szekely 1996). This methodology of abstracting the concepts in a design problem and representing those concepts using analogous familiar objects from the real world is the concept behind Object-Oriented Design (OOD) (Sutcliffe 1999). OOD vocabulary includes definitions and techniques for representation of different objects that are instantiations of the elements being represented, attributes that are the characteristics of the element, methods including the functions of the object and messages to communicate with other objects.

Object-oriented methodology in software development is an implementation of object modeling (Cattell et al. 1997; Jacobson, Christerson, Jonsson and Overgaard 1992). The concept of Object Modeling (OM) is based on the perception of the object based on their representations using identifiable objects from the physical world. It assumes that creating an abstraction of reality is a fundamental way in which individuals understand the world (Powell 1995). This technique uses successive decomposition and refinement of a problem until the components of the objects are abstracted as objects resembling objects in the physical world. Mental models of the objects are formed based on the preliminary information gathered when individuals assimilate information from the representation of the objects. Individuals process the information by continuously storing, retrieving and intermediate steps of analyzing the information (Silva and Paton 2000). The process of abstraction in OM helps individuals in object recognition by reducing the cognitive processing required to analyze the visualization. Recognition of objects happen by perceiving their different parts as represented by the abstracted physical objects and their relative association as conveyed by the relationships of the abstracted objects. The abstracted representation of the system helps to uncover details of the objects and their relationships that would otherwise not be so obvious (Bodart and Vanderdonckt 1996; Johnson 1992).

In software development methodology, object modeling has been extended and used to design, analyze and build software systems. In software designing, object modeling helps focus the designers' attention on different and uncommon issues of the design problem and attempts to facilitate the process of transforming problem requirements into software solutions (Harmelen 2001). By abstracting out the unnecessary details of the problem, individuals can analyze by focusing only on the design issues that need their attention. This process of abstraction and use of the abstracted representation has been successfully implemented for problem-solving in multiple paradigms.

The specific type of diagram under investigation is one of the commonly used diagrams in UML called the class diagram. In UML class diagrams, an object is defined as an entity that is generally drawn from the vocabulary of the problem space. A class is a description of a set of common objects. Every object has three attributes: identity, state and behavior (Unified Modeling Language 2001). UML class diagrams can be used to represent any physical or virtual object, using the guidelines outlined for developing UML class diagrams. Since any object would have numerous behavior attributes, for reasons of simplicity only those attributes are listed that have a direct bearing on the design being considered. Figure 2.1 shows a UML class diagram representing a person (or customer) in a banking scenario. The first section in Figure 2.1 is the name of the class. In this case, the class is called *Person*. The second section shows the attributes of the *Person* and the third shows the functions of the *Person*. Only the attributes (income) and functions (isMarried, isUnemployed, birthDate, age, firstName, lastName, sex) applicable to a banking scenario are presented here.

Person
income(Date) : Integer
isMarried : Boolean isUnemployed : Boolean birthDate : Date age : Integer firstName : String lastName : String sex : enum {male, female}

Figure 2.1 UML representation of a class layout.
(Source: Booch, Rumbaugh and Jacobson 1999).

Similarly, any physical object can be represented using a UML class diagram. Figure 2.2 shows the UML representation of a horse. The name of the object "horse" is shown in the first section. Attributes or properties of the horse are shown in the second section and functions are shown in the third.

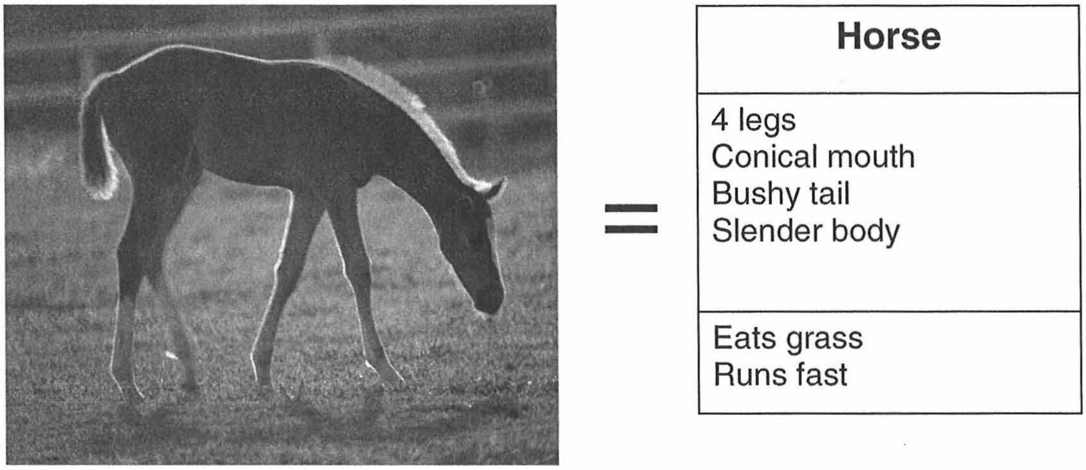


Figure 2.2 UML representation of a physical object (horse).

Since UML class diagrams are used to depict objects, properties of the objects and relationships of the objects with other classes, UML class diagrams will be used as one of the candidate visualizations. The next section discusses another type of visualization.

2.1.3 Geon Diagrams

Geon stands for *Geometrical Ions*. Geon diagrams consist of 3D primitive shapes like cones, cylinders, cubes and wedges, which can be combined to form a set of generalized cones. These generalized cones can be attached to one another in various ways to represent the object.

Geon diagramming is an implementation of Structural Object Perception Theory (SOPT) (Biederman 1987). SOPT is a theory of object perception that analyzes the structure of the object independent of the viewpoint or direction in which the object is viewed. It is based on *recognition-by-components* (Biederman 1987) and proposes a series of processing stages culminating in object recognition. In SOPT there are three steps leading to object recognition. First, the visualization is analyzed and decomposed into primitives at the edges, based on luminance, color or texture, so that the boundaries of objects can be extracted. The object is parsed at the concave edges simultaneously with the edge detection. Second, a structural skeleton is identified, that contains information about how the components are interconnected (Biederman and Gerhardstein 1993; Marr 1982). Third and finally, all the information is combined for identification of the object (Biederman 1987).

The first stage of edge identification of an object is done with the five detectable optical properties of objects: curvature, co-linearity, symmetry, parallelism and co-termination (Biederman 1987). These five properties help in dissecting an object into a number of simple geometric, convex and volumetric components such as cylinders, blocks, wedges and cones. Since the geometric shapes have convex faces and are volumetric, these shapes are invariant over changes in orientation, object position and presentation quality (Biederman 1987). That is, these shapes can be perceived to be the same by an individual, regardless of their orientation, rotation or direction of viewing. Another characteristic of such geometric volumetric components is that they can be determined from just a few points on each edge (Biederman and Gerhardstein 1993; Marr 1982). Consequently, an object formed with these geometric components can be extracted or perceived even with a large variation in viewpoint, occlusion and noise (Biederman 1987). When a geometric component is perceived, the continuity of the occluded portion is mentally completed to form the perceptually complete object in the mind of the individual (Ware 2000). Apart from the five optical properties already mentioned, additional properties and characteristics that aid easy recognition and extraction of the geometric components include texture and color.

The second stage of determining the skeletal structure of the object helps to mentally form an arrangement of all the components of the object which is then matched against a representation in the memory in the third step. In a nutshell, the stress in SOPT is on recognizing an object based on its constituting primitives or components and the way the components are connected to one another.

An object represented as a geon diagram is perceived by individuals using the three stages of object detection mentioned earlier. The first stage of processing is the early edge extraction stage. The differences in surface characteristics like luminance texture or color provide this information for the object. This results in the decomposition of the object into a set of geons which are the component of the object. The second stage involves the detection of the regions of concavity from the non-accidental properties of the image, like co-linearity and symmetry, to give the skeletal structure of the object. This leads to understanding how the different geons are attached to each other. The final stage is matching the geon structure and its associations against the representation of the object in the memory to complete the identification process (Biederman 1987; Biederman and Gerhardstein 1993).

Implementing geons to represent objects is governed by rules for their creation and layout. Geons can be used to represent very rich node-link diagrams. Different geons combined in different ways are used to form the nodes. The links between the nodes are represented by different geon shapes between corresponding geon structures. Minor subcomponents are represented as small geon components attached to the larger ones. Geons can be shaded to make their 3D shape clearly visible. Different attributes of entities and relationships of geons are represented by color and texture or by symbols mapped onto the surface of the geons (Biederman 1987; Biederman and Gerhardstein 1993). All geons should be visible from the chosen viewpoint, and junctions between geons should be clearly visible. The geon diagram should be laid out in the plane orthogonal to the direction of viewing. Figures 2.3, 2.4 and 2.5 show how different objects can be formed from simple geometric shapes. Figure 2.4 shows that the same two shapes can be joined in different ways to form very different objects. As shown in Figure 2.3, these geometric shapes are invariant over changes in orientation and can be determined from a few points on each edge, even with a large variation in viewpoint, occlusion and noise (Biederman 1987).

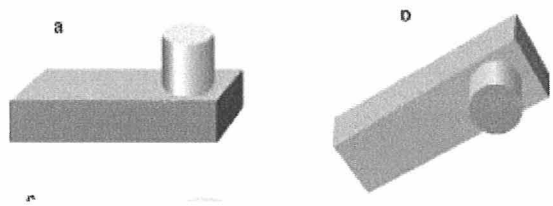


Figure 2.3 Different layouts are readily identified as being the same shape (Source: Irani and Ware 2003).

Figure 2.4 Different arrangements of geon components produce different objects (Source: Biederman 1987).

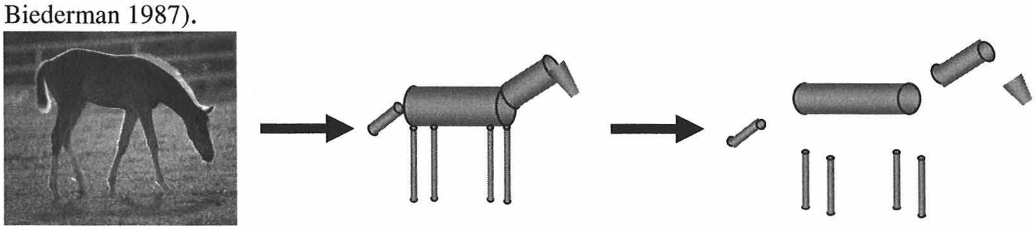


Figure 2.5 Geon representation of a physical object (horse) and constituent shapes.

Table 2.1 summarizes the difference in UML and geon diagrams' representation of a node-link diagram.

Table 2.1 Summary of Difference Between UML and Geon Diagrams

	UML	Geon
Main concept	Nodes are perceived as the representation of the abstracted entities. Links provide information to form an association among the different nodes.	Objects are decomposed at the regions of concavity to form geons. Connectivity of the object gives a meaning to the overall object structure.
Steps in recognition	Nodes are perceived first; links provide supplementary information for associating the different nodes. As the nodes are recognized and the associations are formed between the nodes, the object tends to become specific until ultimately, it forms something that uniquely identifies some system or concept that is already present in the user's memory. If it does not result in a match, the object may become a new entry in the user's memory.	Object representation is parsed at the region of concavity. The structure is identified as object skeleton based on the different object blobs and the way the different geons are attached. The resulting structure is matched in the user's memory to existing patterns for object recognition
Recognition strategies	Individuals first locate the main entities (or nodes). The nodes are grouped mentally before proceeding with the links to form a mental association image. A mental model is formed based on the preliminary knowledge gathered during the comprehension phase. The mental image keeps forming as the first node is perceived and as more nodes and links are perceived ("part-to-whole").	Individuals may locate any part of the representation as a convex blob. The mental image is formed after all the blobs are recognized and the individual is able to form a skeletal structure of the representation based on the connectivity of the different blobs ("whole-to-part").
Perception of representation	Representation seen as composed of different nodes and therefore, seen as different objects or components of objects joined by some rule of association	The whole representation is treated as one object that has various regions of separation

After presenting the two visualizations, the next section discusses another factor, viz., diagrammatic complexity that impacts cognitive processing in visual problems.

2.1.4 Diagrammatic Complexity

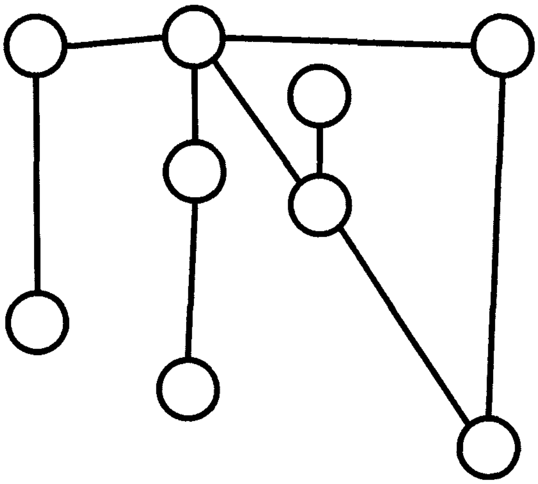
This section discusses another factor, diagrammatic complexity, which impacts cognitive processing in visual problem solving. Complexity of visualization is a measure of the ease or difficulty in understanding it either computationally or cognitively. Though numerous definitions of complexity have been developed in different studies, the current focus is on defining the measure of complexity as a measure of diagrammatic complexity.

A working definition of complexity of node-link diagrams may be found in graph theory (Ware, Purchase, Colpoys and McGill 2002). This definition is a function of the readability of the node-link diagram. Readability of a graphic visualization is defined as the relative ease with which an individual finds the information sought. That is, the more readable the visualization, the faster the individual executes the task at hand and the lower the number of errors made. If the individual answers quickly and correctly, the visualization has high readability for the task. If the individual needs a lot of time or answers incorrectly, then the visualization is not well-suited for that task (Ghoniem, Fekete and Castagliola 2004).

The complexity of a node-link diagram is a measure of its readability. With the increase in the number of nodes or with the increase in link density in the node-link diagrams, the diagrams become harder to comprehend because of occlusions arising out of overlapping links, crossover links and undistinguishable nodes and links (Batagelj and A. Mrvar 2003; Ghoniem, Fekete and Castagliola 2004; James 2006; Shen and Ma 2007). Thus, it becomes difficult for individuals to visually explore the node-link diagram or interact with its elements (nodes and links) as the complexity of the diagram increases (Ghoniem, Fekete and Castagliola 2004).

Previous studies in the information visualization community focused on understanding the impact of complexity of node-link diagrams from a cognitive point of view by evaluating graph layout algorithms using different sizes of node-link diagrams (Keller, Eckert and Clarkson 2006; Ware and Bobrow 2005). These studies show how the comprehension of node-link diagrams decreases as the number of nodes and the number of links per node increases (Ware and Bobrow 2005). A few other studies evaluate the aesthetic criteria for graph creation and graph layout algorithms (Purchase 1998; Purchase, Carrington and Allder 2002; Purchase, Cohen and James 1997). The contribution of these studies is a set of guidelines that improve the presentation of the node-link diagrams in an aesthetic sense. Other experiments included node-link diagrams in 2D and 3D (Bertin 1983; Cohen, Eades, Lin and Ruskey 1994; Ghoniem, Fekete and Castagliola 2004; Herman, Melançon and Marshall 2000) that concentrated on understanding how increasing a dimension in representation impacts the understanding of node-link diagrams. Therefore, from all these studies, it can be concluded that the complexity of a node-link diagram consists of an objective part based on the number of nodes and links in the diagram, as well as the qualitative part of aesthetic compliance of the layout of the nodes and links.

The number of nodes and the link density of a node-link diagram greatly influence its readability (Ware and Bobrow 2005). Link density d in a node-link diagram is defined as $d = \sqrt{(l/n^2)}$: where d is the density, l is the number of links, and n is the number of nodes in the node-link diagram (Ghoniem, Fekete and Castagliola 2004). This value varies between 0 for a node-link diagram without any edge to 1 for a fully connected diagram. Figure 2.6 shows a node-link diagram. There are 9 nodes (n) for this diagram and 9 links (l). The link density for this node-link diagram is $d = \sqrt{(9/(9)^2)} = 0.33$.



$d = \sqrt{(l/n^2)} = 0.33$

Figure 2.6 A node-link diagram showing the link density.

The readability of node-link diagrams tends to deteriorate as the size of the node-link diagram and its link density increases. Previous studies have shown that for a node-link diagram with a very large number of nodes and a large link density (typically greater than 0.6), a matrix representation tends to be more suitable than a node-link diagram (Ghoniem, Fekete and Castagliola 2004) for understanding the information used to develop the matrix or node-link diagram. Therefore, construction of node-link diagrams when the link density is greater than 0.6 is not recommended and is out of scope of this research.

For reasons of clarity and ease of presentation in a regular sized presentation medium, a typical node-link diagram used has less than 20 nodes and 30 links (Ware and

Bobrow 2005). Also, the number of nodes that can be comfortably represented on a computer screen or a sheet of paper is approximately 20. This ensures that individuals do not have to scroll or refer to multiple pages to look at the complete node-link diagram. For specification on the link density, a node-link diagram used to show a large number of nodes and links does not exceed a link density of 0.6, with the majority of them in the range of 0.3 and 0.6 (Ware and Bobrow 2005).

However, there are factors other than complexity that impact the readability of node-link diagrams. There are established principles and methods drawing effective graphs that can be used to draw node-link diagrams more effectively (Ware, Purchase, Colpoys and McGill 2002). Drawing the node-link diagrams according to guidelines of aesthetic principles improves their presentation by increasing their readability (Battista, Eades, Tamassia and Tollis 1999). Some of these principles include minimizing the length of the edges, minimizing the number of edge crossings and minimizing the sum of the lengths of the edges (Ware, Purchase, Colpoys and McGill 2002). Other principles include minimizing the number of branches emanating from nodes in the node-link diagram, displaying the symmetry of the node-link diagram and minimizing the number of bends in the links or edges (Koffka 1935). In practicality, it may not be possible to eliminate all edge crossings and bends and it may be worth allowing an occasional crossing in a node-link diagram if it reduces the bendiness of path. It can be argued that with good guidelines, it is possible to create a node-link diagram perceivable by individuals that can help reduce the cognitive load of those individuals that use them to accomplish a task via visualization of the system.

Complexity of node-link diagrams is taken as a function of the number of nodes, the number of links and the maximum number of links emerging out of a node. While the aesthetic factors of drawing node-link diagrams do not contribute to its complexity, every effort should be made to incorporate these factors in drawing node-link diagrams to make them more efficient and avoid compounding factors.

To address the impact of different visualization type and complexity on the cognitive processing of individuals, a scope of the task expected to be accomplished using the visualization needs to be defined. As discussed earlier, visualizations are particularly effective in problem-solving activities because they reduce the cognitive processing required by individuals to complete the activity. Problem-solving activities such as searching, recognizing relevant information and drawing inferences from that information have benefited from visualizations (Simon and Hayes 1976). Therefore, the task that will be designed to investigate individual cognitive differences for different visualization types and complexities will be a problem-solving task. This is discussed in detail in Section 2.1.5.

2.1.5 Visual Problem-Solving Task

A visualization is an external pictorial representation that makes it easy to see certain patterns in data (Shneiderman and Maes 1997). A visual problem-solving task includes understanding the visual elements and being able to identify an element of interest based on certain conditions in a given visualization. For this research, the task is a what-if type, where the individuals are asked to analyze the implications given that a certain node or link has been removed.

Two important activities accomplished during a problem-solving task are search and decision-making. Both these activities depend on an individual's cognitive skill and pattern regarding how they seek and use information (Wolfe 1998). Individuals look for information either by searching or scanning, depending on various factors like the nature of the problem, nature of the visualization, time at hand, amount of information available and kind of expertise at hand (Vandenbosch and Huff 1997). Any system developed to help individuals work with the underlying information should be able to provide them with an interface to search, scan, evaluate and transparently integrate between them without requiring additional cognitive processing to understand and process the interface (Treisman and Kanwisher 1998).

In the context of a node-link diagram, the result of the impact of a what-if type of decision-making problem is a substructure which is usually a set of nodes and links that depicts a concept from the visualization of the problem. The problem space of a given visual problem is the set of states and valid transformations between the states to solve the problem and complete the task. The terminating state in the problem space represents the goal of the task. In a visual problem-solving task, the terminating state is reached when the impacted substructure is found. Also, tasks making use of visualizations like recognition, decision-making or analyzing involve a search task. Therefore, the current research proposal focuses primarily on visual problem-solving tasks.

The cognitive difference between individuals using informationally equivalent but visually different visualizations will be understood using a pre-defined problem-solving task. To understand the difference, it is necessary to understand the cognitive level processing by individuals doing a visual search task. It is also necessary to devise a way to measure and quantify parameters to measure cognitive processing. The next section discusses different ways in which the impact of visualization on cognitive processing by individuals can be measured.

2.2 Impact of Visualization on Cognitive Processing of Individuals

A good visualization helps decision-makers act on the visualization and make decisions as if they were working on the actual system. To understand the effectiveness of any visualization, it is necessary to be able to quantify the parameters used to measure cognitive processing. These measures are developed in this section.

2.2.1 Effectiveness of Visualization

Effectiveness of any visualization is the extent to which the visualization helps derive results in a visual problem-solving task. When different visualizations are used to represent the same information, and individuals are asked to solve a problem using both, one ends up being cognitively richer compared to the other (Kosara 2003; Treisman 1988). The more effective visualization helps the individuals to comprehend the problem better and solve the problem more effectively. Two common parameters for comparing the relative effectiveness of two visualizations are precision and duration (Freitas et al. 2002; Kobsa 2004; Plaisant, Grosjean and Bederson 2002). Precision (a.k.a. accuracy) can be defined as the degree of conformity of an indicated value to an accepted standard or ideal value (Pickett 2000). Duration is the time taken to solve a problem (Pickett 2000). Prior studies have established that visualizations can be developed so that they lead to greater effectiveness in time to task completion and precision, compared to existing representation techniques in the domain of visual problem-solving and decision-making (Johnson 1992; Larkin and Simon 1987). Apart from measuring effectiveness based on the result of a visual task, effectiveness of a visual task can also be measured by understanding the cognitive processes of individuals doing the task (Johnson 1992). Two such measures are discussed next.

2.2.2 Visual Search Path

To find an embedded structure in a given visualization, individuals look for the presence of particular elements and/or their combinations. To locate a particular element, an individual in some way navigates the visual space until the search element is located or the individual decides to give up the search process. This navigated path that the individual takes to locate a search element in the visualization is called the search path. When individuals are looking for information of interest in a given visualization, they may attempt mentally to divide the visualization into subparts to look for the information in each subpart, moving to other subparts in succession (Halverson and Hornof 2004). Individuals tend to fix their attention at certain points on the visual display and then transfer their attention to other locations (Chen, Cribbin, Kuljis and Macredie 2002; Pirolli and Card 1995). The number and sequence of fixations and the nature of elements and their features also influence the search process (Halverson and Hornof 2004; Hu, Dempere-Marco and Yang 2003).

In visualizations containing numerous elements and relationships between the elements, individuals tend to perceive multiple elements in a single fixation (Hornof 2001), while the number of objects that can be examined with single fixation decreases during a visual search (Hornof 2001; Treisman 1988). Individuals may also randomly miss or ignore certain elements during a searching exercise (Hornof and Halverson

2003). Analyzing an individual's traversal through different visualizations helps in understanding how individuals perceive and process information encapsulated in the visualization (Smilek, Enns, Eastwood and Merikle 2006).

In node-link diagrams, the search path shows the sequence of nodes and links traversed by individuals in completing the search task. The sequence and length of the search path helps in understanding the elements that are traversed and, more importantly, the set of elements that are skipped by individuals while doing the search task. Therefore, the search path helps to identify the difference in the information being used to complete the search task when different visualizations are used to present the same information.

2.2.3 Visual Search-Steps

The cognitive process for identifying an element in a given problem visualization requires the individual to memorize the element to be identified and use the problem visualization to look for evidence to support accepting or rejecting the presence of the element (Proulx 2007). The mental organization and navigation of the subparts of the visualization of a problem differs from individual to individual. The presence or absence of textual labels in visualizations, impacts a user's search in certain ways. Depending on the task at hand, the methodology applied and the goal in mind, individuals may stop searching for the substructure once they find it or continue to search for multiple instances or patterns in a given visualization.

Search-steps can be used as a measure to quantify the cognitive process of individuals in a search task. The task of searching for a pre-defined element can be condensed to a set of basic steps (Hornof and Halverson 2003; Hu, Dempere-Marco and Yang 2003). The first step is to define and formulate a suitable query. The second step is to identify an entry point either randomly or by using an index or other search parameters. The third step is to examine and evaluate the search results and rate their relevance. The fourth step is to accept or reject the result. Steps 2-4 are repeated until the desired result is achieved.

Node-link diagrams can be classified as unstructured and structured visualizations. In unstructured visualizations, where the representation is neither hierarchical nor follows a systematic top-down approach, a visual search may or may not follow an ordered search (Hornof and Halverson 2003). The eyes may move directly to a random element with the sudden recognition of the target (Hornof 2001). The eyes may also move haphazardly from one node to another, resulting in an unordered scanning until the target is located. In an unstructured layout of nodes and links, the eyes of the individual move from one particular element to another until the candidate structure is located (part-to-whole).

On the other hand, in a node-link diagram with a better hierarchical structured layout, an individual searches a substructure in an organized path that starts from a top level set of abstracted elements and successively moves to a more specific set of nodes and links (whole-to-part) by eliminating the elements that do not conform to the search conditions (Hornof and Halverson 2003). Therefore, depending on the organization in the diagrammatic layout, the search can be either part-to-whole or whole-to-part. The next section integrates and summarizes the concepts of different visualization types, based on different perception theories and the different complexities to visualizations, to develop research propositions that will be addressed in this proposal.

2.3 Discussion

The theoretical details provided so far can be summarized as follows. Use of visualizations can increase the effectiveness of individuals presenting and analyzing information. Effective visualizations can be developed based on different perception theories. Two such visualizations are UML diagrams and geon diagrams. These two diagrams are selected as candidate visualizations that will be used to understand the difference in cognitive processing of individuals in visual problem-solving. Another factor that will be studied as a part of this research is the diagrammatic complexity of the visualization, which is a function of the number of nodes and the link density of the visualization.

Different measures used to understand the difference in cognitive processing of individuals include effectiveness of the visualization measured in terms of the time taken to complete a search task and the precision of the result of the search task. The measures of cognitive processing of individuals are expected to contribute to the major results of this research. These measurements include the search path and the search-steps used by individuals to complete the search task. The difference in the underlying theories of object perception gives rise to the difference in the effectiveness and the cognitive processes of individuals using the visualizations. There are a few assumptions underlying this research design. These are discussed in the next section.

Assumptions

There are certain assumptions underlying the research model and design. A problem-solving task involving a “what-if” scenario is the only task type being considered in the study. It may be argued that different types of tasks have different cognitive requirements, and a search task may not reflect the same cognitive processing as other visual tasks. But because the given problem type is a task that would benefit from a cognitively rich visualization, it is more relevant to use this as a basis for the research.

Only two types of visualizations are being considered in the research. As discussed previously, not many theories are widely used to develop visualizations. Therefore, the most often used visualizations have been used as a basis for selecting the theories for this research.

The research design will take advantage of analyzing the verbalizations of the participants as they complete the search task. The effect of verbalization on the time taken to complete a task is not taken into consideration. There is a possibility that, because of verbalizing their actions, the individuals may slow the task they are doing. However, given the expected benefit of the analysis of the verbalization of the participants, the effect of talking aloud while doing the experiment will be ignored. Also, the increase in time for each task can be assumed to be in the same proportion for every experimental condition. Hence, it can be assumed with high confidence that the results will not be skewed because of protocol analysis.

Given the background of the research and after presenting the key concepts used to develop the research design, a set of research propositions are developed to uncover and explain differences in cognitive processing in a search task by using geon and UML diagrams. The answer to the research propositions will reflect the cognitive differences of individuals in understanding and using different node-link diagrams.

2.4 Research Propositions

In node-link diagrams, simple search tasks require individuals to identify nodes and links in the visualization. Using different node-link diagrams results in differences in the way the visualization is understood and the visual problem-solving task is performed. The following subsections develop research propositions to understand the difference in the search process for the two visualizations that are informationally equivalent but visually different.

2.4.1 Effect of Visualization Type on Task Effectiveness

Effectiveness of any visualization is the extent to which the visualization helps to derive results in a visual search task. Two common parameters for comparing the relative effectiveness of two visualizations are precision and duration (Freitas et al. 2002; Kobsa 2004; Plaisant, Grosjean and Bederson 2002). As discussed earlier, prior studies have established the advantages of developing cognitively richer visualizations that result in greater effectiveness over existing representations (visual or sentential) in problem-solving and decision-making (Shneiderman and Maes 1997). Because of the inherent differences in different types of visualizations (Gershon 1994; Gordon 1989; Gregory 1990; Ware 2000), it is expected that different visualizations will have different effectiveness for a given problem scenario. To understand the effectiveness of the results derived using SOPT (Structural Object Perception Theory) and OM (Object Modeling), time taken to complete the task and the error rate of the task result are measured. In a paper on diagrammatic perception (Irani and Ware 2003), the research proposition of the effectiveness of identification of a substructure in a larger visualization is measured (Irani and Ware 2003). The first research proposition is formulated based on the results of this research as:

Proposition 1: A problem-solving task using geon diagrams will require less time and result in lower error rate.

2.4.2 Effect of Visualization Type on Search Path

In the visual search task, individuals are required to find a given substructure in UML and geon diagrams. The search path of an individual doing a visual search task is affected by factors like motivation, cues presented, and prior information (Halverson and Hornof 2004). The individual's search process will include looking for particular nodes and links and/or their combinations, or multiple nodes and links based on these factors (Halverson and Hornof 2004; Hu, Dempere-Marco and Yang 2003). UML class diagrams represent the set of classes and the relationships between the classes. Such diagrams are comprehended by understanding the classes in the context of the problem and the different relationships that govern interaction between the classes (Sutcliffe 1999). Therefore, to assimilate a set of such diagrams will require individuals to look at the classes and see if the relationships are as anticipated or stored in their memory. In UML class diagrams, visualizations are interpreted by first understanding the objects in the visualization and then the subsequent association between the objects. Therefore, individuals will first tend to look for the objects to identify a substructure, and will then look for relationships (associations) between the objects only if satisfactory results have not been obtained.

In geon diagrams, the visualization is understood using the geometric shapes and the attachment of the shapes to one another (Biederman and Gerhardstein 1993; Marr, Pascoe, Benwell and Mann 1998). In recognizing geon diagrams, the arrangement of components is matched against a substructure in the memory (Biederman 1987). Individuals using geon diagrams will try to segregate out the convex shapes (objects or relationships or their combinations) and try to match them against the representation of the substructure in their memory (Biederman and Gerhardstein 1993). During the search task, as individuals keep referring to the candidate geometric shapes in the visualization, a combination of the different shapes is assimilated in the individual's memory as a single object. Therefore, as the search task progresses, individuals start referring to combinations of multiple geometric shapes rather than a single one. The object recognition happens in the stage when the candidate structures are matched against the structure in the memory (Biederman 1987). Over time, individuals will tend to recognize the combination of objects and relationships as a single object. Therefore, fewer steps will be required to reach the result. To address the difference in search path in the visualizations developed using UML and geon diagrams, the research proposition can be formalized as follows.

Proposition 2: A problem-solving task using UML diagrams will lead to longer and more node-dominant search paths than the one using to geon diagrams.

2.4.3 Effect of Visualization on Search-Steps

In a search task, the individual's cognitive processes of reasoning while traversing the visualization can be condensed to a set of steps consisting of *initiate*, *locate*, *evaluate*, and *decide* that the individual takes to identify a substructure in the visualization (Halverson and Hornof 2004; Hu, Dempere-Marco and Yang 2003). After *initiating* the search process, *locate* is the identification of nodes and links in the visualization, and *evaluate* is the evidence used to support accepting or rejecting the identified substructure (Halverson and Hornof 2004). The search process iterates through the *"locate"* and *"evaluate"* steps until a decision is reached (Halverson and Hornof 2004; Hu, Dempere-Marco and Yang 2003). The number of *locate* and *evaluate* steps and their sequence aids comprehension of the mental process of individuals as they complete the search task.

In UML diagrams, searching for a substructure consists of looking for objects (Kim and Lerch 1992). Once a familiar object is found, individuals try to locate additional information about relationships between the objects to determine whether or not the substructure is found. Once a satisfactory substructure is located by the individual, based on the objects and the relationships between the objects, the search task is completed (Kim and Lerch 1992). Therefore, the stress in UML diagrams is on *locating* the right objects.

In geon diagrams, recognition of objects happens at the last stage when the components extracted are matched against a mental image of the individual (Biederman 1987). The individual *evaluates* the geometric shapes or their combinations against a mental image before accepting or rejecting the identified substructure (Biederman 1987). Hence, in geon diagrams, the stress in the search-steps is on *"evaluate"* steps. This leads to research proposition 3.

Proposition 3: In a visual problem-solving task, visualizations developed using UML class diagrams will result in *locate*-dominant search-steps while visualizations developed using geon diagrams will result in *evaluate*-dominant search-steps.

2.4.4 Effect of Diagrammatic Complexity on Effectiveness

For all types of visualizations with low complexity, since the number of nodes and links is much fewer, the time taken to navigate through all the nodes and links is lower, as compared to visualizations with higher complexity. Similarly, the error rate in a task is much lower in visualizations with lower complexity as compared to visualizations with higher complexity. The scope of making an error increases with the increase in the number of nodes and links that an individual has to process while completing a visual task. Also, limitations on the number of nodes and links that can be evaluated simultaneously result in more errors when working with visualizations of higher complexity. This leads to the research proposition 4.

Proposition 4: More complex visualizations lead to lower effectiveness in a visual search task.

2.4.5 Effect of Diagrammatic Complexity on Search Path

The search path of an individual in a visual problem task depends on the diagrammatic complexity of the visualization, where the complexity of the visualization is a function of the number of nodes and the link density (Batagelj and A. Mrvar 2003; Ghoniem, Fekete and Castagliola 2004; James 2006). For a very trivial task involving a very small number of nodes, the node-link diagram is a very sparse representation of the system elements and their connections. In such a node-link diagram, the completion of the task may not require the individual to refer to the visualization more than once. For a more complex visualization, the limits on the individuals' working memory restrict the number of nodes and links that can be perceived and evaluated by the individual to complete the visual search task (Ghoniem, Fekete and Castagliola 2004). For a task using low-complexity visualizations, an UML or geon diagram aids better system understanding; for high-complexity visualizations these benefits may be overshadowed by the enormous number of different nodes and links that the individual must store in their working memory. Therefore, the advantage provided by easily recognizing of nodes and links in the visualization is overshadowed by the large number of nodes and the large number of nodes per link, and the complexity of placement of the nodes and links relative to one another. This leads to the research proposition 5.

Proposition 5: High-complexity visualizations lead to longer search paths in a visual search task.

2.4.6 Effect of Diagrammatic Complexity on Search-Steps

Different complexities of visualization lead to different search steps for completing a problem-solving task. A high-complexity visualization limits the number of nodes and links that can be located and evaluated by individuals (Ghoniem, Fekete and Castagliola 2004). More iterations of *locate* and *evaluate* steps will be required to investigate the visualization to locate the substructure for a visual search task (Batagelj and A. Mrvar 2003; James 2006). Also, because the number of links per node also increases for high-complexity visualizations, the number of *locate* steps for the same node or link may also be higher for such visualizations. If the number of nodes as well as the link density of the visualizations is low, individuals are expected to complete the search task in a single iteration of traversing the visualization. But as the number of nodes and the link density increase, the number of elements (nodes, links or combinations) that can be simultaneously located and evaluated by an individual decreases (Ghoniem, Fekete and Castagliola 2004). Therefore, there is a possibility that the individual may have multiple traversals of the same information. This leads to a higher number of "*locate*" and "*evaluate*" steps when individuals are using a complex visualization. This leads to proposition 6.

Proposition 6: High-complexity visualizations lead to more search-steps as compared to low-complexity visualizations.

2.4.7 Interaction Effect of Visualization Type and Complexity

The impact of visualizations based on different perception theories and different complexities of visualizations on the cognitive processing of individuals has been presented earlier. To investigate if one factor has a compounding effect on the other (i.e., does the impact of varying complexity of geon diagrams differ from the impact of varying complexity of UML class diagrams), the interaction of the two factors needs to be investigated. When the complexity of the visualization is varied for a given visualization, there may be a change in the way the visualization is traversed and understood by individuals. This is so because with the increase in the number of nodes and links per node, the visual space becomes denser (Batagelj and A. Mrvar 2003; Ghoniem, Fekete and Castagliola 2004; James 2006). Also, the working memory of individuals is limited in terms of the number of objects that can be remembered (Ghoniem, Fekete and Castagliola 2004). When the number of nodes and link density in any visualization increases, the problem space enlarges. The solution paths also become longer. Therefore, the time taken to complete a task and the error rate also vary as the visualization type and complexity of the problem vary.

While geon diagrams can aid in cognitive processing of a visual problem, a more complex layout of a geon diagram may lead to increased processing of the elements (nodes and links) that may lead to longer search paths and a larger number of search-steps (Halverson and Hornof 2004). Also, while UML class diagrams require processing and traversal techniques that are different from geon diagrams (Biederman 1987; Sutcliffe 1999), increasing the complexity of the visualization by increasing the number of nodes and the number of links per node, may change the way the visualization is processed and traversed. Therefore, with the increase in the complexity of UML class diagrams and geon diagrams, the effectiveness, search path and search-steps of individuals are impacted in different ways. This leads to propositions 7, 8 and 9.

Proposition 7: When UML class diagrams and geon diagrams are varied in terms of complexity, the time taken to complete the task and the error rate in UML class diagrams continue to be higher, and the magnitude of difference is greater with the increase in complexity.

Proposition 8: When UML class diagrams and geon diagrams are varied in terms of complexity, search paths in UML class diagrams continue to be longer and node-dominant for complex visualizations, although magnitude of difference may reduce with the increase in complexity.

Proposition 9: When UML class diagrams and geon diagrams are varied in terms of complexity, the search-steps in UML class diagrams continue to be "locate" dominant and the search-steps in geon diagrams continue to be "evaluate" dominant, although the difference in the search-steps reduces with the increase in the complexity of the visualization.

To analyze the research propositions, testable hypotheses of the propositions need to be developed. The next section develops the experimental scenario and operationalizes the independent and dependent variables with respect to the scenarios and experimental task. After discussing the task and the parameters to be measured in the task, the hypotheses are developed using the measured parameters.

CHAPTER 3

DESIGN OF EXPERIMENTS

This section operationalizes the propositions developed in Section 2.4. It develops the research task and hypotheses that will be used in the current research. Following the experimental design and process for data collection, the plan for the data analysis is provided. The proposed research model will help to explain how different visualization types and visualization complexity impact individual navigation and search-steps in visual problem-solving. The problem-solving strategy will be investigated by answering the research propositions developed earlier.

3.1 Scenarios

The experimental scenarios will be developed for a set of complex geographical systems. Complex geographical systems are geographical systems consisting of a large number of interrelated or interconnected parts, entities or agents. Some of these physical systems are crucial for the economic well-being and security of a nation. These are called critical infrastructure systems. The United States government has identified eight infrastructure systems as critical infrastructure systems. These include emergency services; transportation; information and communications; electric power; banking and finance; gas and oil production, storage and transportation; water supply; and government. These services may not be degraded, whether by willful acts such as terrorism or by natural or random events such as earthquakes, design flaws or human errors, as their operation is mandatory for the regular operations of the nation and its people. (U.S. General

Accounting Office 2001). The degradation of these infrastructures, by willful or natural acts, results in substantial damages in terms of money, life and recovery efforts (U.S. General Accounting Office 2001). Also, since these infrastructures are viewed as interconnected and interdependent systems of systems, they must be managed over geographic space and time. The optimum management of complex systems is non-trivial and is crucial to the flawless functioning of all the individual systems, as well as to the individuals who utilize the services provided by these systems. Improved methods are needed for constructing visual tools for the management of interdependent infrastructure systems (Chakrabarty and Mendonça 2004). Even in practice—as in the response to the 2001 World Trade Center attack—system visualizations such as maps are used extensively in managing critical infrastructures (Kendra and Wachtendorf 2003). This leads to the need for developing a good visualization of the interdependent systems which can be used by the managers of the systems to understand and manage them.

The critical systems mentioned above are good examples of complex geographical systems. For example, consider the system of telecommunication. Entities of the telecom network like transmitters, telecom stations, and hubs are interconnected in the real world with other infrastructure systems like buildings, transportation infrastructure and electricity. Such interdependency of different infrastructure systems with other systems increases the complexity of their management and maintenance. The different types of interconnections and interrelationships between different infrastructures can be identified as *input, mutually dependent, shared, exclusive-or* and *co-located* (Rinaldi, Peerenboom and Kelly 2001; Wallace et al. 2003). *Input* interdependency occurs when one infrastructure requires as input one or more services from another infrastructure to provide some other service. *Mutually dependent* interdependency occurs when at least one of the activities of each infrastructure in a collection of infrastructures is dependent upon each of the other infrastructures. (An example of mutual dependence between two infrastructures occur when an output of infrastructure A is an input to infrastructure B, and an output of infrastructure B is an input to infrastructure A.) *Shared* interdependency means that some physical components or activities of the infrastructure used in providing the services are shared. *Exclusive-or* interdependency refers to the condition when only one of two or more services can be provided. Exclusive-or can occur within a single infrastructure system or among two or more systems. *Co-located* refers to components of two or more systems that are situated within a prescribed geographical region (Lee 2006).

Management of complex systems provides a special challenge with regard to the depiction of these systems to the managers. This was evident in different situations as shown during the aftermath of the 2001 World Trade Center attack (Mendonça, Lee and Wallace 2004), as well as power blackouts in the U.S. (U.S.-Canada Power System Outage Task Force 2004). The set of complex interdependent infrastructure systems now goes beyond physical systems. Apart from the physical infrastructure, there is also the information infrastructure (Luiijf and Klaver 2004). The extent and usage of these systems have grown by leaps and bounds over the last decade, and current research work on interdependent systems now includes information systems as well (Luiijf and Klaver 2004).

A disruption in an infrastructure can involve a wide variety of infrastructures as a result of these interdependencies. To illustrate the point, consider an example of "input" interdependence between a telecommunications company and the switching station for which it is responsible. The switching station is used to route calls through the network. Power from an electric utility's transformer is required to operate the switching station, thus creating an input interdependency from power to telecommunications. An incident involving loss of power in the power system would therefore lead to a disruption in the telecommunications system.

The integration of models of complex infrastructure systems with GIS (Geographic Information Systems) leads to a wide range of benefits upon investigating the behavior of spatio-temporal processes through simulation studies. These studies incorporate human decision-makers. Currently such models of complex systems are based on environmental models (e.g., transportation, hydraulic), which follow directly from the human perception of infrastructures being a part of the environment (Brown and Afflum 2002; Sui and Maggio 1999; Treinish 2002; Yoo et al. 2000). With the increasing capabilities of computer systems (including the Internet) has come the opportunity to ease the process of developing and rendering visualizations (Huang and Worboys 2001). This has also led to the model becoming more interactive, real time, and has been successful in leveraging the added benefits of concurrent usage of the model for decision-making. Given these complexities and interdependencies, management of interdependent and complex systems is likely to require a variety of tools. Given the wide implications of the use of visualizations in the management of complex systems, it has been chosen as the scenario on which the experimental tasks will be focused.

The scenarios being developed are hypothetical layouts of complex interdependent infrastructures. The scenarios have been developed based on the research, "Assessing Vulnerability and Managing Disruptions to Interdependent Infrastructure Systems: A Network Flows Approach" (Lee 2006). Consider the electrical substations, subway system and telephone networks in a large city. The electrical substations supply electricity to certain residential and commercial organizations in specific geographical areas. The electric substation also supplies electricity to the nearby subway stations. That implies that the electric substations provide electricity as "*input*" to the residential, commercial and transport systems. This is referred to as *input* interdependency. Telephone switching stations also receive their electric supply from the substation. The electric substation supplies the telephone exchange with electricity supply and the telephone exchange serves the electrical substation with telecom lines to provide it the necessary monitoring facility (SCADA - Supervisory Control And Data Acquisition) and basic telecom connection. This is an example of the *mutually-dependent* type of interdependency. The telephone switching station is also responsible for providing services to nearby residential and commercial organizations. This is another example of input interdependency. As in any practical layout, it is essential to note that some of these entities are located in the same geographical area. This is referred to as *co-located* interdependency. Given this general backdrop, two sets of scenarios are created as described below.

To develop the visualizations for the UML and geon diagrams, Table 3.1 and Table 3.2 serve as the key. Table 3.1 provides the key used to develop the UML and geon equivalents of the elements used to visualize the complex systems. Table 3.2 provides the UML and geon equivalents of the different interdependencies present among the elements of the complex interdependent systems.

Table 3.1 Key of Elements of Complex Systems Used to Develop UML and Geon Diagrams

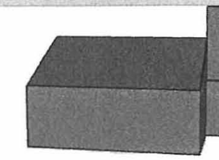
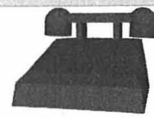
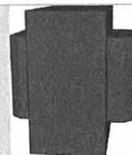
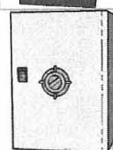
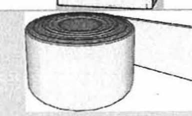
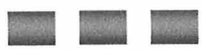
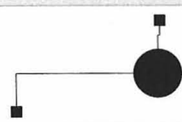
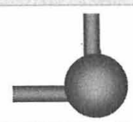
Elements	UML	Geon
Residential area	Residential Area -Location1	
Subway station	Subway Station -Location1	
Telephone central office	Telephone Central Office -Location1	
Electric substation	Electric Substation -Location1	
Financial organization	Financial Organization -Location1	
Stock exchange	Stock Exchange -Location1	

Table 3.2 Key of Interdependencies Used to Develop UML and Geon Diagrams

Interdependencies	UML	Geon
Input		
Shared		
Exclusive-or		
Mutually dependent		
Co-located		

The first set of scenarios is low-complexity visualizations. They consist of less than nine nodes of infrastructure elements like residential areas, financial institutions, electric substations, telephone switching stations, and subway stations. The various interdependencies among all the infrastructure nodes are also shown. The link density for these visualizations is below 0.2. Sixteen such visualizations are developed in UML and geon. The second set of scenarios represents a larger geographic region consisting of a larger number of infrastructure nodes (greater than 18). The interdependencies among all the nodes are represented. The link density is maintained between 0.3 and 0.6. The higher number of nodes and the higher *link density* makes the visualization in this set of scenarios involving complex visualizations. Fourteen such visualizations are developed in UML and geon. All the visualizations are provided in Appendix A.

The experiment for the current research is designed to understand the impact of different visualization types and diagrammatic complexity on individual cognitive processing. The impact of difference in visualization type and complexity on search tasks is the specific focus in this experiment. There are two independent variables in this study: visualization type (*UML* vs. *geon*) and diagrammatic complexity (*low* vs. *high*). The dependent variables are *search time, search precision, search path* and *search-steps.*

Task

To pick a task that is suitable for the visualizations developed using the key provided, the different tasks that can be accomplished using node link diagrams are investigated. There are different ways tasks based on node-link diagrams have been classified, including the list of generic tasks (Ghoniem, Fekete and Castagliola 2004) that can be accomplished using node-link diagrams and task taxonomy for graph visualization (Lee et al. 2006). The task taxonomy classifies the different tasks as follows.

- Topology-based tasks: These include finding adjacency (direct connection), accessibility (direct or indirect connection), common connection or connectivity.
- Attribute-based tasks: These include tasks on specific nodes or links.
- Browsing tasks: These include tasks that include following a path or revisiting parts of the graphs.
- Overview tasks: These include compound exploratory tasks to obtain estimated values like size of the diagram quickly.

For the present research on evaluating the cognitive differences of individuals doing a task using visualizations of complex infrastructure systems, a topology-based task is chosen that requires the participants to determine all the nodes that are impacted when a certain link is disrupted. The specifications of the task are derived from a couple of pilot experiments conducted using the candidate UML and geon diagrams.

3.2 Pilot Studies

Two pilot studies were conducted before the experiment design was finalized. The results from the pilot studies motivated further research in this area and the final experimental design. Both studies are discussed next.

3.2.1 Pilot Study 1

A pilot study was conducted to understand the difference in the cognitive processes that underlie reasoning about theoretically based visualizations that are informationally equivalent but visually different. Two visualizations of the same problem were presented to a set of participants in an experiment where individuals were asked to search for a substructure in a given visualization. Two sets of ten UML diagrams and their equivalent sets of geon diagrams were used. A substructure consisting of a few nodes and links was constructed for each set of diagrams. For the first sets, the substructure had two nodes; and for the second sets it had four nodes. A substructure is said to be present in a diagram if the substructure's nodes and links are present in the diagram. However, the orientation can be different so that it is not as trivial as a simple template-matching task. Using two substructures in two different visualizations leads to four experimental conditions: two-node substructure in UML; four-node substructure in UML; two-node substructure in geon; and four-node substructure in geon.

Participants were first given three practice problems with three complete diagrams. After the practice session, they were presented with 10 random diagrams. The diagrams appeared on the computer screen with a *"yes"* and *"no"* button at the bottom of the screen. The participants had the option of clicking either "yes" or "no" for each of the diagrams based on whether the substructure was present or not. The response time of each participant and the correctness of the response were recorded unobtrusively via the computer interface. They were asked to "talk aloud" as they were doing the task. The complete experiment was recorded using a camera.

A task under each experiment involved identifying a substructure in a set of 10 randomly presented diagrams. The experiment was designed as repeated measures where all the participants were asked to complete a task under all the four conditions (2 UML and 2 geon diagram based tasks). The order in which the participants were presented the task was randomly selected. The problems represented in UML and geon diagrams are hypothetical problems. In UML class diagrams, labels are used to identify each class. The geon diagrams did not use any text labels, and shapes and texture are used to distinguish different classes. In the experiment, the individuals were first shown a substructure and then asked to identify its presence or absence in a given set of diagrams. The time to complete the task, the error rate of the results, the search path used by the participants and the search-steps were used to study differences arising out of visualizations based on different theories of object perception.

3.2.2 Results From Pilot Study 1

The results of this experiment are explained in four parts. The first part discusses the descriptive statistics and enumerates the average time and error of each participant under each condition. The second part describes the results derived based on the original experiment (Irani and Ware 2003) reflected in research proposition 1. The third and fourth parts discuss some results from the protocol analysis to present the results of research questions 2 and 3, respectively. All hypotheses were tested at $\alpha = 0.05$.

Descriptive Statistics

Table 3.3 shows the average time taken (in seconds) by the four participants for each problem set. The time taken by participants S1, S2 and S4 was more for geon diagrams as compared to UML diagrams. The time taken for participant S3 was higher for UML diagrams.

Table 3.3 Pilot Study 1 Result: Average Time for Each Participant

	UML 2-node	UML 4-node	Geon 2-node	Geon 4-node
Participant S1	8.8	8.4	9.8	9.3
Participant S2	13.7	13.8	17.9	22.9
Participant S3	9.2	7.9	8.1	6.1
Participant S4	8.6	10.6	11.5	12.2
Mean	10.1	10.2	11.8	12.6

Table 3.4 shows the number of errors made by each participant under each experimental condition. For UML two-node diagrams, no participant made an error. For UML four-node diagrams, all but participant S1 made at least 1 error. For geon diagrams, only 1 participant made an error under the two-node condition.

Table 3.4 Pilot Study 1 Result: Error Rate of Each Participant

	UML 2-node	UML 4-node	Geon 2-node	Geon 4-node
Participant S1	0	0	0	0
Participant S2	0	1	2	0
Participant S3	0	2	0	0
Participant S4	0	1	0	0
Mean	0.0	1.0	0.5	0.0

Results for Research Question 1: Effectiveness

For testing the hypotheses for research question 1 concerning the effectiveness of a diagram, the time taken by each participant to solve a problem and the correctness of the solution are recorded. The average time required by the participants to find the presence or absence of a substructure is used to test hypothesis 1.1. Average number of incorrect answers in the four sets of questions is used to test hypothesis 1.2. The number of observations n is equal to 16.

As seen from the results in Table 3.5, on average the participants took 12.24 seconds to identify (correctly or incorrectly) the presence of the substructure in the geon diagram and 10.13 seconds for the UML diagrams. The research hypothesis (H1.1) suggested that the time taken to recognize substructures in geon diagrams is less than the time taken to identify substructures in UML diagrams. A sign test was done to test the difference in the two diagrams. But the results imply that the participants spent more time with the geon diagrams as compared to the UML diagrams. As a result, the null hypothesis (H1.1_0) was not rejected. The sign test shows this difference to be not significant ($p = 0.3371$).

Hypothesis H1.2 hypothesized that the error rate is lower in geon diagrams as compared to UML diagrams. The results of the experiments show that the error rate is higher in the UML diagrams (5%) than the geon diagrams (2.5%). Among the four participants, two participants correctly identified the substructure in more geon diagrams than UML diagrams, one participant identified the substructure equally often with the geon diagrams and the UML diagrams and the remaining one is more accurate with UML diagrams. Therefore, this result agrees with the result in the original experiment. The sign test result, however, shows this difference is not significant ($p = 0.625$).

Table 3.5 Pilot Study 1: Summary of Results for Research Question 1

Hypothesis		**Geon**	**UML**	***p*-value**
H1.1 Time taken to recognize substructures in geon diagrams is less than time taken to identify substructures in UML diagrams.	Identification time (sec)	12.24	10.13	0.3371
H1.2 The error rate is lower in geon diagrams as compared to UML diagrams.	Error rate	2.5%	5%	0.625

The results from the current experiment are about the same as the results from the prior experiment (Irani and Ware 2003). However there are certain deviations in the results of the current experiment. In the original experiment, the participants took significantly less time using geon diagrams as compared to the UML diagrams. The summary of the statistics from the hypotheses of RQ1 is presented in Table 3.5.

Results for Research Question 2: Search Path

To understand the difference in the search path of individuals while using different visualizations during visual problem-solving, the transcripts of the participants are coded. The transcripts of the protocols are coded to see patterns in the solution path of the participants. The number, sequence and type of the nodes and links traversed are coded from the participant's verbal transcripts. The length of the solution path is calculated as the number of nodes and links traversed by the participant to identify the presence or absence of the substructure. A *t*-test is used to understand if the difference in search path is significant or not when using different visualizations of the same problem ($\alpha = 0.05$).

The results are shown in Table 3.6. All null hypotheses except $H2.2_0$ are rejected with significant *t*-test results. The results in Table 3.6 show significant differences in the search paths when different visualizations are used for the same task. Therefore, the search path of participants tends to differ based on the type of visualization presented. The effect that arises out of the complexity of the diagram presented is not analyzed, but it is expected that as the diagrammatic complexity increases, the participants will take more steps to traverse through the diagrams, implying larger cognitive load. The next part reports the results pertaining to search-steps.

Table 3.6 Pilot Study 1: Summary of Results for Research Question 2

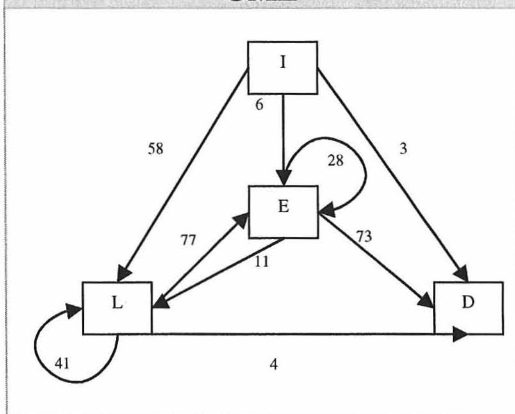
Hypothesis	*p-value*	Result
H2.1: Number of nodes traversed during the search process is greater in UML as compared to geon. H2.1_0: Number of nodes traversed during the search process using UML is less than or equal to the number of nodes traversed using geon diagrams.	0.0004	Reject null hypothesis
H2.2: Number of links traversed is higher in geon as compared to UML H2.2_0: Number of links traversed when using geon is less than or equal to the number of links traversed using UML.	0.1605	Fail to reject null hypothesis
H2.3: Number of components (combinations of one or more nodes and/or links) traversed is higher in geon as compared to UML. H2.3_0: Number of components traversed using geon is less than or equal to the number of components traversed using UML.	0.0045	Reject null hypothesis
H2.4: Number of total elements (nodes/links/components) traversed is higher in UML as compared to geon diagrams. H2.4_0: Number of total elements traversed using UML is less than or equal to number of total elements traversed using geon diagrams.	0.0276	Reject null hypothesis

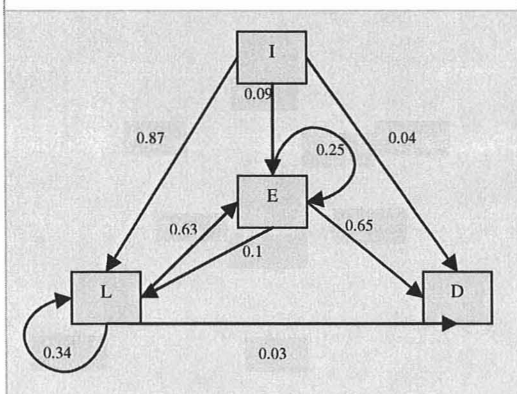
Results for Research Question 3: Search-Steps

To analyze the difference in search-steps, verbal protocols of the participants are coded again. The transcript from the verbal protocol for each task is coded as a sequence of *"Initiate (I)", "Locate (L)", "Evaluate (E)",* and *"Decide (D)"*. Individual's search-steps are analyzed by examining the coded protocol of the participants solving the problem. The counts and sequence of these coded protocols are used to develop directed graphs as shown in Table 3.7. The coded sequence is used to count the transitions from one state to another. The first row in Table 3.7 shows the graphs with the raw counts of the participants' traversals. The arc from state *i* to state *j* shows the total number of transitions between them. The bottom row of the table provides the normalized weights of the arcs in terms of number of transitions made between the states for each type of visualization. As can be seen, the sum of the normalized weights on the outgoing arcs from any node is equal to 1. The graph provides evidence that participants went through a conscious cognitive process while performing the given task.

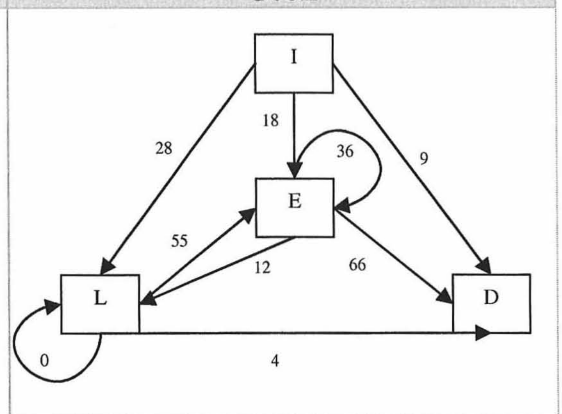
Table 3.7 Search-Steps for UML and Geon Diagram

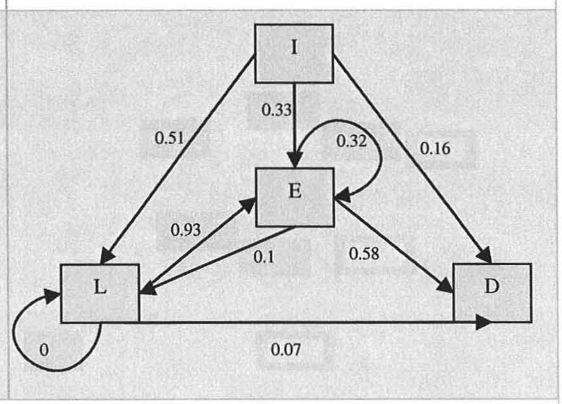
UML





Geon





* Raw counts above; normalized weights below.

To analyze the differences in the sequences of UML and geon diagrams, the counts of the transformations from each state (*I, L, E,* and *D*) to every other state is counted and represented in a matrix. The process represented in Table 3.7 is modeled as a Markov process resulting in a 3X3 (*L, E, D)* matrix. The asymptotic state occupancy statistics of the two visualizations are evaluated to obtain the steady state behavior of the search-steps over a very large number of iterations. The transition probability matrix for the UML diagrams evaluates to α_{UML} = (0.68, 0.23, 0.09) and for geon diagrams is α_{geon} = (0.03, 0.82, 0.15). Therefore, for *locate* transition, the probability for UML is 0.68 and for geon is 0.03. For *evaluate* transition, the probability for UML is 0.23 and for geon diagrams is 0.82. The probabilities for locate and evaluate transitions for UML and geon diagrams indicate that there are differences in the number of transitions based on the type of visualization. The probability of *locate* transitions is higher in UML diagrams as compared to geon diagrams and the probability of *evaluate* transitions is higher in geon diagrams as compared to UML diagrams. The significance in the difference in the probabilities for the two visualizations is analyzed by modeling the state transitions as binomial probabilities. For analysis purposes, success is assumed as the transition of interest (*locate* or *evaluate*). The number of replications, n is 160 (4 participants * 4 conditions * 10 tasks). Because the value of $np > 5$ for every case, normal approximations of the binomial distributions can be used. A t-test shows the difference to be significant for *locate* transition at $\alpha<0.05$ (p <0.0001). For *evaluate* transitions, the difference is significant at $\alpha<0.05$ (p <0.0001).

The experiment results in the preceding sections provide detailed insight into the way individuals understand and traverse different visualizations while searching for information. Apart from the time taken by individuals to process the information layout, and the error rate in the result of the task, parameters such as the search path of the individuals and the search-steps were included to understand the underlying cognitive processes of individuals while performing a search task. The results bring out significant differences in the way individuals look for cues and interpret visualizations that are informationally equivalent but visually different.

The summary of the research results is presented in Table 3.8. Summarizing the results, analyzing the verbal protocols in the experiment shows considerable differences between different visualizations. The path traversed in the process of problem-solving is shortened using geon diagrams. The number of nodes traversed is much larger for UML diagrams as compared to geon diagrams. More participants tend to recognize link components and combinations (of nodes and links) in geon diagrams as compared to UML diagrams. For search-steps of the participants completing the search task, the number of transitions to locate elements is higher in UML diagrams than in geon diagrams. Therefore, participants tend to search or locate for the nodes and links but do not evaluate the nodes and the links. In geon diagrams, the number of transitions to evaluate steps is significantly greater than in UML diagrams. This shows that there is considerable difference in the way individuals navigate the visual space to search for information of interest.

Table 3.8 Pilot Study 1: Summary of Findings for Research Propositions

Research Question	Result
Proposition 1: A problem-solving task using geon diagrams will require less time and result in lower error rate.	~ Time taken to recognize substructures in geon is not significantly less than time taken to identify substructures in UML diagrams. ~ The error rate is not significantly lower in geon diagrams as compared to UML diagrams.
Proposition 2: A problem-solving task using UML diagrams will lead to longer and more node-dominant search paths than the one using to geon diagrams.	~ Number of nodes traversed during the search process is significantly greater in UML as compared to geon. ~ Number of links traversed is not significantly higher in geon as compared to UML. ~ Number of components (combinations of one or more nodes and/or links) traversed is significantly higher in geon as compared to UML. ~ Number of total elements (nodes/links/components) traversed is significantly higher in UML as compared to geon diagrams.
Proposition 3: In a visual problem-solving task, visualizations developed using UML class diagrams will result in *locate*-dominant search-steps while visualizations developed using geon diagrams will result in *evaluate*-dominant search-steps.	~ UML diagrams will result in significantly more locate sequences compared to geon diagrams. ~ Geon diagrams will result in significantly more evaluate sequences compared to UML diagrams.

3.2.3 Discussion of Results from Pilot Study 1

An experiment was designed and conducted to understand the difference in cognitive processing of individuals using two sets of visualizations that are informationally equivalent but visually different. Search path and search-steps were the parameters chosen, with the two visualizations based on SOPT and object modeling (geon and UML, respectively). The test results underscore the difference in cognitive processing of the two visualizations in terms of search path and search-steps.

The results of research proposition 1 present some deviations from the original experiment (Irani and Ware 2003). In the current experiment, the time taken to identify the geon substructure was not faster as expected from the results of the original experiment. The reason could be because of the inclusion of "protocol analysis" during the experiment where the participants spent additional time justifying their steps which they would have avoided in the original experimental setup. The fact that the average times were higher in all the cases, as compared to the original experiment, reinforces this justification. Participants may have spent more time on the geon diagrams because it took more time to explain the 3D shapes and connectors as compared to the UML diagrams, and because, unlike the UML diagrams, the geon diagrams did not have a well-established vocabulary. On the other hand, the UML notations were more easily described using an existing vocabulary and the labels that appear on the classes in the class diagrams.

The verbalization of the participants was analyzed to draw insights into the cognitive process of individuals doing a visual search using visualizations that are informationally equivalent but visually different. Apart from the results of accuracy and speed, understanding the process of solving the task helps to bring forth the differences in visual problem-solving using two sets of visualizations that lead to different processes for a similar nature of tasks.

The results of research proposition 2 show the difference in search path of individuals when using different visualizations. When solving the visual problem using geon diagrams, participants tended to treat a group of nodes and links as a single component. This was because over time participants tended to recognize multiple connected components together, leading them to identify an entire group of nodes and links as a single component. This helped them to reduce the time and effort required to recognize substructures in geon diagrams. Participants using geon diagrams looked for clusters of nodes and links and then resolved to evaluate the individual nodes and links, suggesting a whole-to-part approach. When using UML diagrams, individuals spent more time looking for nodes. This indicates more cognitive effort in looking for initial fixation points. But once the initial node or link was located, less effort was required to validate secondary information. In UML diagrams, search usually began at one of the end nodes and proceeded according to the structure of the layout of the nodes and links, indicating a part-to-whole approach. Therefore, search path of individuals in a visual problem can be indicative of their cognitive processing.

Research proposition 3 evaluates the search-steps of individuals in a visual problem-solving task. The results of research proposition 3 show the difference arising out of the different visualizations in the search-steps of participants. Evaluation dominates the search-steps in geon diagrams, whereas locating steps dominates UML diagrams. Over the course of the task in geon diagrams, participants moved from evaluating one node to evaluating the whole substructure. This followed from the ability of the participants to eventually assimilate the whole substructure as a single component. The two steps in the set of search-steps - *initiate* and *decide* - were not considered in the analysis. For the *initiate* step, feature played an important role in enabling the participants to locate an initial node or link in the visual problem.

During this experiment participants began the problem solving process in different ways. In some cases, they began by repeating the problem statement. For example, participant S1 opening statements were "… so this is the substructure I need to find … (1.1)". For the second problem, too, participant S1 reinstated the problem statement as "… User library - user library the label has to be the same … (1.15)". In other cases, participants began with the first candidate node in the problem diagram. For example, participant S3 said "… Ok elevator - elevator button ok … (3.37)". The *decide* step had either active pressing of the *"yes"* and *"no"* buttons (explicitly stating that they were pressing the button and the task was completed) or a passive pressing of the buttons (with no verbalizations).

The diagrams that were used in the experiment are of relatively small dimensions i.e., they are easily viewed on a computer screen without having to scroll the window in any direction. None of the problem diagrams have more than ten nodes. However, despite the simplicity of the diagrams, most participants scanned the problem diagram to find objects of interest. That is evident from some of the verbalizations, where the participants listed all the nodes and links present in the problem diagram as they were trying to look for the substructure.

The next pilot was conducted using the visualization of hypothetical scenarios of critical infrastructure systems.

3.2.4 Pilot Study 2

The results of pilot study 1 clearly indicate regarding the potential of addressing the research propositions on the differences in cognitive processing of individuals when using different visualizations for completing a task. The results on the whole show that, apart from the measures of precision and time to completion, factors such as search-steps and search path provide significant insight into how individuals interact with different diagrams while completing a search task.

To understand the cognitive impact of visualizations that are informationally equivalent but visually different, a second pilot experiment was conducted considering the factors: visualization type and diagrammatic complexity. This experiment used UML and geon diagrams as candidates for node-link diagrams. Hypothetical scenarios were constructed to depict interdependent complex systems. Another contributing factor was the diagrammatic complexity of the visualization. Complexity is an objective measure that is a function of the number of nodes in the visualization and the link density of the visualization. Therefore, there are four visualizations that were used to complete the search tasks. These four visualizations correspond to the four cases arising out of two types of visualizations (UML vs. geon) and two levels of diagrammatic complexity (*low* vs. *high*).

The specific task given to the participants was to find the system elements having the given type of relationship. Four sets of five visualizations were developed and presented to the participants. An additional 10 visualizations were developed to serve as practice cases for the participants. The visualizations were presented as a handout for the participants to work with. A camcorder was set up to record the proceedings of the experiment. Participants were given a tutorial on the type of visualizations and were tested on their proficiency. They were asked to talk aloud while completing the tasks. There was no time limit set for them to complete the task. The recordings of the participants were transcribed and coded.

Two participants were recruited to complete the tasks. The students were graduate students from the *Master of Infrastructure Planning (MIP)* program in the *College of Architecture and Design*. Both the participants were asked to complete the tasks under all the conditions. The complete protocol of the experiment was followed to ensure that there was no problem with the experiment instructions.

3.2.5 Results from Pilot Study 2

The process of conducting pilot study 2 helped to formalize the experiment protocol. One of the main outcomes of pilot study 2 was standardization of the coding instruction for the transcribed protocols. Two different coders were asked to code the transcribed protocols, and the inter-rater reliability was evaluated. Based on the outcomes of the coding process and the inter-rater reliability analysis, the coding instructions were fine-tuned.

Another outcome of pilot study 2 was modification of the experimental task. As a result of this experiment, the simple search task was modified to a problem-solving task. The specific task given to the participants in the main experiment as developed after the two pilot studies was:

- Find the nodes that are impacted when the shown interdependency fails.

The complete experiment material is presented in Appendix A.

3.3 Experiment Design and Participant Assignment (Main Study)

The experiment design in this study uses a repeated-measures design with two independent variables (visualization type and complexity). There are two dependent variables: time taken to complete task and correctness of the result. Within-subjects repeated-measures ANOVA is used to analytically test the effect of visualization type and complexity. A repeated-measures design offers greater power than a between-subjects design that does not use repeated measures (Kutner et al., 2004). Repeated-measures ANOVA carry the standard set of assumptions associated with an ordinary analysis of variance: multivariate normality, homogeneity of covariance matrices, and independence (Steven 1996). Repeated-measures ANOVA is robust to violations of the first two assumptions. Violations of independence produce a non-normal distribution of the residuals, which results in invalid F ratios. The assumption of independence of the variables is violated when either random selection or random assignment is not used (Steven 1996).

The total number of participants or the sample size is 25. The sample size is sufficient to ensure adequate power of the result of the experiment. The experimental design is shown in Table 3.9. Because each participant completes tasks under all the four conditions, there are 100 observations per condition.

Table 3.9 Sample Size for Experiment

Complexity \ Visualization	UML	Geon
Low	25	25
High	25	25

The experimental conditions (visualization type and complexity) are fixed. There are four sets of tasks (two visualizations X two complexities). As shown in Table 3.10, the sets of tasks include tasks using low-complexity UML diagram (T1), the high-complexity UML diagrams (T2), the low-complexity geon diagrams (T3) and the high-complexity geon diagrams (T4). Each set of tasks consists of five visualizations and five tasks. Figure 3.1 shows sample visualizations for each condition corresponding to Table 3.10. The UML diagrams are shown in the left column, and the Geon diagrams are shown in the right column. The low-complexity visualizations are shown in the top row, and the high-complexity visualizations are shown in the bottom row. The low-complexity visualizations (L) have a complexity factor of 0.15, and the high-complexity visualizations (H) have a complexity factor of 0.60.

Table 3.10 Setup of Experimental Tasks

	UML	Geon
Low-complexity visualization	T1	T3
High-complexity visualization	T2	T4

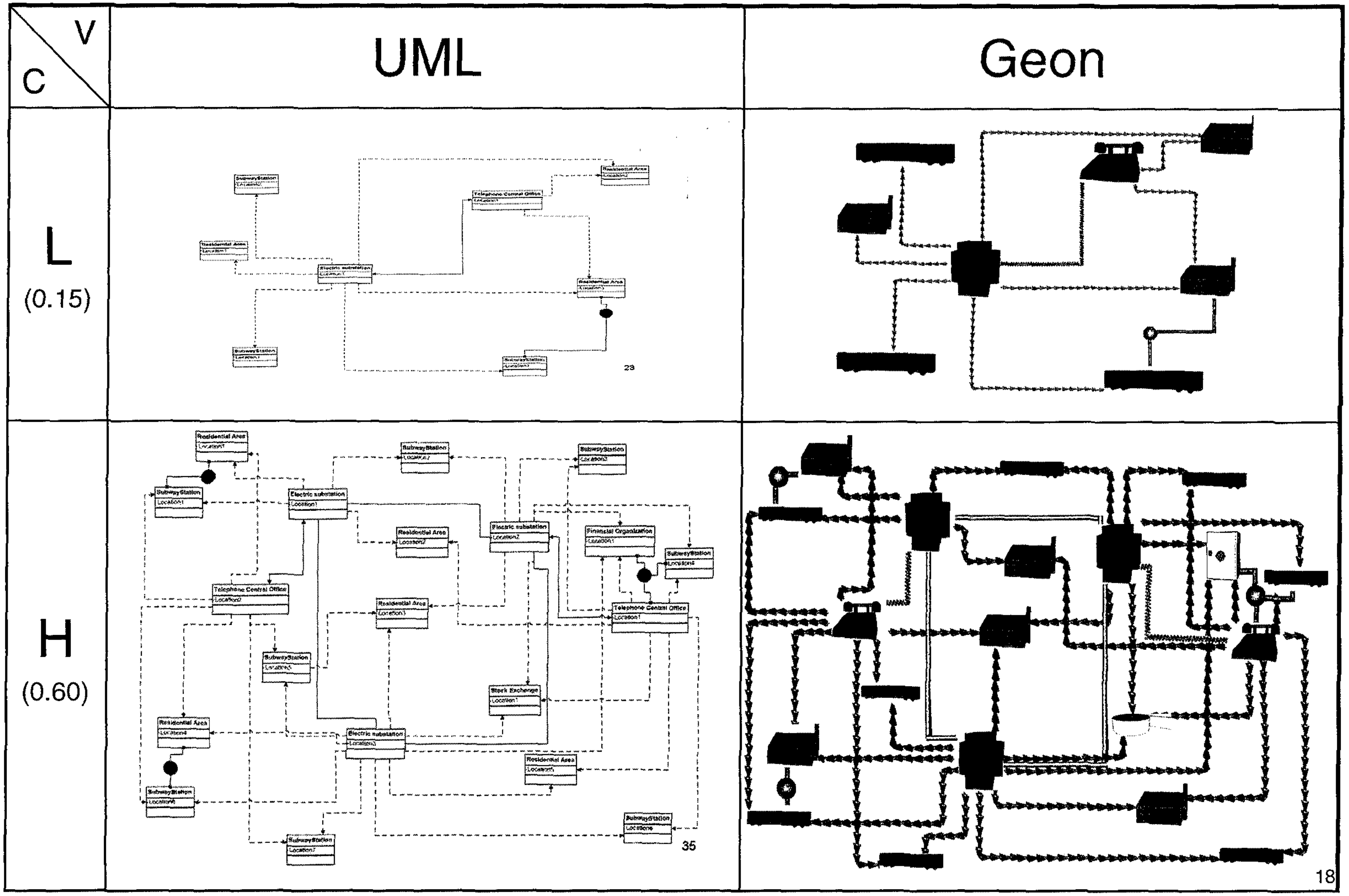


Figure 3.1 Example of visualizations for low-complexity and high-complexity UML and geon diagrams.

All 25 participants are required to complete the task in all four conditions. To reduce variability arising due to differences in individuals, each participant is asked to complete all tasks in all sets (a total of 20 tasks). Therefore, the study is designed as a balanced complete block design with random assignment. The randomization in the task allocation to the participants is done as follows. Firstly, the order of the tasks in a task set is randomized. That means the presentation of the visualization of a task set to the participant will be randomized. Secondly, the order in which the sets of tasks will be allocated to the participants will be randomized. The order of the sets of tasks ensures that for a given visualization type, the participant completes the low-complexity visualizations before the high-complexity visualizations. Completing the high-complexity visualizations before the low-complexity visualizations may result in minimal verbalization from the participants while working with the visualizations with lower complexity one as the specific traversal through elements may become too "obvious" for them to say it aloud. The task order is shown in Table 3.11. For example, the task order for participant S1 is T1, T2, T3, and T4. This means that the participant first completes the set of tasks using the low-complexity UML diagrams (T1); followed by the set of tasks using the high-complexity UML diagrams (T2); followed by the set of tasks using the low-complexity geon diagrams (T3) and finally the set of tasks using the high-complexity geon diagrams (T4). The randomization processes will ensure that the variability arising out of task order and task set order is minimized.

Table 3.11 Order of Task for Participants – S1, S2, S3 and S4

Participant	Task order
S1	T1, T2, T3, T4
S2	T3, T4, T1, T2
S3	T1, T3, T2, T4
S4	T3, T1, T4, T2

3.4 Solicitation of Participants

A total of 25 participants were recruited for completing the experiments. All participants were male undergraduate students from the Civil Engineering department majoring in *Infrastructure Planning*, *Civil Engineering* or *Transportation Engineering*. All the participants satisfied the requirement that they had completed a course related to critical infrastructure systems. To minimize any confounding factor leading from speech rate differences and articulation of thoughts by the participants, all the participants were selected such that they were native speakers of English. All the students were males to control for the gender differences in spatial information processing. These participants were familiar with different infrastructure systems and their functioning and were exposed to working with different types of systems and their representations. None of the participants had any experience with UML or geon diagrams. Each participant completed all the tasks (for a total of four conditions and 20 tasks per condition). The participants were all awarded a 2 GB flash drive for successfully completing the entire experiment. In addition, a raffle was conducted where they will had a chance to win a GPS, a digital picture frame or one of two gift cards.

3.5 Measures

Of the four measurements planned, there were two objective measurements taken for each participant under every experimental condition. The *time* taken to complete the search task was measured for each task. Since each task has a correct result, the *accuracy* of the result could be measured after the experiment by checking the number of errors the participants made under each condition. The two other measured parameters were *search path* and *search-steps*. *Search path* was measured as the sequence of nodes, links, components (combinations of nodes and links) and total number of elements (sum of nodes, links and components) traversed by the participant to complete a search task. Length was calculated as the count of nodes, links and combinations of nodes and links navigated. *Search-steps* were measured as the length and sequence of "locate" and "evaluate" steps that the participants used to complete the task. Length was calculated as the number of "locate" and "evaluate" steps used by the participant. Sequence was calculated as the number of transitions from one state to another ("locate" to "evaluate" and vice-versa).

3.5.1 Independent Variables

Visualization type: Visualizations for all the hypothetical scenarios were developed in

- UML – Notations from standardized UML class diagrams were used to represent nodes (classes) and links (relationships between classes)

- Geon – Notations were created using geon structures attached to one another to make the nodes and links.

Diagrammatic complexity: As mentioned in Section 2.1, a typical node-link diagram used in practice that can be effectively displayed in any regular display environment so that the individual does not have to scroll the page, is less than 20 nodes and 30 links (Ware and Bobrow 2005). In practice, a node-link diagram used to show a large number of nodes and links does not exceed a link density of 0.6, with the majority of them ranging from 0.3 to 0.6 (Ware and Bobrow 2005). Based on these objective measures, low and high complexity visualizations are operationalized as:

- Low-complexity visualization – A visualization having less than nine nodes and a link density of less than 0.2.

- High-complexity visualization – A complex node-link diagram has between eighteen and twenty nodes and a link density of 0.3 to 0.6.

3.5.2 Dependent Variables

- Search time – Duration or the time taken to solve the visual search task. It is measured as the time taken by the participants from the time of reading the task till the time of task completion (location of the substructure)

- Search precision – Conformity of the indicated substructure, as discovered by the participant during the experiment to an indicated or accepted value. The accuracy of the task completed (*error*) is measured as correct (1) or incorrect (0).

- Search path – The navigated path consisting of the explicit nodes and links that the participant takes to locate a search element in the visualization is called the search path. The *search path* is calculated as the total number of nodes, links, and components (combinations of one or more nodes and/or links) and total number of elements (nodes + links + components) traversed by the participant to identify the search substructure.

- Search-steps – Search-steps are the cognitive processing involved in assimilating and using available information to determine the substructure. It is counted as the "locate" and "evaluate" steps of the participants as they complete the visual search task. The *search-steps* is calculated as the total number of "locate" and "evaluate" steps and the number of transformations between the "locate" and "evaluate" steps taken by the individual in the process of identifying the substructures.

3.6 Protocols

The total duration of the experiment was estimated to be 45 to 60 minutes. The introduction, consent form and completion of the background questionnaire took about 5 minutes, and the practice case took about 10 minutes.

The consent forms and questionnaires are coded and stored safely. These are accessible only to the investigator and faculty related to the project. Each participant had one consent form and one background questionnaire. An ID was issued to each participant that will be used to identify their consent forms and questionnaire.

The four sets of five visualizations (total of 20: 10 UML and 10 geon diagrams with 5 low-complexity and 5 high-complexity diagrams for UML and geon diagrams) were developed to be presented to the participants (shown in Appendix A). An additional 10 visualizations (five UML diagrams and five geon diagrams) were developed to serve as a practice set for the participants. Participants were shown the visualizations on the computer screen. A camcorder was set up to record the participants for the whole duration of the experiment. Another camera was set up right above the computer screen to record the eye movement of the participants. The recordings of this camera can be used to study the eye-movements of the participants. For the current study, the recordings of the eye-movements are not analyzed. Visualization type and complexity were manipulated by assigning participants to a pre-determined order of tasks.

Once a participant arrived to participate in the experiment, the participant was given an introduction to the experiment. The participant was then asked to sign the consent form. After that the participant was handed a background questionnaire. The background questionnaire was a set of questions intended to ascertain the demographics of the participants and their fluency in English. A copy of the background questionnaire is provided in Appendix C. Participants were tutored so that they understood protocol analysis, the two different visualizations and the different interdependencies. Each participant was asked to complete a problem-solving task which asked them to identify the impacted nodes when a particular link fails. As a practice session, participants were first shown the ten practice visualizations (5 UML and 5 geon) and asked to complete the task. Then the participants were shown the experimental visualizations one at a time to complete similar tasks. There was no time limit to complete the task.

After completing the experimental task, the participants were asked the following questions.

- Which visualization did you prefer?
- What did you like about the UML diagrams?
- What did you dislike about the UML diagrams?
- What did you like about the geon diagrams?
- What did you dislike about the geon diagrams?

These questions were not be coded for search path and search-steps. The answers to these questions were intended to be used for exploring any issue or problems that the participant may have had.

3.7 Data Collection and Coding Preparation

For analyzing individual search techniques in problem visualization, a search task is considered to be the unit of analysis. Data is collected in two different ways. First the time taken by each participant to complete the task and the correctness of the result are recorded unobtrusively for each task. The time to completion for each task is logged automatically in a log file as the participants move from one condition to another. These two values were used to test the effectiveness of the visualizations as formulated in the hypotheses resulting from research proposition 1. The second part of the data is gathered from audio and video recordings of the participants as they perform the tasks during the experiment. The hypotheses from research propositions 2, 4, 6 (related to search path) and 3, 5, 7 (related to search-steps) were tested by investigating the cognitive process of the participants while using different visualizations of the same problem. For this, audio recordings were transcribed and coded to analyze the results. Five verbalizations were chosen at random and given to a second coder for coding. This resulted in twenty percent of the verbalizations being coded by two coders. The inter-coder reliability was calculated to check acceptable reliability levels. Coding instructions provided in Appendix D was given to the coders to complete the coding.

3.8 Research Hypotheses

The specific hypotheses are developed in this section for each of these measures as explained for each research proposition.

3.8.1 Effectiveness of Visualization Type

The results from the experiment on diagrammatic information structures (Irani and Ware 2003) strongly suggest that using geon diagrams significantly reduces the time taken to recognize a substructure from a given problem visualization. The error rate is also significantly lower for geon diagrams when compared to UML diagrams. In order to understand the impact of the search task on the result of the task, the time and error rate in completing the visual task are measured. The hypotheses for proposition 1 (A problem-solving task using geon diagrams will require less time and result in lower error rate.) are adapted from the experiment on diagrammatic information structures (Irani and Ware 2003). The human visual system contains significant processing machinery designed to decompose the visual image into a set of generalized cone primitives. Therefore, individuals should be able to process diagrams created using these same primitives, because they would be more effective. 3D diagrams using geon primitives may provide a better match to high-level processes that occur in human object recognition, and because of this they should be easier to interpret and remember. The hypotheses are:

H1.1: Time taken to complete a visual task using geon diagrams is less than time taken to complete a visual task using UML diagrams

H1.2: The error rate is lower in geon diagrams as compared to UML diagrams.

3.8.2 Effect of Visualization Type on Search Path

Search path is measured as the number of nodes, links and components (combinations of one or more nodes and/or links) that are traversed by the participants while completing the search tasks. The sum of the nodes, links and components traversed by the participants is considered as the total number of elements. UML diagrams are interpreted by first understanding the classes in the diagram and then the subsequent relationships between the classes. It can therefore be proposed, that individuals using a UML diagram will first try to look for classes (nodes) to identify a substructure, and will look for relationships (links) between the classes (nodes) only if satisfactory results have not been obtained. In geon diagrams, geon structures are used to represent nodes and the links between the nodes. The substructure to be searched in the geon diagram is also a set of nodes and links formed using geon structures. Therefore, as per SOPT, individuals using a geon diagram will try to segregate out the convex shapes (nodes or substructures or links) and try to match them against the representation of the substructure in their memory. Over time individuals will tend to recognize a combination of geon structures (nodes and links) as a single object. Therefore, fewer steps will be required to reach the result. Operationalizing the research proposition on search path (Proposition 2: A problem-solving task using UML diagrams will lead to longer and more node-dominant search paths than the one using to geon diagrams.) using the variables that were measured as a part of this experiment leads to the following hypotheses:

H2.1: Number of nodes traversed while completing the visual task is greater in UML as compared to geon.

H2.2: Number of links traversed while completing the visual task is higher in geon as compared to UML.

H2.3: Number of components traversed while completing the visual task is higher in geon as compared to UML.

H2.4: Number of total elements traversed while completing the visual task is higher in UML as compared to geon diagrams.

3.8.3 Effect of Visualization Type on Search-Steps

The dependent variable *search-steps* is determined as the number and sequence of "locate" and "evaluate" steps of the participants in completing the visual search task. Since search-steps include multiple instances of *locate* and *evaluate* steps, the difference in the length and sequence of *"locate"* and *"evaluate"* steps will indicate the difference in search-steps. In UML diagrams, the search for a substructure is done by locating the individual classes (node). Individuals try to locate additional information on relationships (links) between the objects for confirming the correctness of the search substructure. Therefore, the stress in UML diagrams lies on *locating* the right classes (nodes). Once a familiar object is found by the individual based on the node objects and the relationships between the objects, the search task is completed. Therefore, in UML diagrams, locating the appropriate classes will dominate the search task. In other words, the task completion will consist of more *"locate"* steps. In geon diagrams, recognition happens when the object seen by the individual is evaluated with the stored image of the substructure (node, link or combinations of nodes and links) in the individual's memory. The task completion is therefore, primarily composed of evaluation steps. Therefore, the search-steps in the individual's verbalization are expected to primarily have sequences of *"evaluate"*. Therefore, the two hypotheses for evaluating the research proposition on search-steps developed on the proposition (Proposition 3: In a visual problem-solving task, visualizations developed using UML class diagrams will result in *locate*-dominant search-steps while visualizations developed using geon diagrams will result in *evaluate*-dominant search-steps.) are:

H3.1: UML diagrams will result in more locate sequences as compared to geon diagrams

H3.2: Geon diagrams will result in more evaluate sequences as compared to UML diagrams

3.8.4 Effect of Diagrammatic Complexity on Effectiveness

Complexity of visualization is a function of the number of nodes and links in the visualizations. Therefore, while working with diagrams of higher complexity, more nodes and links have to be navigated by individuals to complete a visual task. As a result the time taken to complete a visual task will increase with the increase in the complexity of the diagrams. Because of the limitation on the number of nodes and links that can be simultaneously processed, the possibility of missing a node or navigating an incorrect path increases with visualizations with higher complexity. Therefore, the error rate will also increase with the increase in the complexity of the visualizations. The two hypotheses that can be developed on the research proposition on complexity and effectiveness (Proposition 4: More complex visualizations lead to lower effectiveness in a visual search task.) can be formalized as follows:

H4.1: The time taken to complete a visual task is higher in diagrams with high complexity as compared to diagrams with low complexity.

H4.2: The error rate in completing a visual task is higher in diagrams with high complexity as compared to diagrams with low complexity.

3.8.5 Effect of Diagrammatic Complexity on Search Path

Complexity of the visualizations is varied by the number of nodes and the link density of the diagrams. Search path is measured as the number of nodes, links, components and total number of elements traversed by the participants to complete the task. Since, the search path is a traversal of the nodes and links in the visualization, for more complex visualizations where the number of nodes and links are more, the number of steps in the search path will be more. Also, because of the limitation of the number of nodes and links that can be simultaneously stored in the working memory of the individual, the search path may contain multiple traversals to the same nodes and links. The proposition (Proposition 5: High-complexity visualizations lead to longer search paths in a visual search task.) can be formulated into hypotheses as:

H5.1: Number of nodes traversed while completing the visual task is greater in the high-complexity visualization as compared to low-complexity visualization.

H5.2: Number of links traversed is higher in the high-complexity visualization than in low-complexity visualization.

H5.3: Number of components traversed is higher in high-complexity visualization than in low-complexity visualization.

H5.4: Number of total elements traversed is higher in high-complexity visualization than in low-complexity visualization.

3.8.6 Effect of Diagrammatic Complexity on Search-Steps

Complexity of the visualization is determined by the number of nodes and link density of the visualizations. Search-steps are determined by the number and sequence of "locate" and "evaluate" steps of the participants in completing the search tasks. If the number of nodes as well as the link density of the visualizations is low, individuals are expected to complete the search task in a single iteration of traversing the visualization. But as the number of nodes and the link density increase, the number of elements (nodes, links or combinations) that can be simultaneously located and evaluated by an individual decreases. This leads to a higher number of "*locate*" and "*evaluate*" steps when individuals are using a complex visualization. The proposition (Proposition 6: High-complexity visualizations lead to more search-steps as compared to low-complexity visualizations.) then leads to the following hypotheses:

H6.1: Search-steps in high-complexity visualizations will result in more locate sequences as compared to low-complexity visualizations.

H6.2: Search-steps in high-complexity visualizations will result in more evaluate sequences as compared to low-complexity visualizations.

3.8.7 Interaction of Visualization Type and Complexity on Effectiveness

When UML and geon diagrams are varied in terms of complexity, the time required to complete the visual task continues to increase for complex visualizations for both the visualization types. In both geon and UML diagrams, with the increase of complexity, the traversal time increases. But in geon diagram, since the individual tends to form clusters for different nodes and links as a single component and tries to traverse the diagram in terms of these components, the increase in time to navigate the diagram is not as high as that in UML diagrams where the individuals primarily tend to consider each node in isolation. For the error rate, as discussed earlier, the error rate in diagrams of high complexity is expected to be higher than the error rate in diagrams of low complexity. Since in geon diagrams, individuals reduce the cognitive load by considering multiple nodes and links as a single component, the increase in error rate is not as high as the increase in the error rate for UML diagrams. Therefore, the magnitude of the difference for time to complete task and the error rate is expected to be larger for visualizations with high complexity as compared to visualizations with low complexity. Therefore, the proposition on interaction between visualization type and complexity on effectiveness (Proposition 7: When UML class diagrams and geon diagrams are varied in terms of complexity, the time taken to complete the task and the error rate in UML class diagrams continue to be higher and the magnitude of difference is greater with the increase in complexity.) can be developed into the following hypotheses.

H7.1: For low-complexity visualizations, geon diagrams will require less time as compared to UML; for diagrams with high-complexity, the difference will increase.

H7.2: For low-complexity visualization, geon diagrams will result in fewer errors; for diagrams with high-complexity, the difference will increase.

3.8.8 Interaction of Visualization Type and Complexity on Search Path

Proposition 8 (When UML class diagrams and geon diagrams are varied in terms of complexity, search paths in UML class diagrams continue to be longer and node dominant for complex visualizations though magnitude of difference may reduce with the increase in complexity.) tries to measure the impact on the search path that results due to the interaction of visualization type with the diagrammatic complexity. For low-complexity visualizations, geon diagrams may result in a smaller number of node traversals. However as the number of nodes increase with the increase in the complexity of the visualization, the limits of the working memory of the individual may restrict the number of elements that can be evaluated by an individual. This may result in multiple references to the same node at multiple points in the search process till an acceptable solution is reached.

The same is true for UML diagrams. It is expected that for UML diagrams, the number of nodes that are accessed are higher than for geon diagrams. As the number of nodes and link density in the UML diagram increases, the search path of the individual tends to include more nodes, links and components. But since the links of UML diagrams do not play a primary role in aiding the individual to understand the visualization, the number of links traversed in UML will continue to be lower in complex UML diagrams. Therefore, the specific hypotheses can be formulated as:

H8.1: For low-complexity visualizations, geon diagrams will require traversals of fewer nodes than UML, but for more high-complexity visualizations, geon diagrams will require traversals of more nodes than UML.

H8.2: For low-complexity visualizations, geon diagrams will require traversals of more links than UML diagrams, for high-complexity visualizations, geon diagrams will require traversals of more links than UML diagrams.

H8.3: For low-complexity visualizations, geon diagrams will require traversals of more components; for high--complexity visualizations, geon diagrams will require traversals of more components than UML diagrams.

H8.4: For low-complexity visualizations, UML diagrams will require traversals of more number of total elements; for high-complexity visualizations, there will be no difference in the number of total elements traversed in geon diagrams as compared to UML diagrams.

3.8.9 Interaction of Visualization Type and Complexity on Search-Steps

As discussed in the Section 2.4, the number of "*locate*" steps is expected to be higher in UML diagrams whereas, the number of "*evaluate*" steps is expected to be higher in geon diagrams. When the complexity of the visualization in increased, the number the nodes as well as the number of links per node increase. With the increase in the complexity of the visualization, the number of "*locate*" and "*evaluate*" steps will increase because of two reasons. Firstly, with the increase in the number of elements (nodes, links, and combination of nodes and links), the number of candidates to be *located* and *evaluated* will increase. Secondly, since the number of nodes, links and combinations (of nodes and links) that can be located, evaluated and remembered tend to be limited for any individual due to limitations of their working memory, the increase in the number of nodes and link density will lead to more repeated traversals for the same nodes and links, thereby increasing the number of "*locate*" and "*evaluate*" steps for the visualization. Therefore, the proposition (Proposition 9: When UML class diagrams and geon diagrams are varied in terms of complexity, the search-steps in UML class diagrams continue to be "locate" dominant and the search-steps in geon diagrams continue to be "evaluate" dominant though the difference in the search-steps reduce with the increase in the complexity of the visualization.) can be developed into the following hypotheses:

H9.1: For low-complexity visualizations, while using UML diagrams, search-steps will have more "*locate*" steps as compared to the search-steps while using geon diagrams. For high-complexity visualizations, there is no significant difference in the search-steps while using UML and geon diagrams.

H9.2: For low-complexity visualizations, while using geon diagrams, search-steps will have more "*evaluate*" steps as compared to the search-steps while using UML diagrams but as the complexity of visualizations increase, there is no significant difference in the "*evaluate*" steps while using geon and UML diagrams.

The research propositions and hypotheses that are developed suggest different visualizations of similar information lead to different approaches in problem-solving which may go beyond accuracy and speed advantages that one type of visualization provides over another.

These research propositions along with the hypotheses are summarized in Table 3.12.

Table 3.12 Summary of Research Propositions and Hypotheses for Main Study

	Research Propositions	Hypothesis
1	**Proposition 1:** A problem-solving task using geon diagrams will require less time and result in lower error rate.	**H1.1:** Time taken to complete a visual task using geon diagrams is less than time taken to complete a visual task using UML diagrams **H1.2:** The error rate is lower in geon diagrams as compared to UML diagrams.
2	**Proposition 2:** A problem-solving task using UML diagrams will lead to longer and more node-dominant search paths than the one using to geon diagrams.	**H2.1:** Number of nodes traversed while completing the visual task is greater in UML as compared to geon. **H2.2:** Number of links traversed while completing the visual task is higher in geon as compared to UML. **H2.3:** Number of components traversed while completing the visual task is higher in geon as compared to UML. **H2.4:** Number of total elements traversed while completing the visual task is higher in UML as compared to geon diagrams.
3	**Proposition 3:** In a visual problem-solving task, visualizations developed using UML class diagrams will result in *locate*-dominant search-steps while visualizations developed using geon diagrams will result in *evaluate*-dominant search-steps.	**H3.1:** UML diagrams will result in more locate sequences as compared to geon diagrams **H3.2:** Geon diagrams will result in more evaluate sequences as compared to UML diagrams
4	**Proposition 4:** More complex visualizations lead to lower effectiveness in a visual search task	**H4.1:** The time taken to complete a visual task is higher in diagrams with high complexity as compared to diagrams with low complexity. **H4.2:** The error rate in completing a visual task is higher in diagrams with high complexity as compared to diagrams with low complexity.

Table 3.12 Summary of Research Propositions and Hypotheses for Main Study (Continued)

	Research Propositions	Hypothesis
5	**Proposition 5:** High-complexity visualizations lead to longer search paths in a visual search task.	**H5.1:** Number of nodes traversed while completing the visual task is greater in the high-complexity visualization as compared to low-complexity visualization. **H5.2:** Number of links traversed is higher in the high-complexity visualization than in low-complexity visualization. **H5.3:** Number of components traversed is higher in high-complexity visualization than in low-complexity visualization. **H5.4:** Number of total elements traversed is higher in high-complexity visualization than in low-complexity visualization.
6	**Proposition 6:** High-complexity visualizations lead to more search-steps as compared to low-complexity visualizations.	**H6.1:** Search-steps in high-complexity visualizations will result in more locate sequences as compared to low-complexity visualizations. **H6.2:** Search-steps in high-complexity visualizations will result in more evaluate sequences as compared to low-complexity visualizations.
7	**Proposition 7:** When UML class diagrams and geon diagrams are varied in terms of complexity, the time taken to complete the task and the error rate in UML class diagrams continue to be higher and the magnitude of difference is greater with the increase in complexity.	**H7.1:** For low-complexity visualizations, geon diagrams will require less time as compared to UML; for diagrams with high-complexity, the difference will increase. **H7.2:** For low-complexity visualization, geon diagrams will result in fewer errors; for diagrams with high-complexity, the difference will increase.

Table 3.12 Summary of Research Propositions and Hypotheses for Main Study (Continued)

	Research Propositions	Hypothesis
8	**Proposition 8:** When UML class diagrams and geon diagrams are varied in terms of complexity, search paths in UML class diagrams continue to be longer and node dominant for complex visualizations though magnitude of difference may reduce with the increase in complexity.	**H8.1:** For low-complexity visualizations, geon diagrams will require traversals of fewer nodes than UML, but for more high-complexity visualizations, geon diagrams will require traversals of more nodes than UML. **H8.2:** For low-complexity visualizations, geon diagrams will require traversals of more links than UML diagrams, for high-complexity visualizations, geon diagrams will require traversals of more links than UML diagrams. **H8.3:** For low-complexity visualizations, geon diagrams will require traversals of more components; for high--complexity visualizations, geon diagrams will require traversals of more components than UML diagrams. **H8.4:** For low-complexity visualizations, UML diagrams will require traversals of more number of total elements; for high-complexity visualizations, there will be no difference in the number of total elements traversed in geon diagrams as compared to UML diagrams.
9	**Proposition 9:** When UML class diagrams and geon diagrams are varied in terms of complexity, the search-steps in UML class diagrams continue to be "locate" dominant and the search-steps in geon diagrams continue to be "evaluate" dominant though the difference in the search-steps reduce with the increase in the complexity of the visualization.	**H9.1:** For low-complexity visualizations, while using UML diagrams, search-steps will have more "*locate*" steps as compared to the search-steps while using geon diagrams. For high-complexity visualizations, there is no significant difference in the search-steps while using UML and geon diagrams. **H9.2:** For low-complexity visualizations, while using geon diagrams, search-steps will have more "*evaluate*" steps as compared to the search-steps while using UML diagrams but as the complexity of visualizations increase, there is no significant difference in the "*evaluate*" steps while using geon and UML diagrams.

3.9 Data Coding and Analysis

To analyze the *effectiveness* of the visualizations, the time taken to complete the task and the correctness (accuracy) of the task result are measured. To understand the cognitive differences of the individuals while using two different visualization types, protocol analysis is used (Simon and Ericsson 1993). The participants are asked to "think aloud" while doing the task. The verbalized thought process of the participants is indicative of the reasoning of the participants and the actions that they take. The verbalizations of the participants are coded. The following sections explain in detail the process of coding and analyzing the *search path* and *search-steps*.

3.9.1 Data Analysis for Effectiveness

The data for effectiveness is recorded as the time taken to complete the task and the error rate in completing the task. The start-time and the end-time of the task are recorded by a script in the experimental instrument (visualizations presented to the users). Time is measured since the start of the experiment.

A sample snapshot of the data for time and error rate is shown in Table 3.13. The first column is the participant ID. The second column is the condition: C_L:U – low-complexity UML diagrams, C_H:U - high-complexity UML diagrams, C_L:G - low-complexity geon diagrams and C_H:G - high-complexity geon diagrams. The next column is the number of errors made by the participant under each condition. For example, Participant 2 made 2 errors with low –complexity UML diagrams. Each time the user moved to a new visualization, the time is recorded. Time is calculated as the difference between the end time and the start time and is recorded in seconds. Mean time to task completion (TTC) is the mean over the five tasks.

Table 3.13 Sample Data for Effectiveness

Participant ID	Condition	#errors	Start time (mm:ss)	End time (mm:ss)	Total time (sec)	Mean TTC (sec)
2	C_L:U	2	37:25	40:06	161	32
2	C_H:U	3	40:06	51:56	710	142
2	C_L:G	0	51:56	54:11	135	27
2	C_H:G	1	54:11	59:36	325	65

The experiment design in this study is a repeated measures design with two independent variables (visualization type and complexity). There are two dependent variables – time taken to complete task and correctness of the result. Within-subjects repeated measures ANOVA is used to analytically test the effect of visualization type and complexity. Repeated measures ANOVA carries the standard set of assumptions associated with an ordinary analysis of variance: multivariate normality, homogeneity of covariance matrices, and independence (Steven 1996). The assumption of independence of the variables is violated when either random selection or random assignment is not used (Steven 1996). There are two nonparametric alternatives to this method that may be used if the assumptions of normality, homogeneity of covariance and independence of the variables are not met. For testing the time taken to complete the task, Friedman's two-way analysis of variance is used. Cochran Q test will be used for testing if the difference in the accuracy of the tasks is significant because the variable (accuracy) is measured in terms of categories – correct vs. incorrect. The data analyses pertaining to the cognitive differences of individuals are discussed next.

3.9.2 Data Analysis for Search Path

The transcripts of the participants are coded to mark the identification of a node or a link or a structure (combination of nodes and links). The search path chosen by the participant is quantified as a count and sequence of nodes and links explicitly identified by the participant before completing the task or aborting the task. The path taken to identify the substructure is represented as the coded string of nodes in the problem space. The process of creating the problem space and the solution path is discussed next.

Problem Space

A problem space is generated for the search path of the participants completing a visual task using a given UML or geon diagram. The problem space provides an exhaustive list of the paths a participant can follow to accomplish the task. All legal state changes are shown as arrows and the transforming event (number of nodes and links recognized) is marked on the arrow in the format node/link. In the first step, the participant can either identify a node (N), or a link (L) or a pair of nodes (S) or a set of nodes and links (S). For example consider the problem space in Figure 3.2 which is developed for the simplest node-link diagram - consisting of two nodes and a link. The inset in Figure 3.2 illustrates such a node-link diagram. Node A of the problem space in Figure 3.2 represents a state in which two nodes and a link are yet to be recognized. The state changes from A to B when one node (node 1 or node 2) is recognized (N). State B denotes that one node and one link are yet to be recognized. One can go to state B from state A only by recognizing one node (N). Similarly, if only one link is recognized (L), the state changes from A to D. Recognizing one node and one link together (S) results in state C. A solution path in the problem state starts at the initial state (A). Analysis of the solution path for determining the search path of the participants is mentioned next.

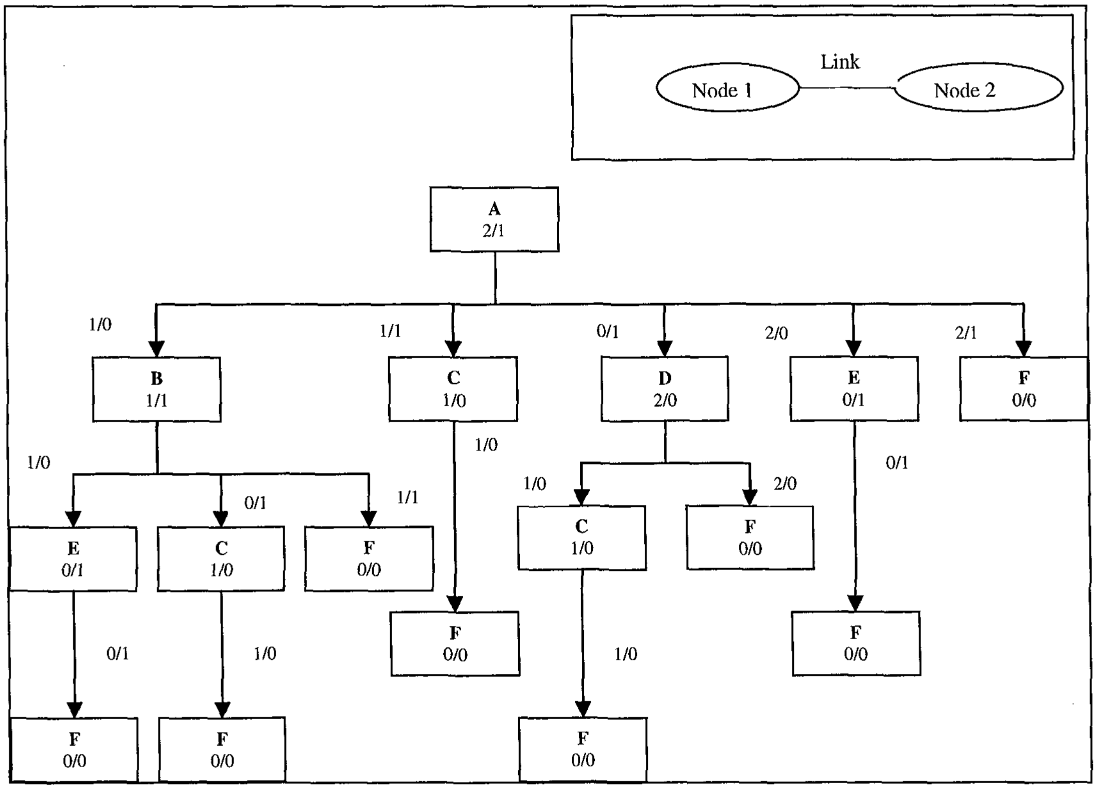


Figure 3.2 Problem space of for a node-link diagram with two nodes and one link.

Solution

Any legal traversal of the problem space can be a solution path. The solution path has certain characteristics. The traversal can terminate in any state – not necessarily in the termination state (F). For example, a participant can identify one node and one link (in one step) and abort the search process. The corresponding path for such a process in the problem space in Figure 3.2 will be shown as AC and will be coded as S. But if the participant first identifies one node (N), followed by the second node (N) and then the link (L), the path traversed will be ABEF or N-N-L. The solution does not necessarily show the correctness or efficiency of deriving the result and is just a reflection of the series of actions taken by participants while completing their task. The search path taken by a participant is derived by coding the verbalizations of the participant recorded during the experiment by applying the above mentioned technique. If there is a reference to a node like *residential areas, subway station, electric substation, telephone central office, financial organization, stock market*, code it as N. If there is a reference to a link like *shared, input, mutually dependent, co-located or connection*, code it as L. If there is a reference to a group of nodes and links like (this *whole cluster, this set of elements, the whole diagram, this area, these two, these three, all these* etc), code it as S. Once the path taken by individuals is determined by coding the verbalizations, statistical analysis will be done to test whether the path derived for UML diagrams is significantly different from the path derived from the geon diagram. The number of nodes, the number of links, the number of combinations (of nodes and links) and the number of total steps taken in each case will be used to perform this analysis. Repeated measures ANOVA will be used to analytically test the effect of the independent factors. If the model assumptions for repeated measures ANOVA are not met, Friedman's two-way analysis of variance will be used.

A sample coding for the search path is shown in Table 3.14. The first column is the identification of each segment. The second column is the actual segment as transcribed from the recordings. The last column is the search path as coded by the coders. For example, the second segment (ID: 2) is "*The substation here is mutually connected with this telephone*". The word *substation* is coded as a Node (N), followed by *mutually connected* coded as (L) and *telephone* coded as (N). Therefore, the search path for segment 2 is coded as N-L-N.

Table 3.14 Sample Coding for Search Path

ID	Segment	Code
1	Here is the broken link	L
2	The substation here is mutually connected with this telephone,	N-L-N
3	and if this telephone does not have [electric] power,	N-L
4	these two financial organizations here can't get telephone [service],...	S-L

This concludes data coding for search path. The next section discusses the coding of the protocols in another way to evaluate the search-steps of the participants.

3.9.3 Data Analysis for Search-Steps

To address research proposition 3, the transcribed protocols recorded during the experiment will be re-coded in a different way. As explained in Section 2.1, the task of searching for a pre-defined element can be broken down to a set of basic steps (Hornof and Halverson 2003; Hu, Dempere-Marco and Yang 2003). The first step is to define and formulate a suitable query (*initiate*). In the second step, an entry point is identified either randomly or by using an index or other search parameters (*locate*). The third step examines and evaluates the search results and rates their relevance (*evaluate*). In the fourth step, the result is either accepted or rejected (*decide*). For analyzing the difference in the search-steps of individuals using different visualizations, each verbalization will be coded as a sequence of *initiate*, *locate*, *evaluate* and *decide*. The coding instructions are as provided below:

- *Initiate* (I) – If a segment begins with a phrase like "*I am looking for ...*", or pointing at a part of the display screen and/or starting a new problem with "*This diagram...*", then it is coded as *initiate*. This is usually the introductory statement made by the participant during the experiment.

- *Locate* (L) – If a segment includes phrases like "*I can see*", "*I cannot find*", "*I am searching*", then it is coded as *locate*. Participants use key words like *search* and *find* when they are trying to locate a candidate node or substructure for evaluation. These fragments signify that the participant is looking for particular nodes in the problem visualization. In the experimental setup, the participant could be looking for a node, a link, a substructure or the whole search substructure.

- *Evaluate* (E) – If a segment includes a phrase like "*It looks like the right node*", "*Is this the one*", it is coded as *evaluate*. Sometimes, participants use a phrase like "*This is different*" to denote their evaluation of a node or link in the problem visualization. The participant may evaluate a node, a link connected to the node, a set of nodes and links or the substructure as a whole.

- *Decide* (D) – If a segment includes a phrase like "*yes, I have completed*" or "*this is it*", it is coded as *decide*. If the participant does not say anything explicitly, then the end of the task marks the end of the search-steps. This action specifies that the participant has made the final decision regarding the visual problem and is ready to proceed to the next task or end the experiment as the case may be.

- *Clarify* (C) – There may be sections of participants' verbalization where the participant is either asking for a clarification from the experimenter or is trying to figure out the working of the computer or mouse. These segments of the verbalization are coded as *clarify*. The number of clarifications under each condition can be counted to see if there is any difference between the two visualization types and complexities.

A sample coding for the search steps is shown in Table 3.15. The first column is the identification of each segment. The second column is the actual segment as transcribed from the recordings. The last column is the search step as coded by the coders. For example, the second segment (ID: 2) is "*The substation here is mutually* *connected with this telephone*". Here the participant is locating elements in the visualization as he is talking about it. Therefore, the search step for segment 2 is coded as L *(Locate).*

Table 3.15 Sample Coding for Search Steps

ID	Segment	Code
1	Here is the broken link	I
2	The substation here is mutually connected with this telephone,	L
3	and if this telephone does not have [electric] power,	E
4	these two financial organizations here can't get telephone [service],...	D

The coded transcripts are then analyzed to understand the difference in the search-steps of the participants using different visualizations to complete a search task. After the coding process is complete, each search task can be represented as a sequence of "I", "L", "E" and "D", which represent the different states that the participant has been in during the search process. The evaluation of the difference in the search sequence is a measure of the difference in their search-steps while completing the search tasks using different visualization types and complexities. The number of transitions from one state to another is analyzed to answer the research propositions on search-steps.

The coded search-steps sequence as mentioned is analyzed as follows to understand the impact of different visualization type and visualization complexities on the search-steps of individuals. The counts and sequence of the coded verbalizations are used to develop the directed graph as shown in Figure 3.3. The coded sequence is used to count the transitions from one state to another. As seen in Figure 3.3, the *decision* state

(D) is an absorbing state, (i.e., once a participant made a decision regarding the given problem, they are expected not to enter any other state). Similarly, the *initiate* state (I) is a source state, i.e., no arrows lead into this state. The arcs in the directed graph show the valid transitions amongst the different states. The value on the arc from one state to another state shows the normalized weights of the total number of transitions between them. The normalized weight between state i and state j is calculated as the ratio of the total number of transitions from i to j and the total number of transitions from state i. Referring to Figure 3.3, w_{il} is the normalized weight of the number of transitions between *initiate* and *locate*. If n_{il} is the total number of transitions from *initiate* to *locate*, n_{ie} is the number of transitions from *initiate* to *evaluate* and n_{id} is the number of transitions from *initiate* to *decide*, $w_{il} = \dfrac{n_{il}}{(n_{il} + n_{ie} + n_{id})}$. The sum of the normalized weights on the outgoing arcs from any node is equal to 1. The search-steps graph created this way shows the transitions between different cognitive activities of the participants. The graph provides evidence that participants went through a conscious cognitive process while performing the given task.

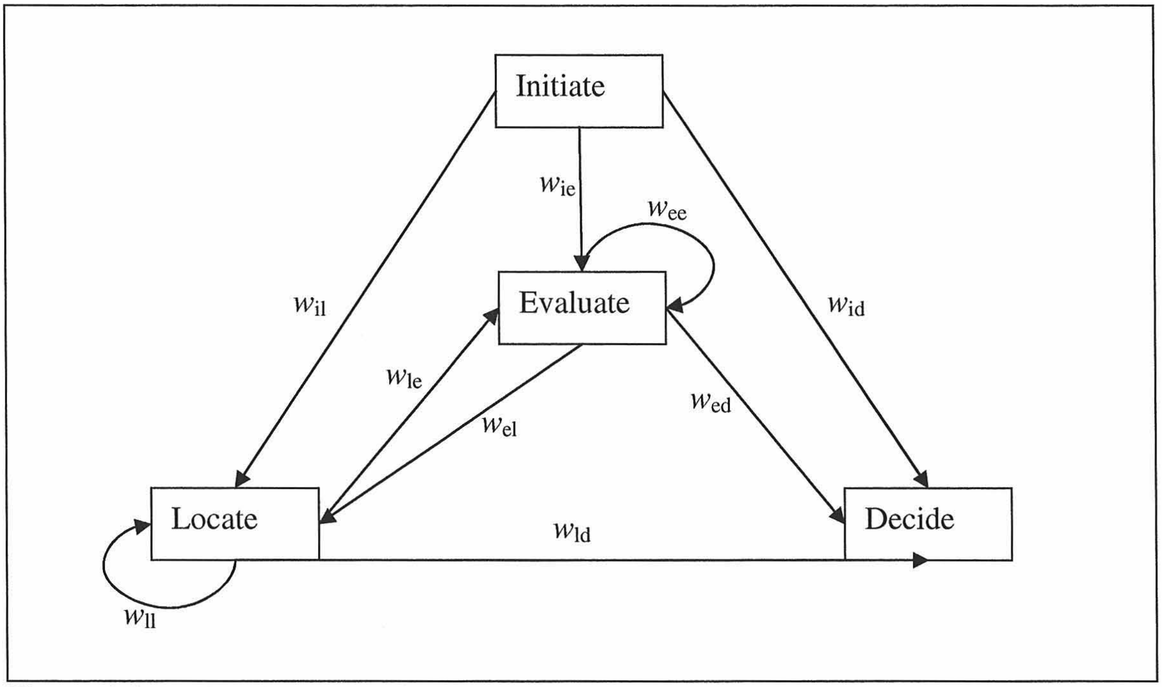


Figure 3.3 Graph representing search-steps.

To determine if the graphs developed for the search-steps of individuals are significantly different for visualizations of different types and complexity, the graphs for each case are modeled as a Markov process. Representing the transitions from each state (*I, L, E*, and *D*) as a matrix, each cell of the matrix represents the number of transitions from the row state to the column state. The square matrix created thus represents a transition matrix of the search task for a given visualization as shown in the Table 3.16.

Table 3.16 Transition Matrix for Search-Steps

	I	**L**	**E**	**D**
I	0	v_{il}	v_{ie}	v_{id}
L	0	v_{ll}	v_{le}	v_{ld}
E	0	v_{el}	v_{ee}	v_{ed}
D	0	0	0	0

This matrix is treated and analyzed as a Markov process matrix (Howard 1971). The state occupancy of a given state in the matrix can be modeled as a state occupancy random variable $v_{ij}(n)$, which denotes the number of times state *j* is entered through time n given the system started at state *i*. The number of transitions is normalized as the fraction of times state *j* is entered given the state started at *i* as compared to the total number of transitions that started at C. Transitions between different states are calculated as the asymptotic mean occupancy statistic. The asymptotic mean occupancy statistic is defined as the steady state transformation matrix of a given set of state transformations and provides the expected transformation probabilities about a large number of iterations of the process. The asymptotic state occupancy statistics of the two visualizations are evaluated to indicate the behavior of the search-steps over a very large number of transformations.

As explained earlier in this section, the process represented in Table 3.16 is modeled as a Markov process. It results in a 4X4 matrix for each case. Since, the graphs in Figure 3.3 are directed in nature, with state '*I*' having no inputs and state '*D*' having no outputs, the corresponding row and column of the matrix are zero as shown in Table 3.16. Therefore, removing the row and one column with no entries reduces the matrix to 3X3 (*L, E, D*). The asymptotic state occupancy statistics of the two visualizations are evaluated to get the steady state behavior of the search-steps over a very large number of iterations. The asymptotic state occupancy statistic can be derived for the two visualizations and the two visualization complexities as a probability vector of the form $\alpha_{\text{viz,complexity}} = (a_{il}, a_{le}, a_{de})$. Four such vectors will be generated for the four experimental conditions. The difference of the four vectors of the four experimental conditions will reflect the difference in search-steps due to different visualization types and complexities. The asymptotic state occupancy vectors will be modeled as binomial probabilities, where success is assumed as the transition to a state of interest (*locate* or *evaluate*). Normal approximations of the binomial probabilities are used to test the significance of the analysis.

CHAPTER 4

RESULTS

The results of this experiment are explained in four sections. Section 4.1 discusses the descriptive statistics and enumerates the average time and error of each participant under each condition. Section 4.2 describes the results corresponding to research proposition 1 on effectiveness. Section 4.3 presents the results corresponding to research proposition 2 on search path and Section 4.4 present the results corresponding to research question 3 on search steps. All hypotheses are tested at $\alpha = 0.05$.

4.1 Descriptive Statistics

Table 4.1 shows the average time taken (in seconds) by the participants for each problem set. The average time taken to complete the task using low-complexity UML diagrams is 34.64 seconds. The average time taken to complete a task using high-complexity UML diagrams is 59.824 seconds. For low-complexity geon diagrams, the average time taken is 30.456 seconds and for high-complexity geon diagrams is 47.440 seconds.

Table 4.1 Table of Means for Time (Seconds) Taken to Complete Task

Complexity / Visualization	Low	High	Mean
UML	34.640 (C)	59.824 (A)	47.232
Geon	30.456 (C)	47.440 (B)	38.948
Mean	32.548	53.632	43.09
* Means with the same letter are not significantly different			

Table 4.2 shows the number of errors made by the participants under each experimental condition. When completing the visual problem-solving tasks, the mean number of errors using low-complexity UML diagrams is 2.0, for high-complexity UML diagrams is 3.16, for low-complexity Geon diagrams is 0.4 and for high-complexity geon diagrams is 0.96.

Table 4.2 Table of Means for Errors in Result

Complexity / Visualization	Low	high	Mean
UML	2.0000 (B)	3.1600 (A)	2.58
Geon	0.4000 (D)	0.9600 (C)	0.68
Mean	1.2	2.06	1.63
* Means with the same letter are not significantly different			

The significance of the results with respect to research question 1 is discussed further in Section 4.2.

4.2 Results for Research Question 1: Effectiveness

For testing the hypotheses for research question 1 concerning the effectiveness of a diagram, the time taken by each participant to solve a problem and the correctness of the solution are used. The average time required by the participants to find the presence or absence of a substructure is used to test hypothesis H1.1. Average number of incorrect answers in completing all the five tasks under each condition is used to test hypothesis H1.2.

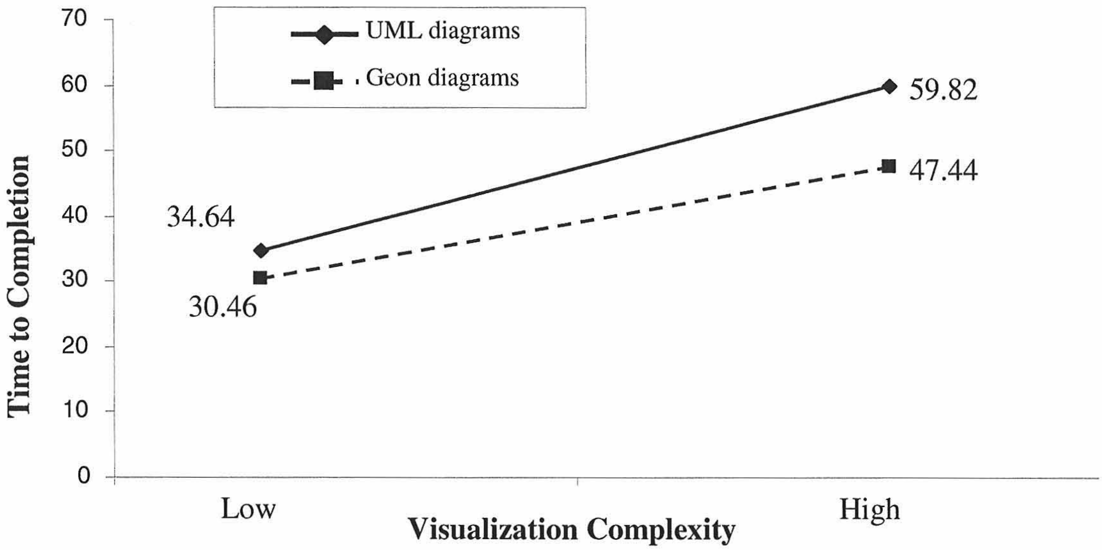


Figure 4.1 Distribution of time to completion for low and high complexity UML and geon diagrams.

Table 4.3 Statistical Results for Time to Completion

	Visualization(V)	Complexity(C)	V*C	Order
F	12.15	40.85	6.02	0.01
p-val	<0.0019	<0.0001	0.0218	0.9149

As seen from the results in Table 4.1, on average the participants took 38.948 seconds to complete the task using geon diagram and 47.232 seconds while using UML diagrams. Hypothesis H1.1 had suggested that the time taken to complete a visual task using geon diagrams is less than the time taken to complete a visual task using UML diagrams. Figure 4.1 shows the time taken to complete the visual task for UML and geon diagrams using visualizations of low and high complexity. Time taken using geon diagrams is lower than the time taken when using UML diagrams. The difference is greater for high-complexity visualizations as compared to low-complexity visualizations. A repeated measures ANOVA was done to test the difference in the four cases. The results of the ANOVA are shown in Table 4.3. The null hypothesis ($H1.1_0$ There is no difference in the time taken to complete a visual task using geon diagrams as compared to UML diagrams) is rejected at $p<0.0019(\alpha=0.05)$. This shows that there is a significant difference in the time taken to complete a visual task when different visualizations are used. The results also show that there is no effect due to the order in which the condition was presented to the participant ($p = 0.9149$).

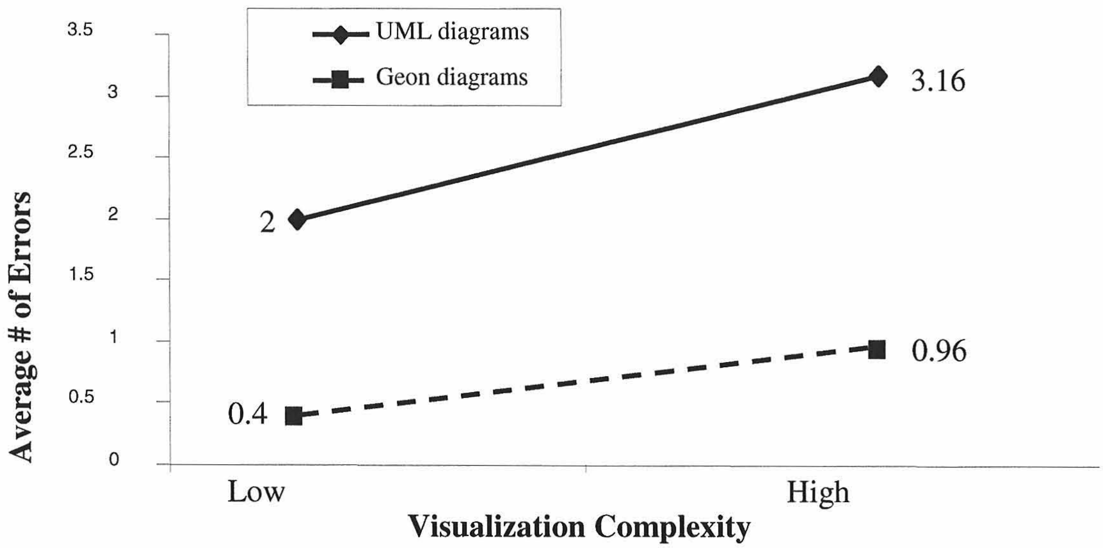


Figure 4.2 Distribution of average number of errors for low and high complexity UML and geon diagrams.

Table 4.4 Statistical Results for Error Rate

	Visualization(V)	Complexity(C)	V*C	Order
F	228.00	70.89	5.14	0.03
p-val	<0.0001	<0.0001	0.0326	0.8734

Hypothesis H1.2 hypothesized that the error rate is lower in geon diagrams as compared to UML diagrams. The results of the experiments show that the error rate is higher in UML diagrams as compared to Geon diagrams. As shown in Table 4.2, the average number of errors per person using UML diagrams is 2.58 and the average number of errors per person for geon diagram is 0.68. Figure 4.2 shows the average number of errors per task when using UML and geon diagrams of low and high complexity. The number of errors that occur for geon diagrams is lower than the number of errors using UML diagrams. The difference is greater for complex diagrams. As shown in Table 4.4, The null hypothesis ($H1.2_0$ There is no difference in the error rate in geon diagrams as compared to UML diagrams) is rejected at $p<0.0001(\alpha=0.05)$. This shows that there is a significant difference in the number of errors made in completing a visual task when different visualizations are used. The summary of the results of the research hypotheses for effectiveness are presented in Table 4.5. The detailed discussion of the interpretation of these results is provided in Section 5.1.

Considering the effect of complexity of visualizations, Table 4.1 shows the mean time taken to complete a visual task using visualizations with low and high complexity. Mean time taken using visualizations with low-complexity is 32.548 seconds and the mean time taken using visualizations with high-complexity is 53.632. The null hypothesis ($H4.1_0$ There is no difference in the time taken to complete a visual task in diagrams with low-complexity as compared diagrams with high-complexity) is rejected at $p<0.0001(\alpha=0.05)$ as shown in Table 4.3. Table 4.2 shows that the mean error rate for visualizations with lower complexity is 1.2 and the mean error rate for visualizations with high-complexity is 2.06. The ANOVA results are shown in Table 4.4. The null hypothesis ($H4.2_0$ There is no difference in the error rate in diagrams with low-complexity as compared to diagrams with high-complexity) is rejected at $p<0.0001(\alpha=0.05)$. The results also show that there is no effect due to the order in which the condition was presented to the participant ($p = 0.8734$).

Considering the interaction effect of visualization type and complexity, the non-parallel lines in Figure 4.1 and Figure 4.2 show that there is an interaction effect for both time to completion and error rate. The ANOVA results in Table 4.3 provide quantitative analysis of this interaction. For time to completion, the null hypothesis ($H7.1_0$ There is no interaction effect in the time taken to complete a visual task due to visualization type and complexity) is rejected at $p =0.0218(\alpha=0.05)$. For error rate, the ANOVA results are shown in Table 4.4. The null hypothesis ($H7.2_0$ There is no interaction effect in the error rate due to visualization type and complexity) is rejected at $p =0.0326(\alpha=0.05)$.

In general, effectiveness is higher for geon as compared to UML diagrams. Complexity has a degrading effect on effectiveness for both UML and geon diagrams. These results are in line with the expected result. The summary of the hypotheses testing is presented in Table 4.5.

Table 4.5 Summary of Results for Research Question on Efficiency

Hypothesis	*p*-value	Result
H1.1$_0$ There is no difference in the time taken to complete a visual task using geon diagrams as compared to UML diagrams	*p* <0.0019	The null hypothesis is rejected
H1.2$_0$ There is no difference in the error rate in geon diagrams as compared to UML diagrams.	*p* <0.0001	The null hypothesis is rejected
H4.1$_0$ There is no difference in the time taken to complete a visual task in diagrams with low-complexity as compared diagrams with high-complexity.	*p* <0.0001	The null hypothesis is rejected
H4.2$_0$ There is no difference in the error rate in diagrams with low-complexity as compared to diagrams with high-complexity.	*p* <0.0001	The null hypothesis is rejected
H7.1$_0$ There is no interaction effect in the time taken to complete a visual task due to visualization type and complexity.	*p* =0.0218	The null hypothesis is rejected
H7.2$_0$ There is no interaction effect in the error rate due to visualization type and complexity.	*p* =0.0326	The null hypothesis is rejected

4.3 Results for Research Question 2: Search Path

Search path analysis required the coding of the verbal protocols as a series of nodes, links, components traversed by the participants to complete the visual task. The inter-rater reliability for coding the transcripts was calculated using *Cohen's kappa* coefficient (Cohen 1960). The un-weighted *kappa coefficient* for coding search path is 0.71 which ranks the coding reliability as *substantial agreement* (Landis and Koch 1977). The *measure of proportion* of agreement (Fleiss 1981) for the two coders is 0.82. The research question on search path involves the number of nodes, the number of links, the number of components (combination of nodes and links) and the total number of elements (sum of nodes, links and components) traversed by the participants to complete the visual task in all the four conditions. Therefore, the results for research proposition 2 are discussed under separate subsections for each of these hypotheses. A repeated measures ANOVA is used for all the cases. The assumptions for repeated measures ANOVA are fulfilled for all the tests.

4.3.1 Number of Nodes

Table 4.6 is the table of means for the number of nodes traversed for UML and geon diagrams. Figure 4.3 presents the means graphically. For both levels of complexity (*low* and *high*), the number of nodes traversed is lower in geon diagrams as compared to UML diagrams. The difference is greater for complex visualizations. A repeated measures ANOVA was done to test if the difference was significant. The results of the ANOVA are presented in Table 4.7. The null hypothesis ($H2.1_0$: No difference in the number of nodes traversed in while completing the visual task in UML and geon diagrams) is rejected at $p < 0.0001 (\alpha = 0.05)$. This shows that there is a significant difference in the number of nodes accessed in completing a visual task using different visualization types for visualizations of both levels of complexity (*low* and *high*).

Table 4.6 Table of Means for Number of Nodes Traversed

Complexity / Visualization	Low	high	Mean
UML	8.4400 (B)	15.8480 (A)	12.144
Geon	5.0320 (C)	8.4640 (B)	6.748
Mean	6.736	12.156	9.446

* Means with the same letter are not significantly different

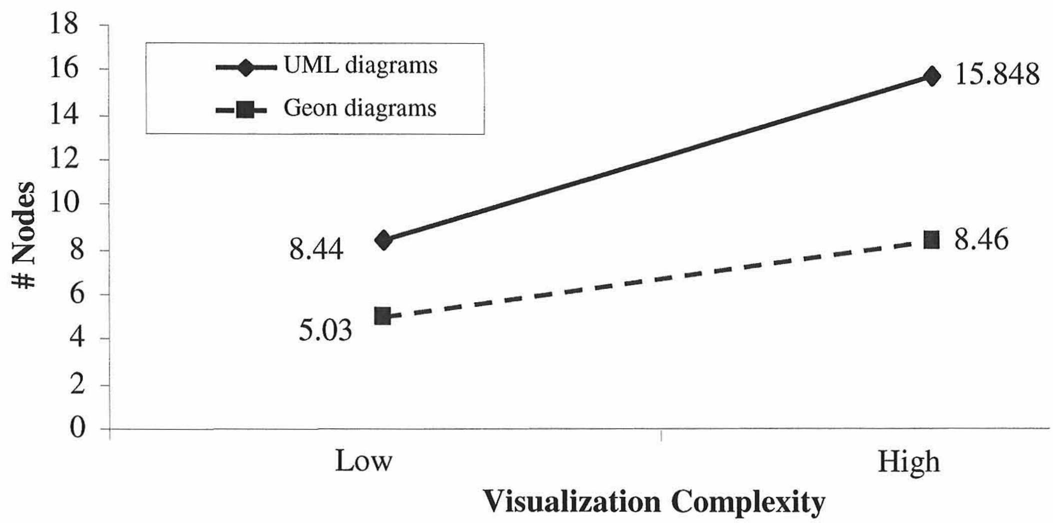


Figure 4.3 Distribution of average number of nodes traversed for low and high complexity UML and geon diagrams.

Table 4.7 Statistical Results for Number of Nodes Traversed

	Visualization(V)	Complexity(C)	V*C	Order
F	65.89	65.50	9.21	0.12
p-val	<0.0001	<0.0001	0.0057	0.7260

As shown in Table 4.6 and Figure 4.3, the number of nodes traversed for low-complexity visualizations is lower than the number of nodes traversed for high-complexity visualizations. The result of the ANOVA is presented in Table 4.7. The null hypothesis ($H5.1_0$: There is no difference in the number of nodes traversed while completing the visual task using high-complexity visualization as compared to low-complexity visualization.) is rejected at $p < 0.0001 (\alpha=0.05)$.

The results show that the average number of nodes accessed was the lowest with low-complexity geon diagrams and most for high-complexity UML diagrams. The difference in number of nodes traversed is higher in high-complexity visualizations as compared to low-complexity visualizations as shown in Figure 4.3. The null hypothesis ($H8.1_0$: There is no difference in the traversal of nodes when complexity is varied for UML and geon diagrams) is rejected at $p = 0.0057 (\alpha = 0.05)$ as shown in the ANOVA results in Table 4.7. The results also show that there is no effect due to the order in which the condition was presented to the participant ($p = 0.7260$).

From the letter in the parenthesis in Table 4.6, it can be seen that the number of nodes accessed is not significantly different for low-complexity UML and high-complexity geon diagram which is a co-incidence and is not a subjected to further interpretation.

4.3.2 Number of Links

Table 4.8 is the table of means for the number of links traversed for UML and geon diagrams. Figure 4.4 presents the means graphically. For both low-complexity and high-complexity visualizations, the number of links traversed is higher in geon diagrams as compared to UML diagrams. A repeated measures ANOVA was done to check if the difference is significant. The result of the ANOVA is shown in Table 4.9. The null hypothesis ($H2.2_0$: no difference in number of links traversed while completing the visual task in geon as compared to UML) is rejected at $p < 0.0001 (\alpha = 0.05)$. Therefore, there is a significant difference in the number of links accessed in completing a visual task when different visualizations are used.

Table 4.8 Table of Means for Number of Links Traversed

Complexity / Visualization	Low	high	Mean
UML	1.1760 (C)	2.3600 (B)(C)	1.768
Geon	3.6080 (B)	5.5040 (A)	4.556
Mean	2.392	3.932	3.162
* Means with the same letter are not significantly different			

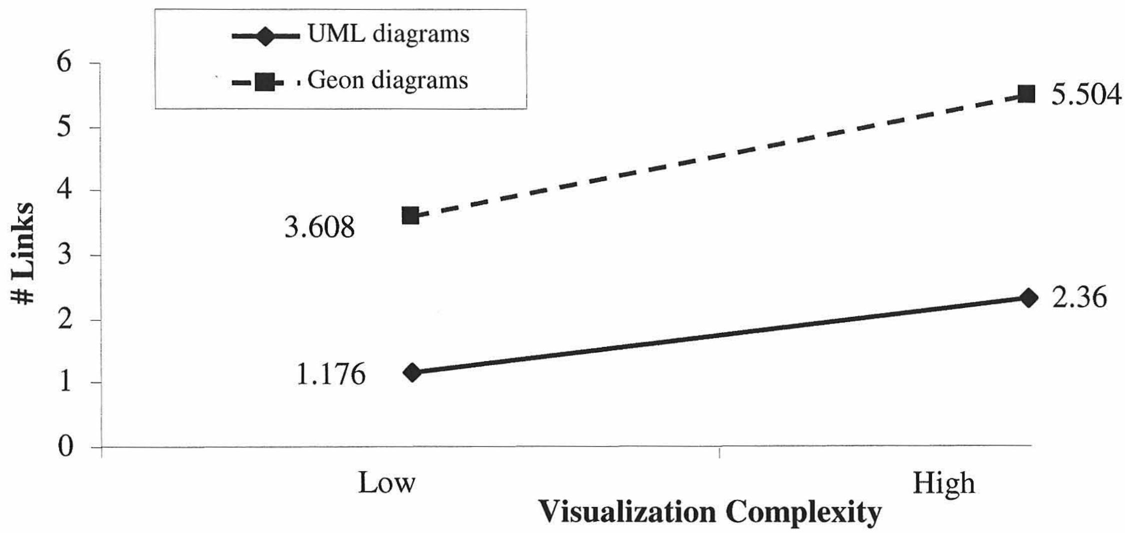


Figure 4.4 Distribution of average number of links traversed for low and high complexity UML and geon diagrams.

Table 4.9 Statistical Results for Number of Links Traversed

	Visualization(V)	Complexity(C)	V*C	Order
F	39.13	23.00	1.42	1.77
p-val	<0.0001	<0.0001	0.2455	0.1867

As shown in Table 4.8 and Figure 4.4, the number of links traversed for low-complexity visualizations is lower than the number of links traversed for high-complexity visualizations. The difference is significant only for geon diagrams. The result of the ANOVA is shown in Table 4.9. The null hypothesis ($H5.2_0$: There is no difference in the number of links traversed while completing the visual task using high-complexity visualization as compared to low-complexity visualization) is rejected $p<0.0001(\alpha=0.05)$. For UML diagrams, the number of links traversed for low-complexity diagrams is lower than the number of links traversed for high-complexity diagrams as shown in Figure 4.4 but this difference is not significant (as shown by the same letter in Table 4.8). The results also show that there is no effect due to the order in which the condition was presented to the participant ($p = 0.1867$).

The results show that the average number of links accessed is the highest with high-complexity geon diagrams and the lowest in low-complexity UML diagrams. The number of links accessed in completing the task using high-complexity UML diagram is not significantly different from the number of links accessed in low-complexity UML diagrams. It is also not significantly different from the number of links accessed in low-complexity geon diagrams. Based on the ANOVA results in Table 4.9, the null hypothesis ($H8.2_0$: There is no difference in the traversal of links when complexity is varied for UML and geon diagrams) cannot be rejected at $p =0.2455(\alpha=0.05)$. Therefore, it can be derived that there is a difference in the number of links traversed while completing visual problem tasks based on the visualization type and complexity but there is no interaction between the type and complexity factors.

4.3.3 Number of Components (Combinations of Nodes and Links)

The table of means for the number of components traversed while completing the visual task using UML and geon diagrams is different as shown in Table 4.10. Figure 4.5 presents the means graphically. For both low and high complexity visualizations, the number of components traversed is higher in geon diagrams as compared to UML diagrams. The difference is greater for high-complexity visualizations. A repeated measures ANOVA was done to check the significance of the differences. The ANOVA results are presented in Table 4.11. The null hypothesis ($H2.3_0$: There is no difference in the number of components traversed while completing the visual task using geon as compared to UML) is rejected for high-complexity diagrams at $p < 0.0001 (\alpha = 0.05)$. The difference is not significant for low-complexity diagrams.

Table 4.10 Table of Means for Number of Components Traversed

Complexity / Visualization	Low	High	Mean
UML	0.8000 (B)	1.7440 (B)	1.272
Geon	2.3760 (B)	5.9360 (A)	4.156
Mean	1.588	3.840	2.714
* Means with the same letter are not significantly different			

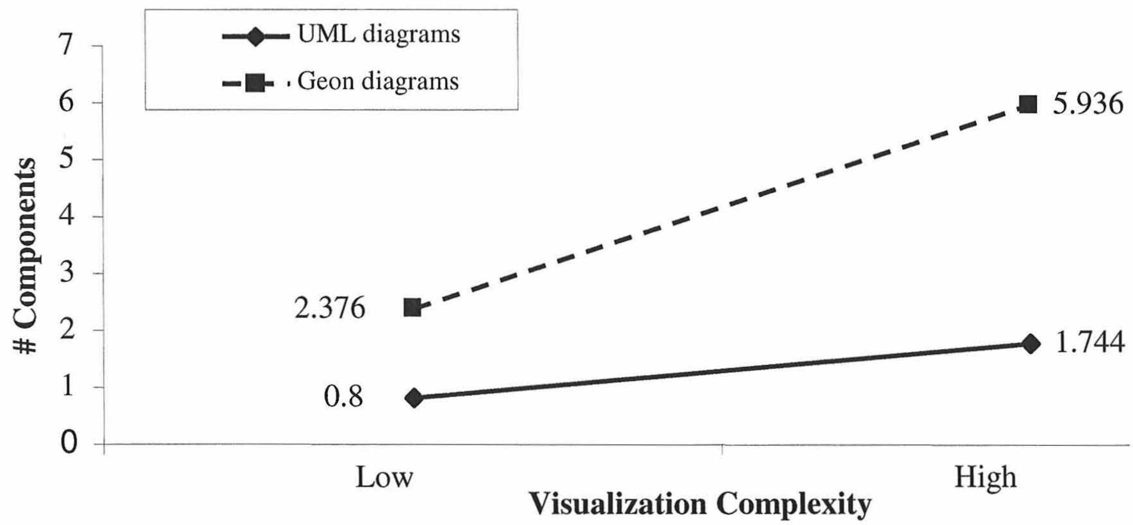


Figure 4.5 Distribution of average number of components traversed for low and high complexity UML and geon diagrams.

Table 4.11 Statistical Results for Number of Components Traversed

	Visualization(V)	**Complexity(C)**	**V*C**	**Order**
F	20.58	30.64	7.68	0.94
p-val	<0.0001	<0.0001	0.0106	0.3342

The number of components traversed for low-complexity visualizations is lower than the number of components traversed for high-complexity visualizations. The ANOVA results are shown in Table 4.11. The null hypothesis ($H5.3_0$: There is no difference in the number of components traversed while completing the visual task using high-complexity visualization as compared to low-complexity visualization) is rejected at $p < 0.0001 (\alpha = 0.05)$. The number of components traversed in low-complexity UML diagrams is lower than the number of components traversed by high-complexity UML diagrams but this difference is not significant. The results also show that there is no effect due to the order in which the condition was presented to the participant ($p = 0.3342$).

The number of components accessed in the highest for high-complexity geon diagrams and lowest for low-complexity UML diagrams. The difference in the number of components traversed is not significant for UML diagrams and low-complexity geon diagrams. The difference becomes noticeable only for high-complexity geon diagrams. The null hypothesis ($H8.3_0$: There is no difference in the traversal of components when complexity is varied for UML and geon diagrams) is rejected at $p = 0.0106 (\alpha = 0.05)$. The ANOVA results are shown in Table 4.11. Therefore, it can be derived that there is a difference in the number of components traversed while completing visual problem tasks based on the visualization type and complexity. It is to be noted that the difference becomes significant only for high-complexity visualizations where there are more nodes and links with more probability of mental formation of components. Also, for UML diagrams, individuals do not tend to have these mental formations of components. Therefore, there is no significant amount of components traversed by individuals when using UML diagrams. The number of components traversed for high-complexity UML diagrams is lower than the number of components traversed for low-complexity geon diagrams.

4.3.4 Total Number of Elements (Nodes + Links + Components)

Table 4.12 shows the table of means for the total number of elements traversed in completing the visual problem-solving task. Figure 4.6 shows the data graphically. A repeated measures ANOVA was done to check if the difference is significant. The ANOVA results are in Table 4.13. The null hypothesis ($H2.4_0$: There is no difference in the number of total elements traversed while completing the visual task using UML as compared to geon diagrams) cannot be rejected ($p = 0.8018$). As shown in the Table 4.12

and Figure 4.6, the means for the total number of elements traversed are almost equal for UML and geon diagrams.

Table 4.12 Table of Means for Number of Total Elements Traversed

Complexity / Visualization	Low	high	Mean
UML	10.416 (B)	19.952 (A)	15.184
Geon	11.016 (B)	19.904 (A)	15.460
Mean	10.716	19.928	15.322
* Means with the same letter are not significantly different			

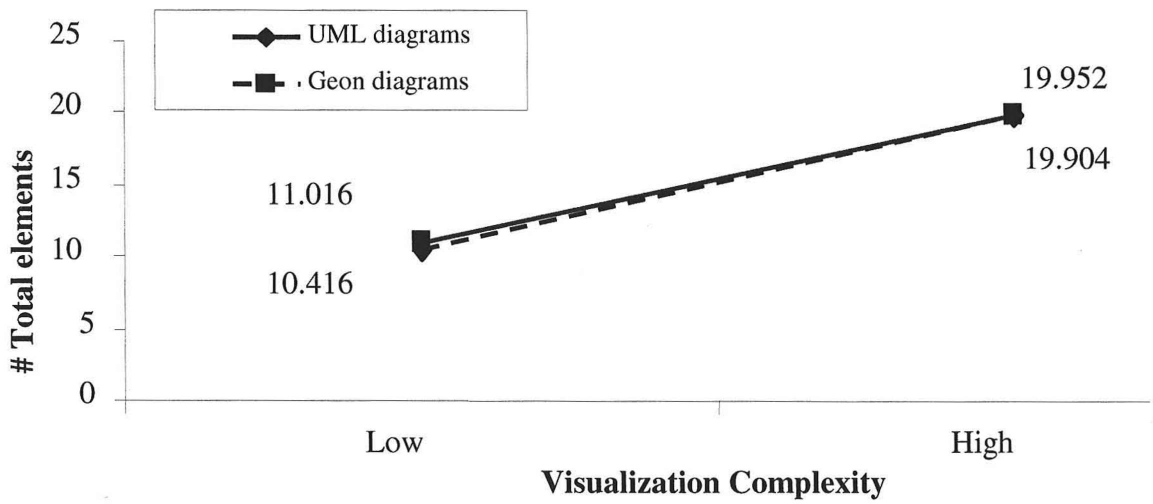


Figure 4.6 Distribution of average number of total elements traversed for low and high complexity UML and geon diagrams.

Table 4.13 Statistical Results for Number of Total Elements Traversed

	Visualization(V)	**Complexity(C)**	**V*C**	**Order**
F	0.06	74.98	0.12	0.10
p-val	0.8018	<0.0001	0.7285	0.7571

The total number of elements traversed for low-complexity visualizations is lower than the total number of elements traversed for high-complexity visualizations. The ANOVA results in Table 4.13 show that the null hypothesis ($H5.4_0$: There is no difference in the total number of elements traversed while completing the visual task using high-complexity visualization as compared to low-complexity visualization) is rejected at $p < 0.0001 (\alpha=0.05)$. Therefore, the total number of elements traversed is significantly lower in low-complexity visualizations as compared to high-complexity visualizations. The results also show that there is no effect due to the order in which the condition was presented to the participant ($p = 0.7571$).

The total number of elements accessed in the highest for high-complexity UML diagrams and lowest for low-complexity UML diagrams. The difference of total number of elements traversed is significant for low-complexity and high-complexity diagrams. The ANOVA result for interaction effect is shown in Table 4.13. The null hypothesis ($H8.4_0$: There is no difference in the total number of elements traversed when complexity is varied for UML and geon diagrams.) cannot be rejected at $p < 0.7285 (\alpha=0.05)$. Therefore, it can be derived that there is a difference in the total number of elements traversed while completing visual problem tasks based on the diagrammatic complexity but not on visualization type. Also, there is no interaction effect. There is almost no difference in the total number of elements traversed for high-complexity UML diagrams and high-complexity geon diagrams. The difference is just noticeable for low-complexity visualizations.

A summary of all the hypothesis and the results developed from the propositions on search path are summarized in Table 4.14.

Table 4.14 Summary of Results for Research Question on Search Path

Hypothesis	*p*-value	Result
H2.1$_0$: There is no difference in the number of nodes traversed while completing the visual task using UML as compared to geon.	*p <0.0001*	The null hypothesis is rejected
H2.2$_0$: There is no difference in the number of links traversed while completing the visual task using geon as compared to UML.	*p <0.0001*	The null hypothesis is rejected
H2.3$_0$: There is no difference in the number of components traversed while completing the visual task using geon as compared to UML.	*p <0.0001*	The null hypothesis is rejected
H2.4$_0$: There is no difference in the number of total elements traversed while completing the visual task using UML as compared to geon diagrams.	*p <0.8018*	Fail to reject null hypothesis
H5.1$_0$: There is no difference in the number of nodes traversed while completing the visual task using high-complexity visualization as compared to low-complexity visualization.	*p <0.0001*	The null hypothesis is rejected
H5.2$_0$: There is no difference in the number of links traversed using high-complexity visualization as compared to low-complexity visualization.	*p <0.0001*	The null hypothesis is rejected
H5.3$_0$: There is no difference in the number of components (combinations of one or more nodes and/or links) traversed using high-complexity visualization as compared to low-complexity visualization.	*p <0.0001*	The null hypothesis is rejected
H5.4$_0$: There is no difference in the number of total elements (nodes/links/components) traversed using high-complexity visualization as compared to low-complexity visualization.	*p <0.0001*	The null hypothesis is rejected
H8.1$_0$: There is no difference in the traversal of nodes when complexity is varied for UML and geon diagrams.	*p <0.0057*	The null hypothesis is rejected
H8.2$_0$: There is no difference in the in the traversal of links when complexity is varied for UML and geon diagrams.	*p <0.2455*	Fail to reject null hypothesis
H8.3$_0$: There is no difference in the number of components when complexity is varied for UML and geon diagrams.	*p <0.0106*	The null hypothesis is rejected
H8.4$_0$: There is no difference in the total number of elements traversed when complexity is varied for UML and geon diagrams.	*p <0.7285*	Fail to reject null hypothesis

A detailed discussion on the interpretation of the result is done in Section 5.2.

4.4 Results for Research Question 3: Search-Steps

Individual's search-step is analyzed by examining the coded protocol of the participants in solving the problem. The coded sequence is used to count the transitions from one state to another. The inter-rater reliability for coding the transcripts was calculated using *Cohen's kappa* coefficient (Cohen 1960). The un-weighted *kappa coefficient* for coding search steps is 0.81 which ranks the coding reliability as *almost perfect agreement* (Landis and Koch 1977). The *measure of proportion* of agreement (Fleiss 1981) for the two coders is 0.82. To analyze the differences in the sequences of UML and geon diagrams, the average number of the transformations from each state (*I, L, E*, and *D*) to every other state is counted and represented as weighted directed graphs. The individual directed graphs showing the normalized weighted transitions for each condition are presented in Appendix E. The value on each arc is calculated as the average number of transitions made between the states for each type of visualization.

The process represented in the directed graphs is modeled as a Markov process resulting in a 4X4 (*I, L, E, D)* matrix as shown in Table 4.15. As can be seen, the sum of the normalized weights on the outgoing arcs from any node is equal to 1.

Table 4.15 Summary Matrix of Distribution of Search-Steps

Complexity / Visualization	Low					High				
		I	L	E	D		I	L	E	D
UML	I	0*	0.88	0.12	0*	I	0*	0.88	0.11	0.01
	L	0*	0.41	0.45	0.14	L	0*	0.52	0.38	0.1
	E	0*	0.5	0.21	0.29	E	0*	0.49	0.34	0.17
	D	0*	0.6	0.34	0.06	D	0*	0.3	0.5	0.2
		I	L	E	D		I	L	E	D
Geon	I	0*	0.59	0.41	0*	I	0*	0.5	0.50	0*
	L	0*	0.13	0.76	0.11	L	0*	0.2	0.74	0.06
	E	0*	0.19	0.49	0.32	E	0*	0.2	0.61	0.19
	D	0*	0.17	0.83	0*	D	0*	0	1	0*

* - The 0 was replaced with a very small number (0.000001) to make sure the matrix was non-zero

The asymptotic state occupancy statistics for all the matrices are evaluated to get the steady state behavior of the search-steps over a very large number of iterations. The transition probability matrix for all the conditions are evaluated and presented in Table 4.16.

Table 4.16 Transition Matrix for Distribution of Search-Steps

	Initiate	Locate	Evaluate	Decide
$\alpha_{UML\text{-}LC}$	0.09	0.63	0.09	0.18
$\alpha_{UML\text{-}HC}$	0.09	0.55	0.27	0.09
$\alpha_{geon\text{-}LC}$	0.09	0.36	0.54	0.01
$\alpha_{geon\text{-}HC}$	0.09	0.09	0.73	0.09

The transition probability matrix for the low-complexity UML diagrams evaluates to $\alpha_{UML\text{-}LC}$ = (0.09, 0.63, 0.09, 0.18), for high-complexity UML diagrams is $\alpha_{UML\text{-}HC}$ = (0.09, 0.55, 0.27, 0.09), low-complexity geon diagrams is $\alpha_{geon\text{-}LC}$ = (0.09, 0.36, 0.54, 0.01), for high-complexity geon diagrams is $\alpha_{geon\text{-}HC}$ = (0.09, 0.09, 0.73, 0.09). These vectors can be interpreted as follows. For *locate* transition, the probability for low-complexity UML is 0.63, for high-complexity UML is 0.55, for low-complexity geon is 0.36 and for high-complexity geon is 0.09. For *evaluate* transition, the probability for low-complexity UML is 0.09, for high-complexity UML is 0.27, for low-complexity geon is 0.36, and for high-complexity geon diagrams is 0.73. The asymptotic transition probability matrix show that *p(initiate)* remains unchanged with different visualization types and complexity levels. *P(locate)* is lower for geon than UML and *p(locate)* is lower when the diagrammatic complexity is high. For evaluate, *p(evaluate)* is higher with geon diagrams as compared to UML diagrams and *p(evaluate)* is higher when complexity is high. There is no pattern evolving out of *p(decide)* values across the four conditions.

To calculate the statistical distance between these vectors, Bhattacharyya distance can be used (Bhattacharyya 1943). The Bhattacharyya distance measures the similarity (or dissimilarity) of two discrete probability distributions (Kailath 1967). It is normally used to determine if two classes in a classification can be separated (Kailath 1967). For discrete probability distributions p and q over the same domain X, Bhattacharyya distance is defined as:

$$D_B(p,q) = -\ln(BC(p,q))$$ where,

$$BC(p,q) = \sum_{x \in X} \sqrt{p(x)q(x)}$$

, is the Bhattacharyya coefficient.

Table 4.17 lists the Bhattacharyya coefficient for the asymptotic vectors for search-steps. The cells comparing the same vectors are denoted by "-". The values outside the parenthesis show the Bhattacharyya's co-efficient. Bhattacharyya's co-efficient is the similarity between the row and column groups. The distance is calculated by subtracting the values from 1. This value is shown in parenthesis in Table 4.17. For example, consider the cell corresponding to "low-complexity UML" and "high-complexity UML" having the value 0.96(0.04). 0.96 is the Bhattacharyya's co-efficient or the measure of similarity for low-complexity UML and high-complexity UML. The value in the parenthesis, 0.04 (1-0.96), is the distance that between them.

Looking at Table 4.17, it is seen that the maximum distance between the search-steps were for high-complexity UML diagrams and low-complexity geon diagrams at 0.87. The next lower value is for the low-complexity UML and high-complexity geon diagrams at 0.34. This implies that the additive effect of visualization type and complexity attribute to the high difference in search-steps when completing a visual problem-solving task.

Table 4.17 Bhattacharyya coefficient (distance) for Search-Steps Vectors

	Low-Complexity UML	**High-Complexity UML**	**Low-Complexity geon**	**High-Complexity geon**
Low-Complexity UML	-	0.96 (0.04)	0.76 (0.24)	0.66(0.34)
High-Complexity UML		-	0.13 (0.87)	0.83(0.17)
Low-Complexity Geon			-	0.89(0.11)
High-Complexity Geon				-

The effect of visualization type can be seen by comparing the distance between low-complexity UML and low-complexity geon and also for high-complexity UML and high-complexity geon. The distance between the vectors representing the search-steps for low-complexity UML and low-complexity geon is 0.24 and the distance for high-complexity UML and high-complexity geon diagrams is 0.17. This is the effect of visualization type. The effect is less than the combined effect of complexity and type.

The distance between the vectors representing the search-steps for low-complexity geon and high-complexity geon is 0.11 and that between low-complexity UML and high-complexity UML is 0.04 which means that the effect of the complexity on the difference of search-steps is the least. The distance between low-complexity UML and high-complexity UML is very less showing that the search-steps are almost similar for a UML diagram irrespective of its complexity. Overall, it can be derived that generally, there is a like with like affiliation for visualization types (UML and Geon). Also, both complexity and visualization type have an impact on the search-steps.

Another perspective on the analysis of the search-steps can be derived from Chebyshev's distance (Cantrell 2000). This statistic complements the analysis based on Bhattacharyya's distance. While Bhattacharyya's distance gives the distance amongst all the vectors, Chebyshev's distance gives the measure of the dimension that contributes most to the distance. Chebyshev distance (or Tchebychev distance), is defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension (Abello Pardalos and Resende 2002). The Chebyshev distance between two vectors or points p and q, with standard coordinates p_i and q_i, respectively,

is $D_{Chebyshev} = \max_i \left(\left|p_i - q_i\right|\right) = \lim_{k \to \infty}\left(\sum \left|p_i - q_i\right|^k\right)^{1/k}$

Table 4.18 shows the Chebyshev's distance for the asymptotic vectors for search-steps and the dimension leading to the distance. The numbers in the cells represent the Chebyshev's distance between the condition in the corresponding row and column. The transformation that leads to the maximum distance between any two search-steps is shown in parenthesis in Table 4.18. As shown in Table 4.18, the difference between low-complexity UML and low-complexity geon can be contributed to e*valuate* steps but for high-complexity UML and high-complexity geon, the impact is the same from e*valuate* and *locate* steps.

Considering the factor of complexity, the difference between low-complexity geon and high-complexity geon stems from *locate* steps and between low-complexity UML and high-complexity UML stem from *evaluate* steps. The difference between low-complexity UML and high-complexity geon is from the *Evaluate* step and the difference between high-complexity UML and low-complexity geon is also from the *evaluate* step.

Table 4.18 Chebyshev's Distance for Search-Steps Vectors

	Low-Complexity UML	**High-Complexity UML**	**Low-Complexity geon**	**High-Complexity geon**
Low-Complexity UML	0	0.18(E)	0.45(E)	0.64(E)
High-Complexity UML		0	0.27(E)	0.46(EL)
Low-Complexity Geon			0	0.27(L)
High-Complexity Geon				0

Chebyshev's distance shows that the effect size is influenced more by evaluate transitions as compared to locate transitions. The two cases where the effect due to locate transitions were more are the difference between (a) high-complexity UML and high-complexity geon and (b) low-complexity geon and high-complexity geon. Overall, the differences in evaluation step usually contribute most to the distance (with the exception of high-complexity geon diagram where the contribution is also from the locate steps).

The combined analysis of Bhattacharyya's and Chebyshev's distance shows that the asymptotic transition matrices for the search steps for the four different conditions are indeed different from each other. The difference is significant when visualization type or complexity is varied. Therefore, based on these analyses, the results of the hypotheses for research proposition 3 are as enumerated in Table 4.19.

Table 4.19 Summary of Results for Research Question on Search-Steps

Hypothesis	Result
H3.1$_0$: There is no difference in the locate sequences in UML diagrams as compared to geon diagrams	Null hypothesis rejected
H3.2$_0$: There is no difference in the evaluate sequences in Geon diagrams as compared to UML diagrams	Null hypothesis rejected
H6.1$_0$: There is no difference in the locate sequences in high-complexity visualization as compared to low-complexity visualizations.	Null hypothesis rejected
H6.2$_0$: There is no difference in the evaluate sequences in high-complexity visualizations as compared to low-complexity visualizations.	Null hypothesis rejected
H9.1$_0$: There is no difference in locate sequences as complexity as varied for UML and geon diagrams.	Null hypothesis rejected
H9.2$_0$: There is no difference in the evaluate sequence as complexity is varied for UML and geon diagrams.	Null hypothesis rejected

CHAPTER 5

DISCUSSION

The interpretation of the results enumerated in Chapter 4 is discussed in this chapter. The discussion is split into three subsections. Section 5.1 discusses the results corresponding to research proposition 1 on effectiveness. Section 5.2 presents the results corresponding to research proposition 2 on search path and Section 5.3 present the results corresponding to research question 3 on search steps.

5.1 Efficiency

The results show that the time taken to complete a visual problem-solving task using geon diagrams is less than the time taken to complete the same task using UML diagrams. This difference is significant when the visualizations are complex. For simpler diagrams, where there are fewer nodes and links, the difference in time taken to complete the task is not significant though the time taken for geon diagrams is still lesser than the time taken using UML diagrams. In simpler diagrams, the cognitive effort is lower as compared to the complex diagrams. Individuals do not require a high degree of cognitive effort in traversing through the diagram. The lower number of nodes and links make it easier for the participants to memorize and work with them. All the elements are perceived with more ease and the participants are able to complete the task without a large number of iterations in going through all the elements in the diagrams. As the complexity of the visualizations is increased, the time difference in using geon and UML diagrams become more significant. This is because in complex diagrams, the participants spend more time to traverse the visualization. They also have to traverse and process a larger number of the different nodes and links. Also, because there are limitations to the number of elements the participants can remember, they tend to traverse to some nodes and links more than once. As a result, the time taken to complete the task increases. The increase is more in UML diagrams because of the information representation technique of UML diagrams as well as the process of working with UML diagram.

In the results of pilot 1 provided in Section 3.2, it was argued that participants spent more time on the geon diagrams because it took more time to explain the 3D shapes and connectors as compared to the UML diagrams because unlike the UML diagrams, the geon diagrams did not have a well-established vocabulary. In the current experimental setup, each geon and UML element was developed on a pre-defined vocabulary. All the participants were trained using this vocabulary before they completed the experimental task. Hence the compounding factor arising out of unavailable vocabulary and element set was removed from the current experiments. Once a well established vocabulary was understood by the participants, the results were more in line with the expectations as set by the research propositions.

For the results on the accuracy or error rate of completing the visual tasks using the different visualizations, the number of errors is significantly lower in geon diagrams as compared to UML diagrams. The trend is the same for simple and complex visualizations. The results show that the average number of errors was the lowest with low-complexity geon diagrams and the most errors were made for high-complexity UML diagrams. The number of errors is increasing as the visualizations become simple to complex and the number of errors is lower for geon visualizations as compared to UML visualizations. Another interesting point that emerges from the result for effectiveness is that a four-fold increase in complexity reduces effectiveness by a factor of roughly two for all measures (time to complete and error rate).

One important note in discussing the difference of error rate in completing a task using UML and geon diagram is that the result of any task was either *correct* or *incorrect.* Therefore, if the answer to a particular task required the participants to point out 5 different elements in the visualization, and the participant only pick out 4 of the 5 correctly, or picked out 4 correct ones and 1 incorrect element, the answer is still considered *incorrect.* There was no attempt to measure the correctness of a result over a scale. Therefore, evaluating the correctness of a task in this experiment takes into consideration the number of tasks where completed with errors for each visualization type. Based on the result of the current experiment, it can be said that using geon diagrams results in lesser errors as individuals do not miss out any relevant node, link or component when working on a given task.

To ensure that there was no effect of a particular task on the correctness of its result, i.e., that all the participants were not making a mistake in using the same diagram, the distribution of the number of errors for a task under each condition is shown in Figure 5.1. The figure shows that the number of errors is evenly distributed over all the visualizations. It fails to show that any particular visualization had a very high number of errors. The highest number of errors (17) was for Task 1 and Task 4 for complex UML visualization. The lowest number of errors (1) was for Task 2 and Task 5 for simple geon diagrams. Therefore, any error that the participants made while completing the visual task was not a function of the particular visual task.

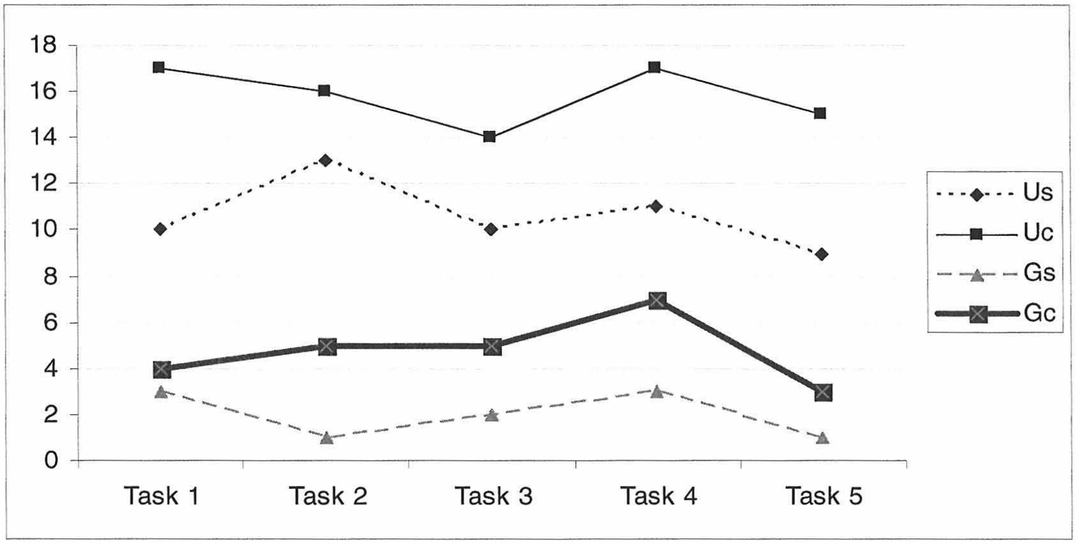


Figure 5.1 Distribution of errors over tasks under different conditions.

To ensure that there was no learning effect on the participants over the set of five tasks for the four conditions, the number of correct answers and the standard error are plotted to see if there is any trend in the data plot. Figure 5.2 - Figure 5.5 show the plots for the number of correct answers and standard errors for low-complexity UML, high-complexity UML, low-complexity geon and high-complexity geon diagrams respectively.

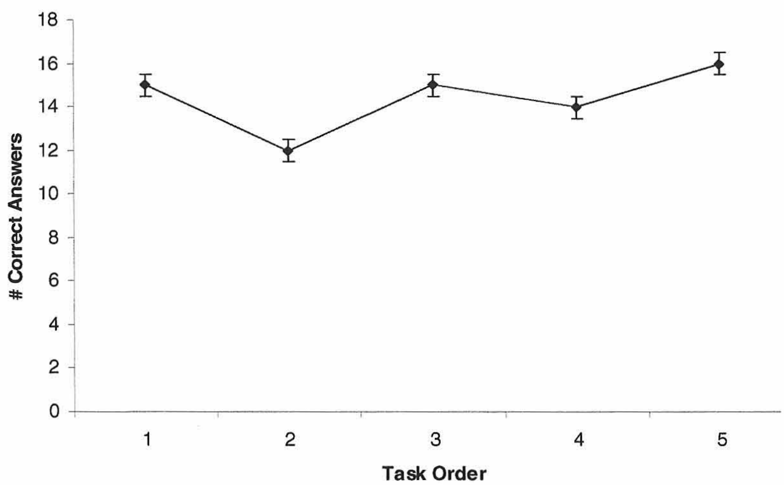


Figure 5.2 Low complexity UML: Plot of correct answers and standard error.

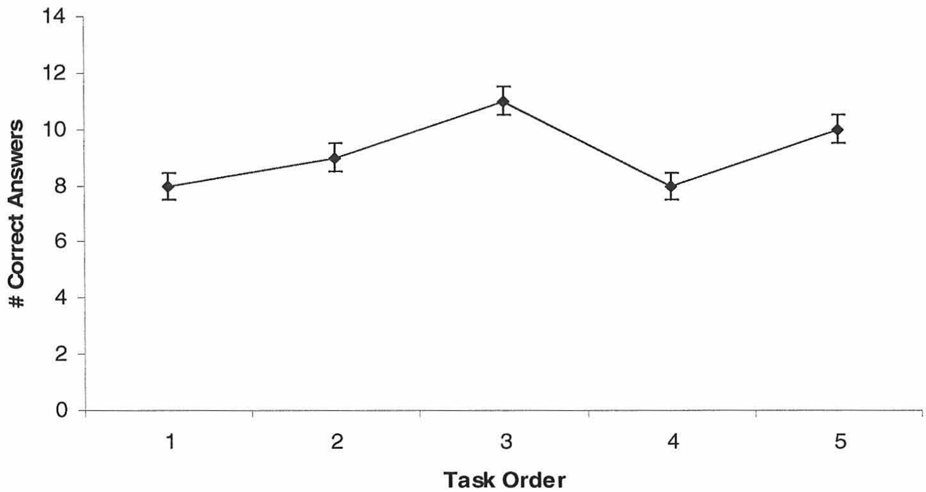


Figure 5.3 High complexity UML: Plot of correct answers and standard error.

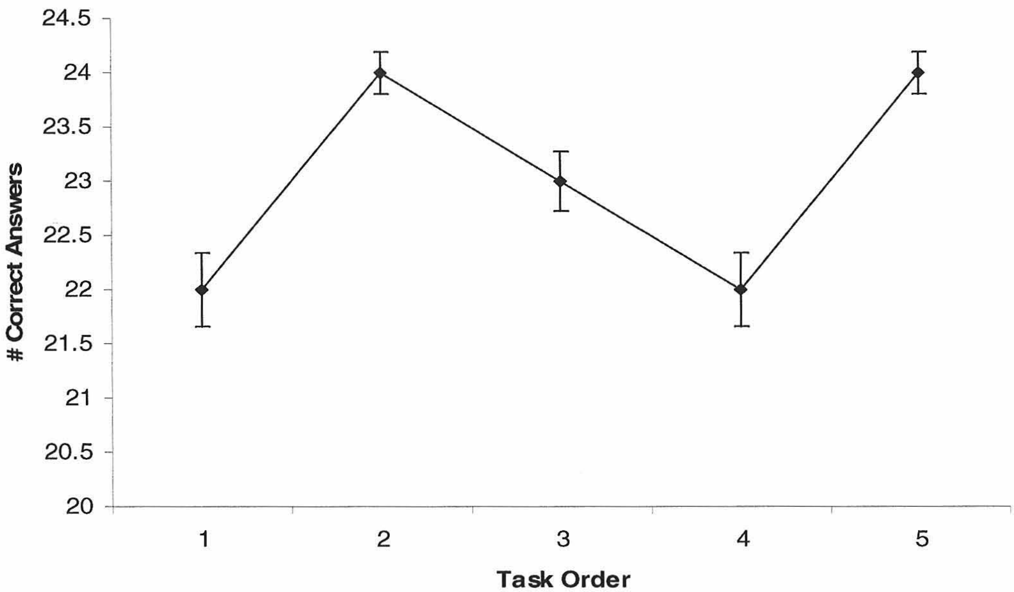


Figure 5.4 Low complexity geon: Plot of correct answers and standard error.

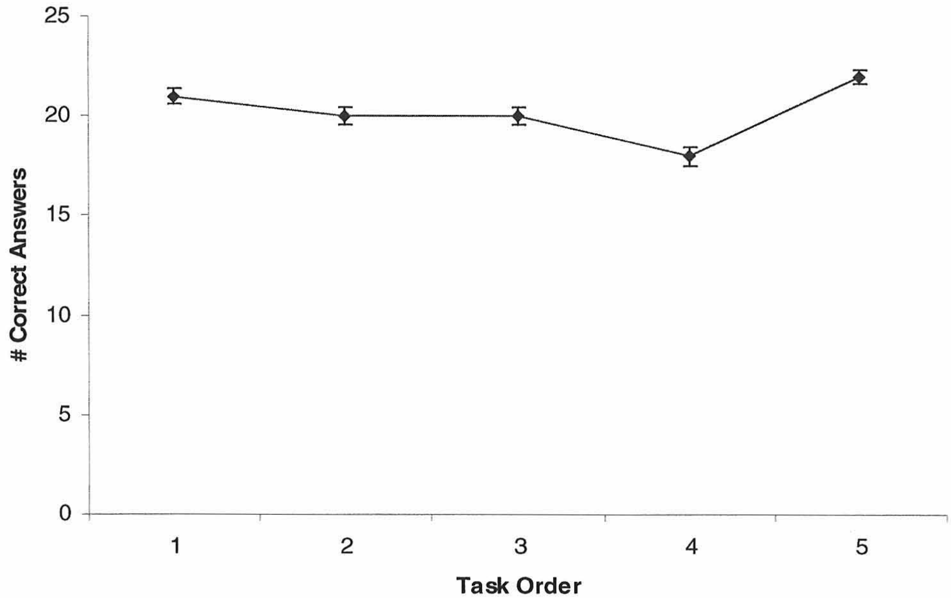


Figure 5.5 High complexity geon: Plot of correct answers and standard error.

From the plotted data, it can be inferred that no learning effect is present in the data as a result of the task presentation order since the lines do not show a consistent increase in the number of correct answers over the task order. To confirm the results analytically, ANOVA was done on the subjects and the task order. The results are shown in Table 5.1. The results confirm that there is no effect due to subject (p = *0.2758*) and due to task order (p = *1.0000*).

Table 5.1 Statistical Results for Subject and Task Order Effect

	Subject	**Task Order**
F	1.19	0.00
p-val	0.2758	1.0000

5.2 Search Path

The results of research proposition 2 show the difference in search path of individuals when using different visualizations. As expected from the results of the pilots in Section 3.2 and the related literature in Section 2.2, when solving the visual problem using geon diagrams, over time, individuals tend to recognize multiple connected components together leading to identifying an entire group of nodes and links as a single component. Participants using geon diagrams look for clusters of nodes and links and then resolve to evaluate the individual nodes and links, suggesting a whole-to-part approach. While using UML diagrams, individuals spend more time looking for nodes as their initial fixation points. In UML diagrams, search usually starts at one of the nodes and proceeds according to the structure of the layout of the nodes and links indicating a part-to-whole approach.

The total number of elements traversed is significantly more in complex visualizations as compared to simple visualizations. One interesting observation can be drawn from the total number of elements traversed by the participants under all the conditions. The total number of elements traversed is not significantly different for UML diagrams and geon diagrams for either simple or complex visualizations. This means that the excessive number of nodes traversed in UML diagrams is balanced by the excessive number of links and components traversed in geon diagrams. This leads to the interpretation that while the total number of elements may not differ across different types of visualizations, the amount and diversity of information processed in a given time is higher in geon diagrams.

This can lead to a couple of interesting observations and questions regarding the use of UML and geon diagrams. Does this mean that the use of geon diagrams is encouraging the participants to process more information to complete a task or does this mean that the increased efficiency of processing the geon diagrams is leading to more information processing as it is evident from Section 4.3 that the time required to complete the task is faster in geon diagrams as compared to UML diagrams?

Another observation worth noting is the distribution of the number of nodes, links and components traversed by the participants while using the UML and geon diagrams. Figure 5.6 and Figure 5.7 show the graphs depicting search path distribution in UML and geon diagrams, respectively. Figure 5.6 shows that the number of nodes traversed in UML diagrams dominates the search path and the number of links and components traversed in UML diagrams are much lower. For geon diagrams, as shown in Figure 5.7, the number of nodes, links and components are comparable with the number of nodes still higher than the number of links and components.

Both Figure 5.6 and Figure 5.7 show that the graphs for simple and complex diagrams have similar shape for a given visualization type. The traversal graph for the simple diagram lies completely inside the traversal graph for the complex diagram. This shows that the ratio of nodes, links and components traversed remains the same when the complexity of the diagram is varied. The distribution for the complex diagram can be derived by blowing up the distribution for the simple diagrams. The factor for blowing up is a function of the complexity of the diagram. The number of nodes, links and components traversed is directly proportional to the complexity of the diagram, which is an expected behavior.

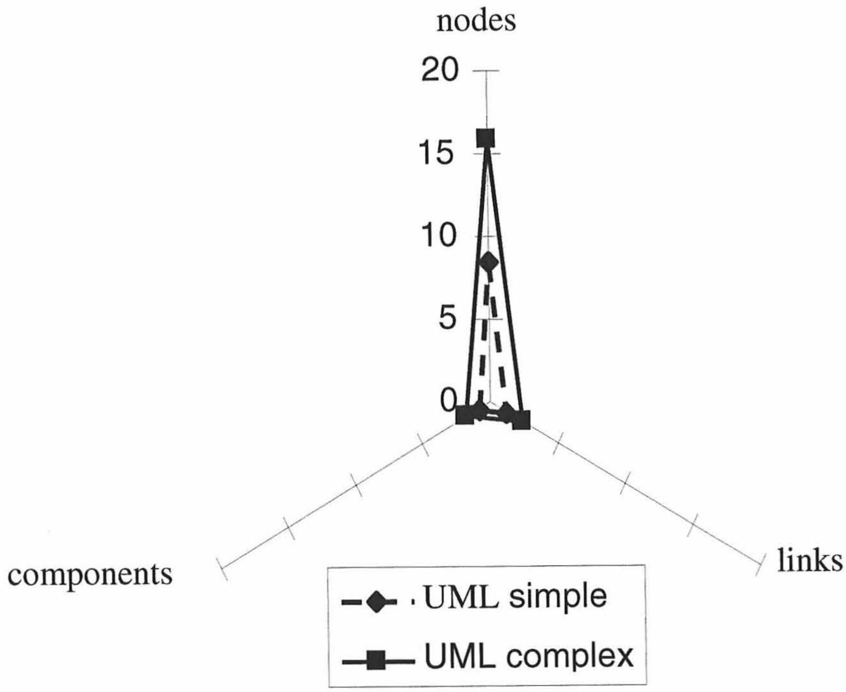


Figure 5.6 Graph depicting search path distribution in UML diagrams.

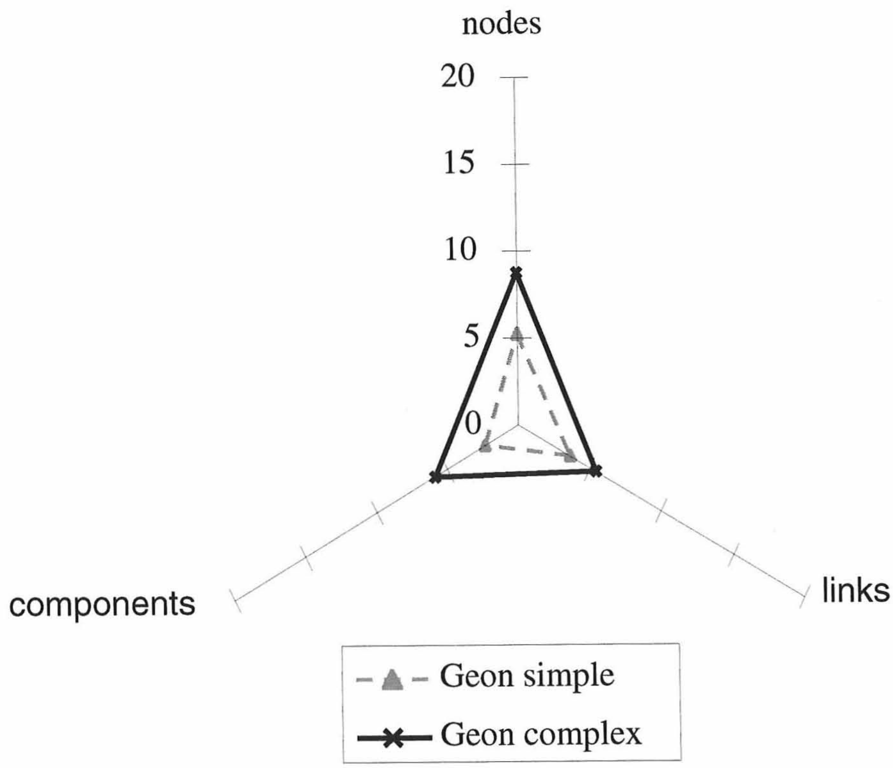


Figure 5.7 Graph depicting search path distribution in geon diagrams.

5.3 Search-Steps

Research proposition 3 evaluates the search-steps of individuals in a visual problem-solving task. The results of research proposition 3 show that there are difference arising out of the different visualizations in the search-steps of individuals in completing a visual task. Evaluation dominates the search-steps in geon diagrams whereas locating steps dominate UML diagrams. Figure 5.8 shows the distribution of *Initiate*, *Locate*, *Evaluate* and *Decide* steps for the simple and complex UML and geon diagrams. The distribution shows that for UML diagrams, there are more transitions to *Locate* as compared to *Evaluate* steps. For geon diagrams, there are more *Evaluate* steps as compared to *Locate* steps.

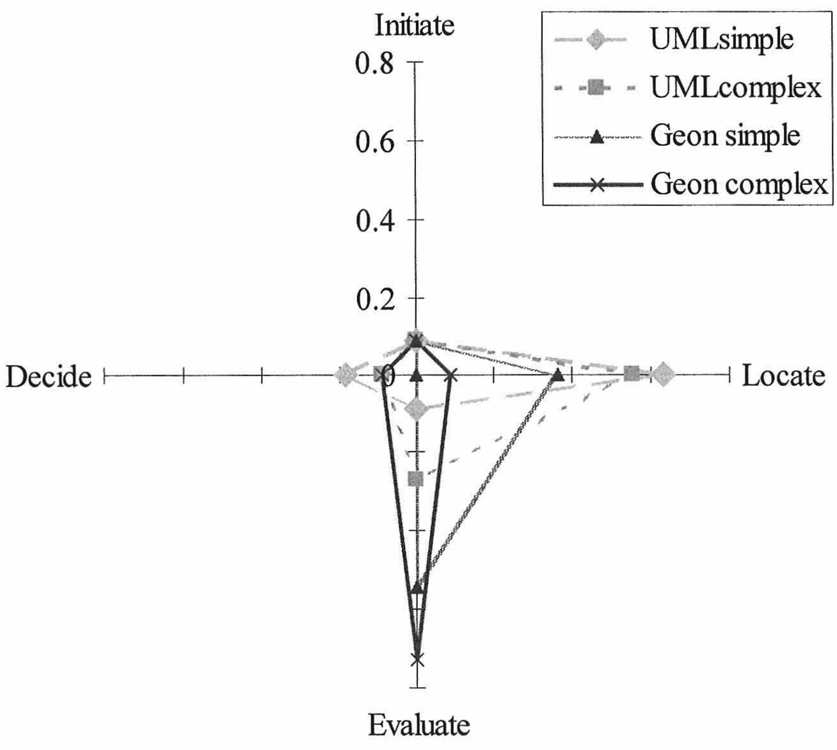


Figure 5.8 Graph depicting search-steps in UML and geon diagrams.

Another observation from Figure 5.8 is that the proportion of *locate* steps in simple geon diagrams is more than the proportion of *locate* steps in complex geon diagrams. The proportion of *locate* steps in simple UML diagrams is also more than the proportion of *locate* steps in complex UML diagrams. As shown in Figure 5.8, this also means that the proportion of evaluate transition steps are more in complex diagrams as compared to simple diagrams, which concurs with the expectation that cognitive load increases with increasing complexity of the diagrams. These numbers are proportions and not to be confused with actual number of *locate* transitions that was made by the user while completing the task.

Since search path and search-steps together provide the process view of task completion, combining the results from search path and search-steps provide a few other interesting insights. As with effectiveness, a four-fold increase in complexity increases length of search path by a factor of roughly two for all measures. Geon appears to be associated with a more holistic approach to interpretation of the information than UML and higher complexity may be associated with narrower focus but stronger evaluation-suggesting that a depth-first approach to search is being undertaken for both UML and geon when complexity is high.

CHAPTER 6

CONCLUSION AND FUTURE WORK

This chapter presents the important contribution, conclusion and the future work for the work accomplished in this thesis.

6.1 Contribution

This research work developed a set of propositions in order to understand how individuals worked with different visualizations in solving a visual problem. The results confirm the propositions that efficiency and process are both a function of the visualization characteristic. The type of visualization and its complexity are both factors that impact the way individuals process information presented to them. The different contributions of this research are enumerated below.

The first and most important contribution of this research is how different visualizations lead to different ways the information is processed by individuals. Individuals tend to focus on different pieces of information when working with different visualizations of the same information. In other words, it can be said that individuals tend to ignore certain pieces of information when working with a given type of visualization. The research presents an assessment of two different types of visualization that can be used to present the same information as node-link diagrams. When the same information is represented using UML and geon diagrams, individuals picked up different cues to answer the same question using the visualizations. For UML diagrams, individuals preferred looking for nodes and interpreting the information represented in the nodes to solve the problem. When the same problem was presented in geon diagrams, the focus of the individuals shifted from a node-dominant approach to an approach where they looked for both nodes and links to look for information. Apart from that, when individuals use geon diagrams, they were more successful in combining different nodes and links as a group to look for information and process them to come to a solution. The results from this research show that based on the way information is presented, individuals pick different cues to understand and work with them.

Another contribution of this research was complementing the effectiveness analysis derived from the results of the task with the analysis from the process of completing the task. This research shows that analyzing the results of a task to measure the effectiveness of the visualizations does not generate the complete picture of the performance of different visualizations in aiding individuals to complete a visual task. Understanding the process of completing the task provides another perspective that is equally important in understanding the difference and challenges presented by different visualizations. Based on the results of this research it can be said that understanding the process that individuals use to solve a visual problem provides additional information of performance as a function of visualization type. The process measurement is complementary to the measures of speed and accuracy that are traditionally used to understand performance. The outcome of this research can be used to design visualizations that will be appropriate for information representation in a specific application domain. The expected result of this research will aid designers and usability experts to develop visualizations that encapsulate information aptly and presents it to the intended users to best address their requirements.

Another important contribution of this research is the integration of the research areas of visual perception, visualizations of node-link diagrams, cognitive psychology and human computer interaction to answer the research propositions. Contributions from prior work in all these areas are integrated to answer the research propositions. This multi-disciplinary approach is an innovative way that is untouched by prior research in this area.

Another contribution of this research lies in the methodology of conducting the experiments to compare the two different visualizations. In this research, the data was collected in multiple ways during the experiment process. Firstly, the time to complete the task was collected unobtrusively as the participants were completing the task. Secondly, the accuracy of the task was collected for each task as whether the result was correct or incorrect. Third, the verbalizations of the participants were transcribed and coded in multiple ways to get the search path and search steps of the participants. Multiple analyses helped to understand the cognitive process that individuals underwent to complete a task. It shows that there are factors inherent in the process of solving a visual task that can help design an appropriate visualization for a task.

The contribution of the experiment in this study is targeted towards a specific user group. Managers of complex systems need to work with visualizations of different systems to understand the underlying system as well as use the visualization to make decisions about the system. The result of this research work is geared towards aiding the work of these managers and helping to reduce their cognitive effort in visual problem solving.

6.2 Limitations

This research focuses on the impact of different visualization types and complexities in a problem-solving task in the domain of interdependent critical infrastructure systems. While the results of this research can be extended to other visualization characteristics, task characteristics and domain characteristics, there are certain limitations that exist in the current study Some of these limitations can emerge as future studies in this area. Some of these limitations are listed below.

6.2.1 Applicability of UML and geon diagrams

As discussed in Section 3.1, the set of complex interdependent infrastructure systems now go beyond physical systems. The extent and usage of information systems have grown by leaps and bounds over the last decade and current research work on interdependent systems now also includes information systems (Luiijf and Klaver 2004). Since these systems do not have a physical shape and form, it is hard to depict these systems using the conventional approach as prescribed by UML and geon diagrams. There may be other similar instances in other application domains where UML and/or geon diagrams cannot be used as intended by their creators. Therefore, unless an acceptable representation technique can be recommended for the representation of these alternate objects, the use of UML and geon diagrams will be limited in these application areas.

6.2.2 Comparability of UML and geon diagrams

UML diagrams are developed at a semantic level whereas geon diagrams are developed at a structural level. This difference has been ignored in this thesis. Also, UML diagrams, by the virtue of their layout, encourage the inclusion of textual information that can provide additional information about the element being represented. Geon diagram does not have provision for inclusion of textual information. In the current research, care has been taken to ensure that only similar information is represented in both diagram types. The effect of the restrictions of each diagram type is not a part of this study and can be considered as a limitation.

6.2.3 Confounding Factors

This thesis focuses on the effect of different visualization types and complexities. The diagrams in each case have been developed on prescribed guidelines. Care has been taken to minimize effects due to external factors. However, some instances of interference may be attributed to the following:

UML diagrams in general do not include any color. Geon diagrams on the other hand prescribe the use of color. Earlier studies have shown that even when colors were removed from geon diagrams, they continued to exceed effectiveness as compared to UML diagrams. Therefore, in this current study, it has been assumed that color does not contribute to the effectiveness that is achieved using geon diagrams. Similarly, it has been assumed for this thesis that text size does not pose any interference when participants are using UML diagrams.

The size of the diagrams in this experiment was limited to diagrams that can fit on the computer screen. In real-life scenarios, it is possible to have a much larger diagram that individuals have to deal with. It may be argued that the same experiment diagrams of larger dimensions may produce different results. Increasing the display size can account for larger diagrams to be displayed without compromising the size of the individual nodes and links. However, a major requirement of managers of critical infrastructure systems is mobility and portability, and the effort in that direction is to reduce the screen size. So there is size-portability balance that needs to be considered to optimize the function of the managers in managing infrastructure systems. This aspect of defining the diagram size is outside the scope of the current research.

Another concern that rises is the speech rate of the participants. Different users think at different rates and they also speak at different rate. Speech rates may or may not be indicative of the thinking-rate of the participants. Having different speech rates leads to difference in the verbalization of the participants. The difference in the speech rate has been accounted for in two ways. First, as a preliminary requirement, only native-English speakers were selected to run the experiment. This ensured that the participants' thoughts and actions were not curtailed because of their command over the spoken language. Second, since the experiment is designed as a repeated-measures design, so each participant acts as his own control. So any difference in verbalization would have the same impact for each participant under all the four conditions.

6.2.4 Hawthorne Effect

Hawthorne effect is an experimental effect where individuals rend to perform better when they are participants in an experiment. There is a possibility of having a factor of Hawthorne effect in the current study; however, the effect should have the same bearing under all the four conditions and the effect should be even lower because the experiment is designed as a repeated-measures design and each participant acts as his own control. Therefore, while being a limitation of the current thesis, it is assumed that there is no significant effect due to Hawthorne effect.

6.2.5 Diagram Layout

This study focused on diagrams having a Manhattan layout. As discussed in Section 2.1.4, having a Manhattan layout increases the bendiness of links in the node-link diagrams. This in turn increases the visual complexity of the diagram (Koffka 1935). Using non-Manhattan layout would require the use of straight or curved lines to represent links between the nodes. Use of straight or curved links would increase the number of edge crossing which would again increase the visual complexity of the diagram (Ware, Purchase, Colpoys and McGill 2002). Therefore, there is a trade-off in preferring crossovers over bendiness of path. To make the comparison between different visualization types without adding any confounding effect due to the nature of the links, this study focuses only on Manhattan layouts. However, it is assumed that any complexity factor that may be introduced as a result of this layout will equally impact the visualizations in all the conditions (for visualization type and complexity). It may be interesting to compare the performance when the links are replaced by straight or curved links.

6.3 Conclusion

The current research (which includes the literature review, experiment design, data collection, processing, analysis and interpretation) has been done to understand the impact that different visualization types and complexities have on the way individuals interact with them. The research attempts to look for patterns in the thinking process of the participants to see if the cognitive differences arising out of the visualizations can be understood from the way individuals navigate and process the visualizations. The research propositions extend further than just analyzing the results of the visual tasks and attempts to understand the differences while working with different visualization types and complexities. The results show that geon diagrams are more effective than UML, but higher complexity degrades performance for both. The results show that two visualizations of the same information lead to different traversal techniques and search-steps. This implies that depending on the visualization being used, different information cues are accessed and processed by individuals during the task completion.

The research helps to explore the details of the cognitive processing of individuals while navigating a visual problem, the specific information accessed by them and the way that information is used to solve the visual problem. The result of this research helps to understand what type of information is used by individuals in different node-link diagrams to complete different tasks. Search with geon is associated with more holistic (i.e., breadth-first) strategies. Higher complexity pushes search with geon and UML towards depth-first strategies. This work offers is a post-hoc, empirical justification for the efficacy of geon diagrams in supporting problem-solving (as opposed to recognition). It may be possible to take a similar approach during the design phase in order to improve visualization design. For example, there is an interest in the area of management of critical infrastructure systems that includes development of GIS models and simulations. In managing interdependent critical infrastructures, there is a need for a broad view (like chasing bugs in software code) and geon diagrams appears to provide a more holistic view of the "system of systems" (as in breadth-first search). Since complexity uniformly degrades effectiveness and increases search effort, there is always a note of caution when expanding the scope of the system view.

This research is not intended to provide answers to the question of which visualization is better than the other. But rather what features of which visualization leads to a specific individual behavior. The research aims to discover measures of impact of visualization by going beyond objective measures of speed and accuracy of results of the given task. It develops measures that can quantify the mental process of the participants while completing the task rather than the results of the task.

6.4 Future Work

Possible extensions, implementations and other related work that can be done in the future include the following. Though eye-tracking data was collected in this study, the analyses did not include any micro-level analysis (e.g., gaze). Another study can be designed using eye-tracking software to drill down another level of analyzing the difference between the perceptual and the cognitive aspects of how individuals interact with visual layout of information of interconnected elements.

This study is specifically designed to understand an individual's problem-solving technique in a visual environment. There was no attempt to understand the impact of different visualization types when a group of individuals worked together to solve the problem. A different study can be designed to understand the group impact on visual problem solving using different types of node-link diagrams.

The research propositions developed as a part of this proposal can be extended to integrate with the computational models of specific application domains. Any experimental tools and procedures developed as a part of this research can be easily extended to other fields. An extension of this research can be in the integration of the contribution of this research with decision tools that can then be applied to other areas like business management or operations research or emergency management. Individuals in these areas are required to solve different types of problems and a tool that can aid them in their decision making can boost their effectiveness in decision making. Another area of extending the research is in visualizing ontologies. Understanding the cognitive processing of individuals working with such problems can lead to development of visualizations suitable for different task-domain scenarios. The results from this work can be merged with other research that depends on development of concepts and entities in any domain. This forms the basis for ontology. Therefore, the research results from this work can be extended to the area of ontology development.

Further exploration of the impact of complexity on processes and outcomes need to be understood. This study focuses on only two levels of complexity. No effort has been made on understanding the variance of effectiveness and process at intermittent levels of complexity. Similarly, this experiment only compares two different diagrams. It made no attempt to connect the diagrams to a semantic level or structure of the diagram or the theory behind the creation of the diagrams. Another future study could look into impact of these characteristics of the diagrams to the way they are interpreted/ used.

Another extension of this work could be in the modeling of user behavior (e.g., agent-based systems). Programming the dynamics of different users can provide beneficial feedback on user behavior under different conditions. Addition of constraints like environment dynamics is another area where this work can be extended. An example of adding constraints could be asking the participants to complete the task under a limited time constraint.

There are certain factors that have been ignored in this experiment. One very important factor is the gender of the users, another being user training. Earlier studies have shown how gender influences how individuals interact with diagrams. Then there are studies that have shown how training can suppress some of these gender based differences. Understanding the compounding factor of gender and training can be studied in another study. Understanding training as a compounding factor in itself can be another extension to this study.

User satisfaction is another factor that is not considered in this study as the focus of this study is to understand user's behavior in interacting to the information presented in a given visualization. While users behave in a certain way in this study, their levels of satisfaction may depend on various other factors like the system they currently use, the level of control they prefer having over the tool and the flexibility of the widgets that make up the tools. User satisfaction is one of the top factors impacting usage of current systems as well as intention of using new systems. User satisfaction can be another area of investigation in future studies.

APPENDIX A

EXPERIMENT MATERIALS USED IN THE RESEARCH

Figure A.1 to A.54 show the slides that were used in the experimentation.

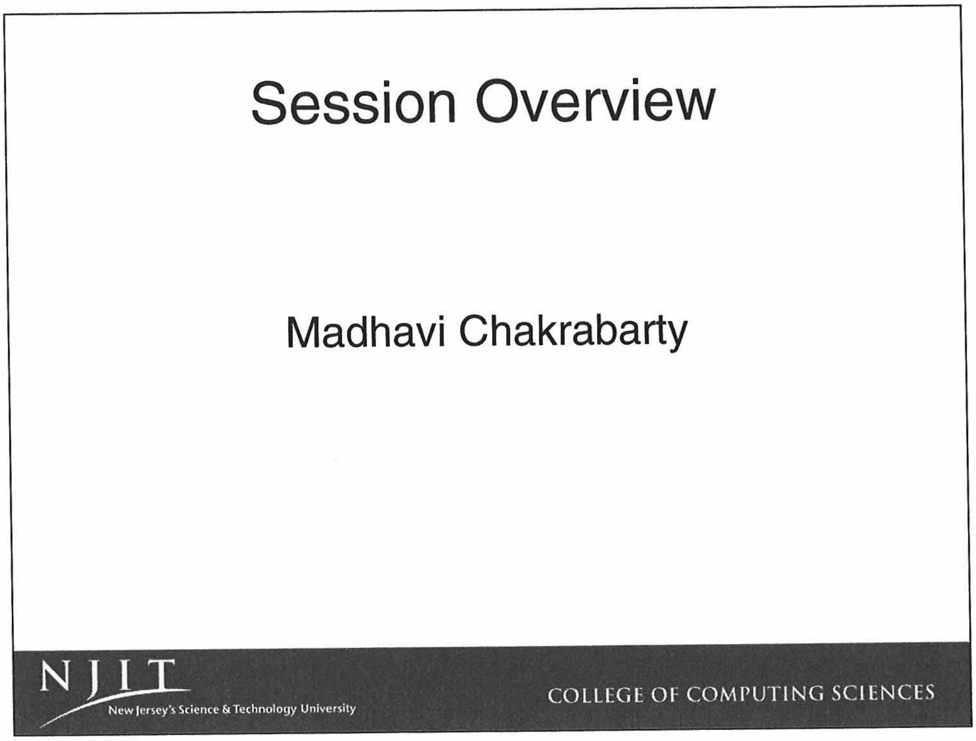


Figure A.1 Slide 1: Introduction to participants.

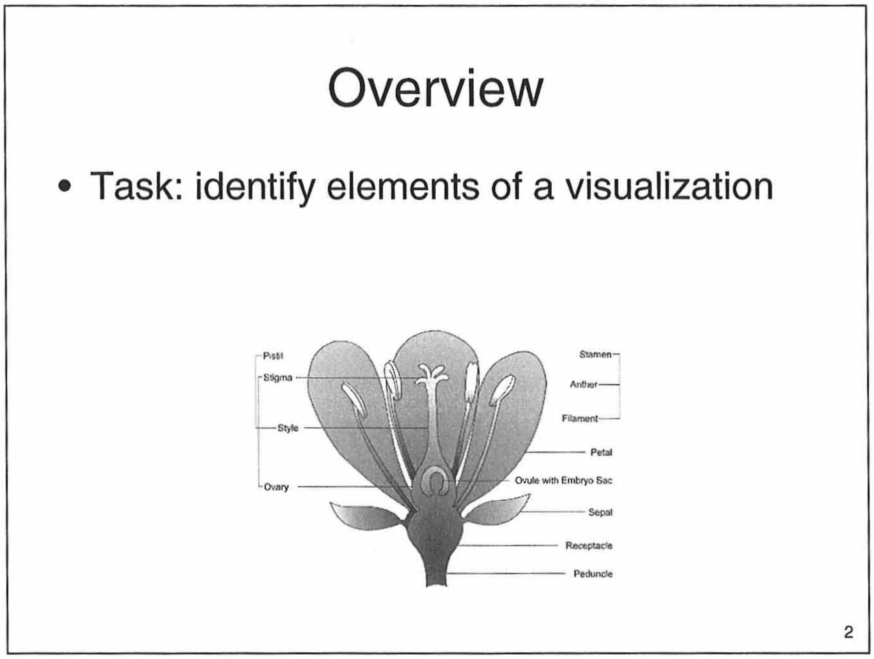


Figure A.2 Slide 2: Overview of experiment.

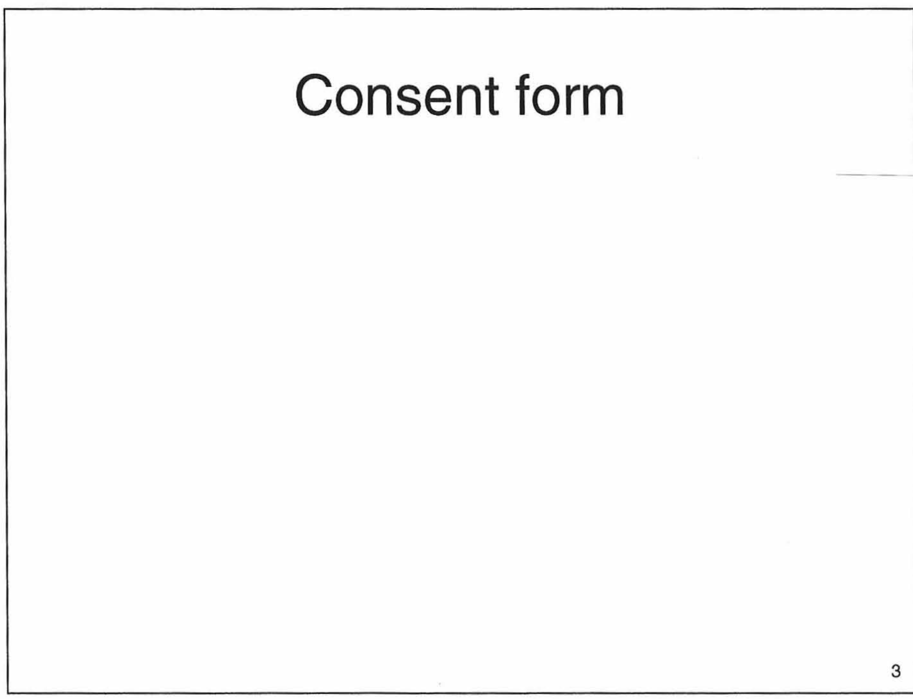


Figure A.3 Slide 3: Explanation and signing the consent form.

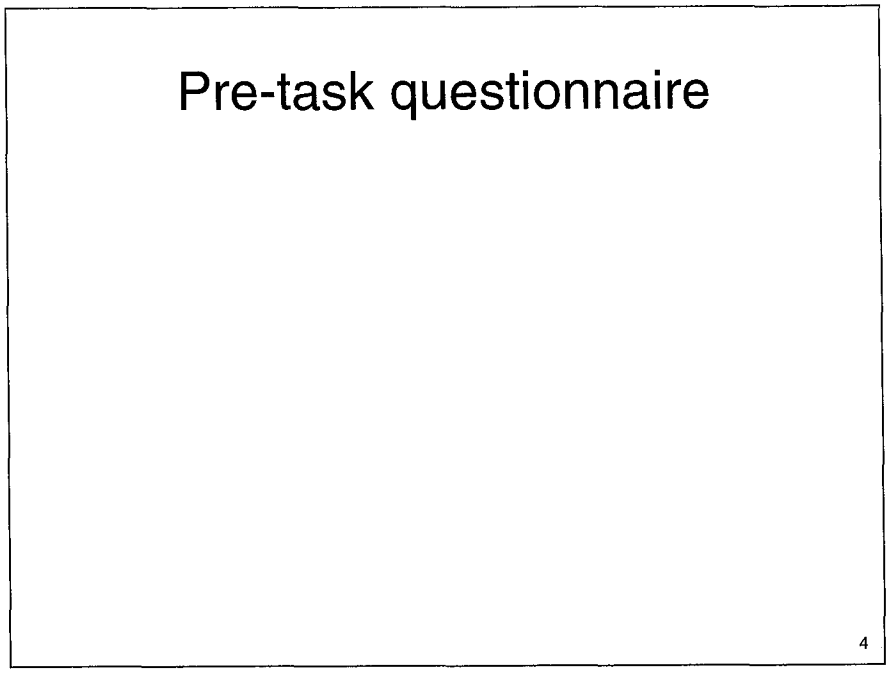


Figure A.4 Slide 4: Pre-task questionnaire.

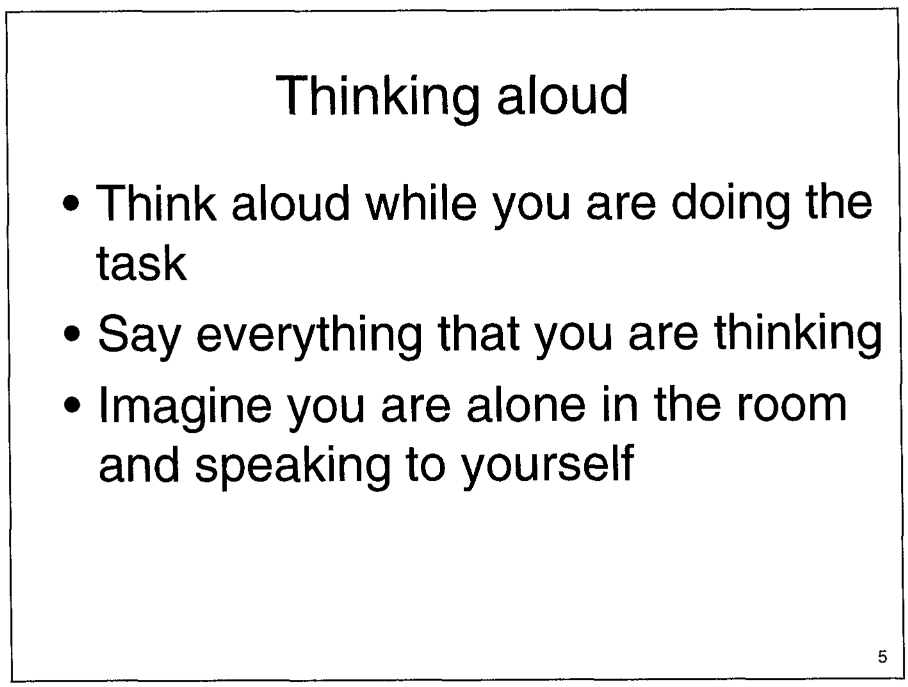


Figure A.5 Slide 5: Tutorial on thinking aloud.

Practice tasks

How many rooms are there in your home?

Where's Waldo?

6

Figure A.6 Slide 6: Practice tasks for thinking aloud.

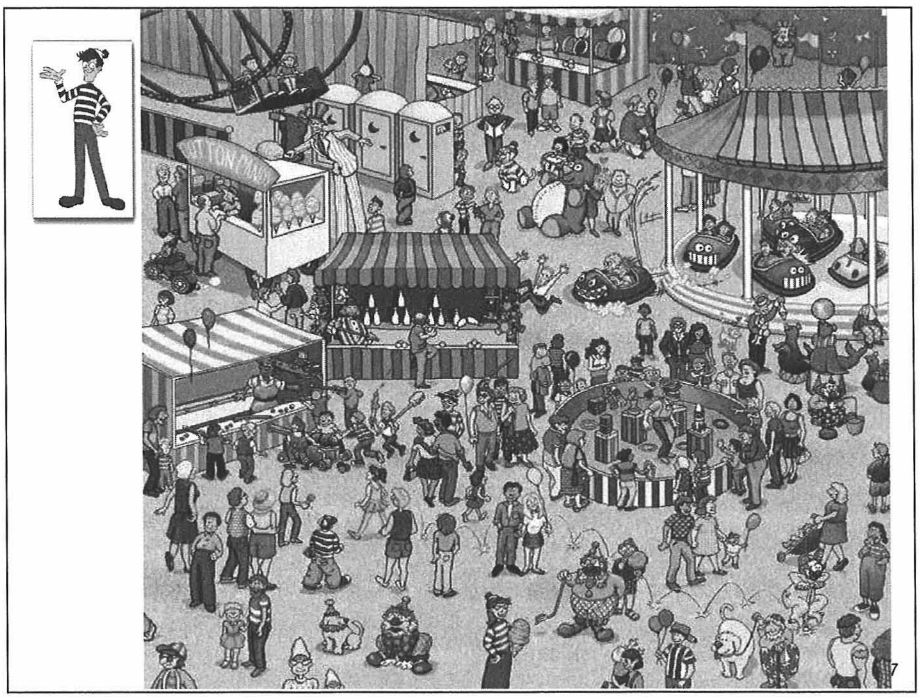


Figure A.7 Slide 7: Practice tasks for thinking aloud picture to find Waldo.

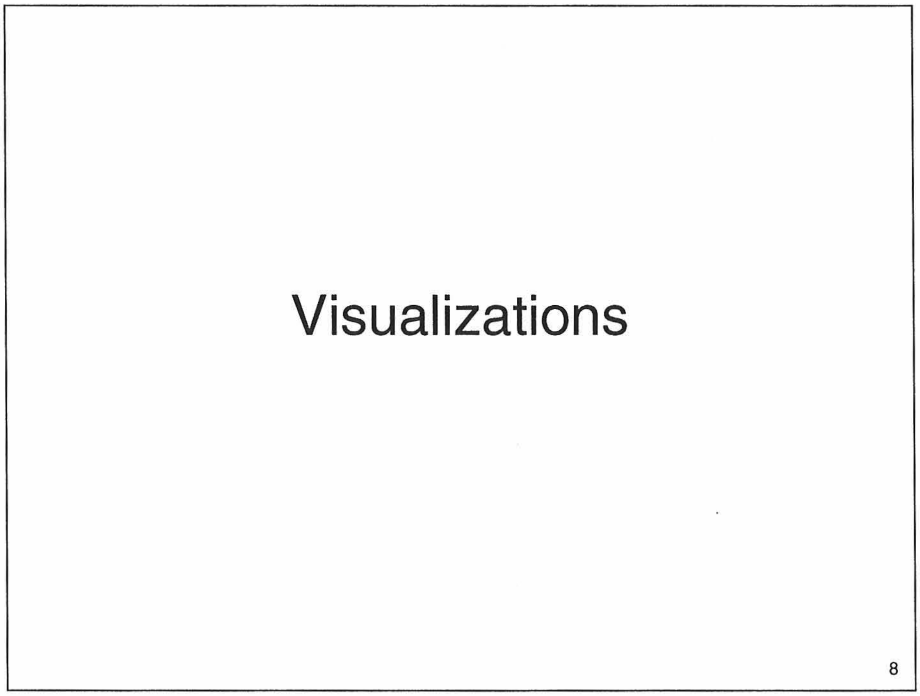


Figure A.8 Slide 8: Start of tutorial for complex systems.

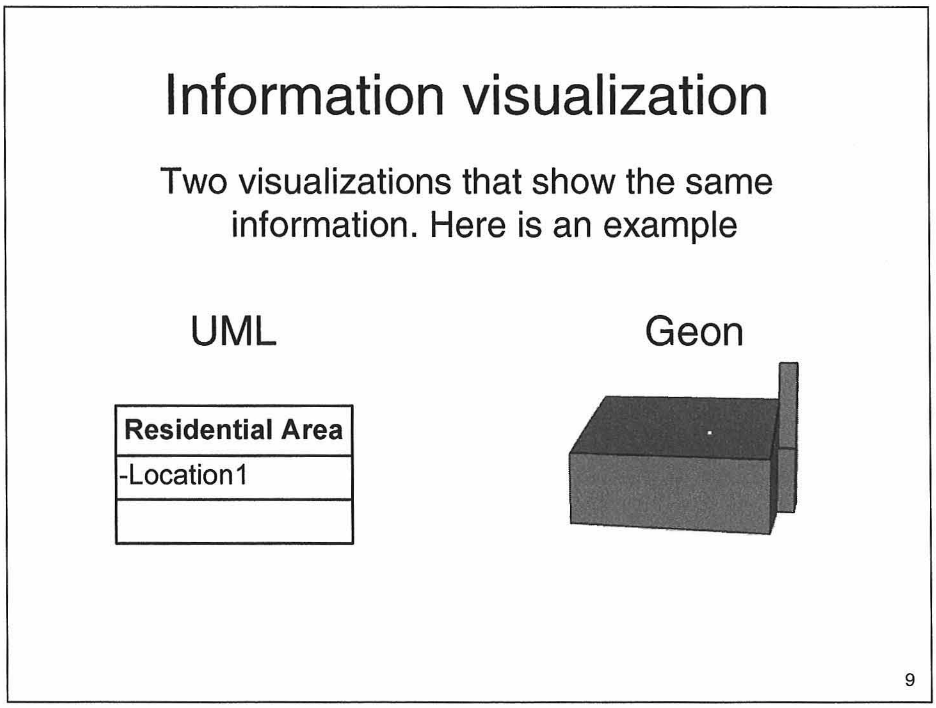


Figure A.9 Slide 9: Tutorial for visualizations of residential area.

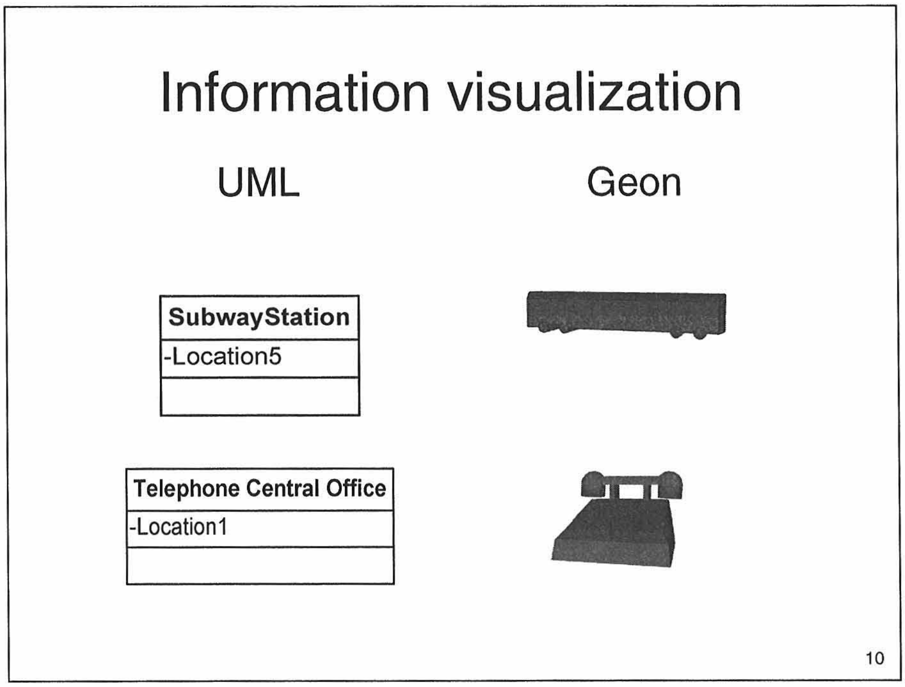


Figure A.10 Slide 10: Tutorial for visualizations of subway station and telephone central office.

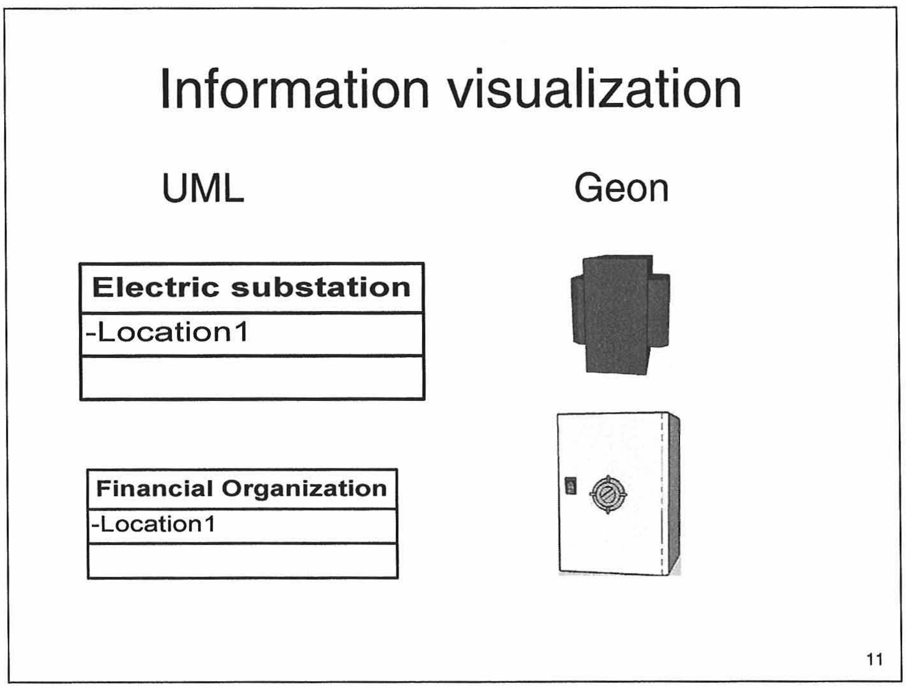


Figure A.11 Slide 11: Tutorial for visualizations of electric substation and financial organization.

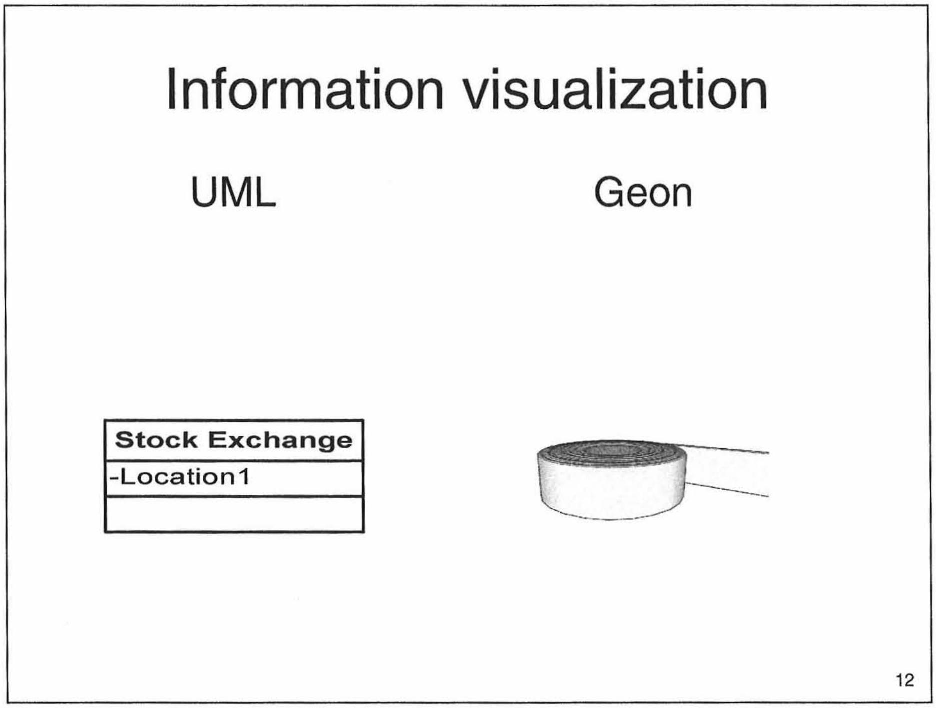


Figure A.12 Slide 12: Tutorial for visualizations of stock exchange.

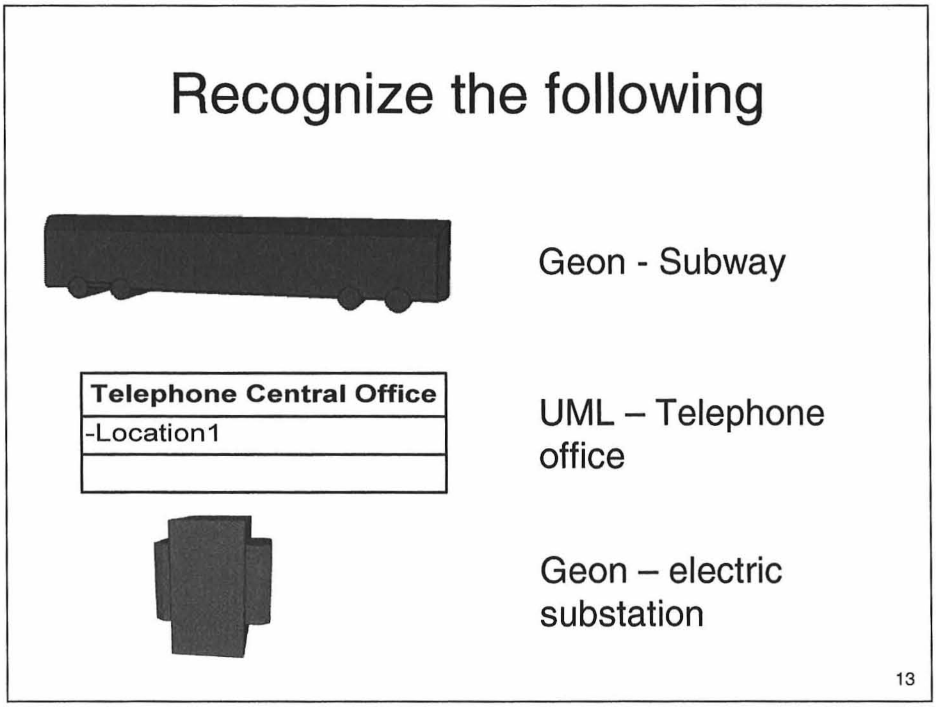


Figure A.13 Slide 13: Practice tasks to test participants' understanding of complex systems.

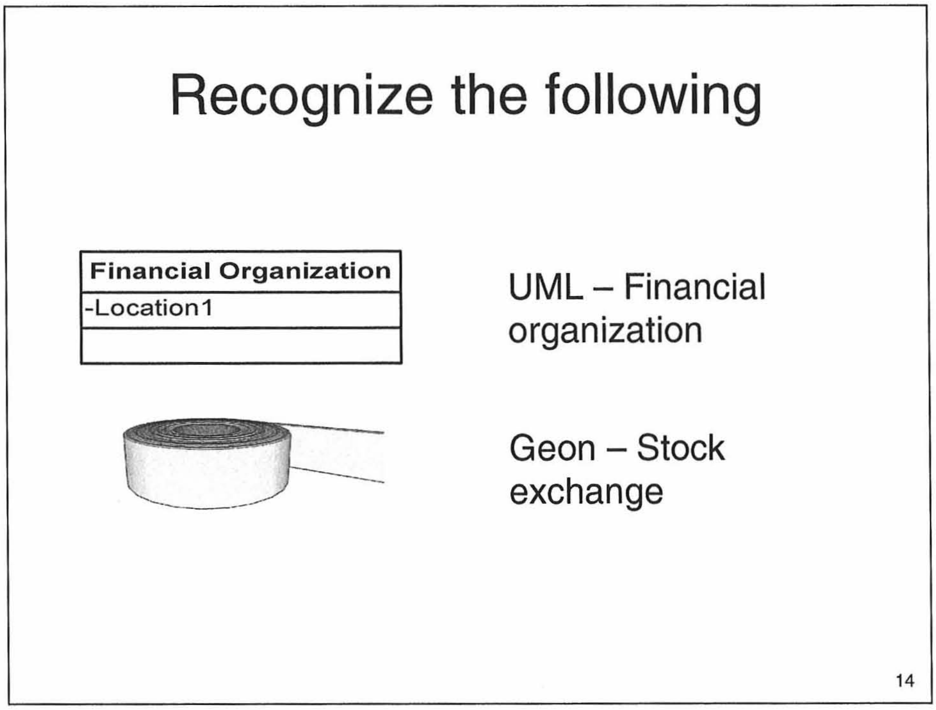


Figure A.14 Slide 14: Practice tasks to test participants' understanding of complex systems (continued.)

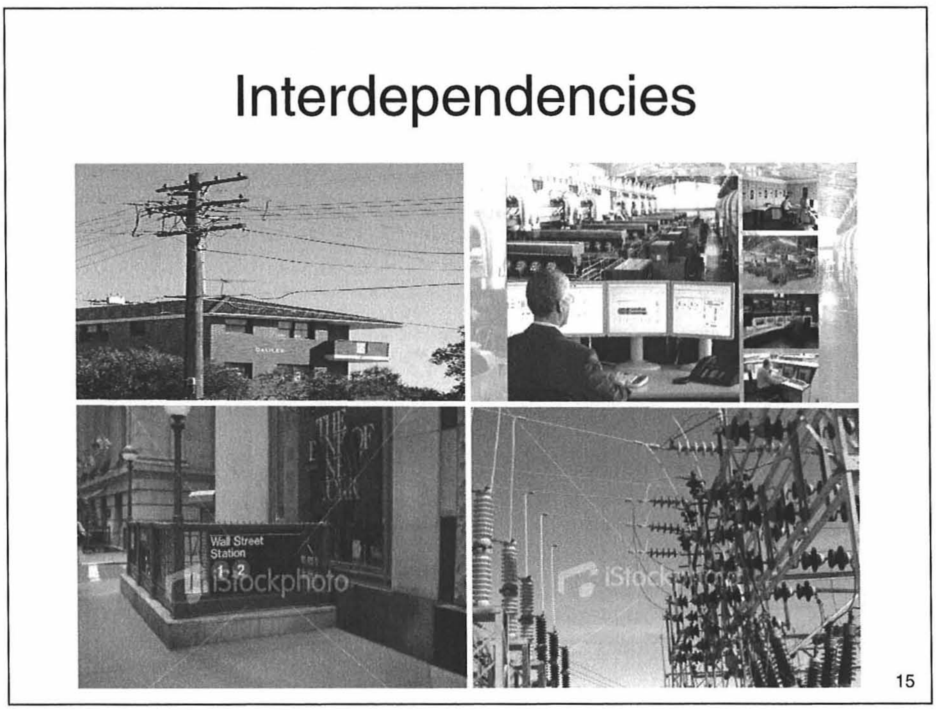


Figure A.15 Slide 15: Start of tutorial for interdependencies.

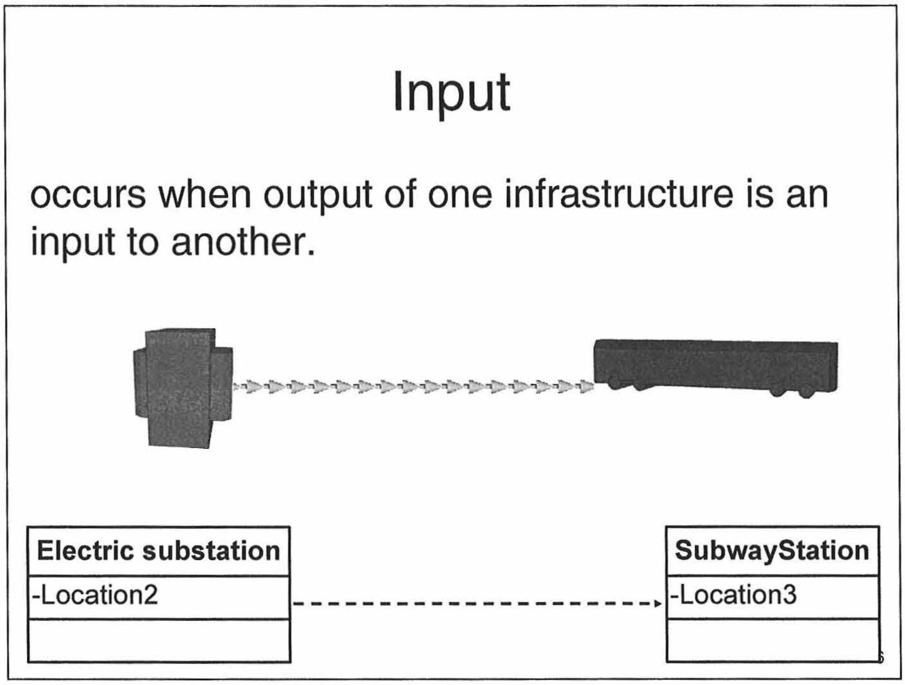


Figure A.16 Slide 16: Tutorial for visualizations of input interdependency.

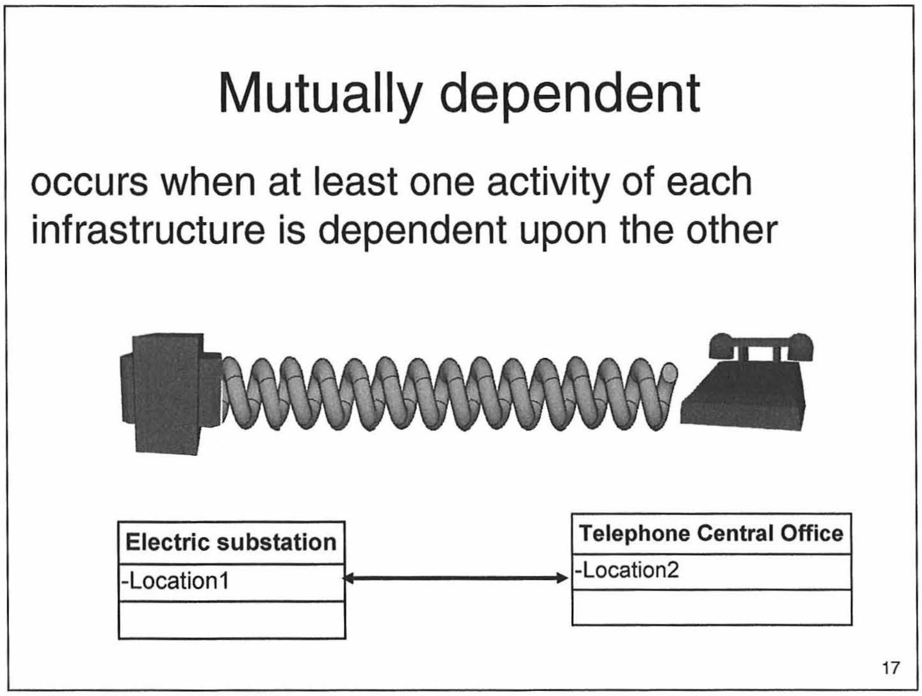


Figure A.17 Slide 17: Tutorial for visualizations of mutually dependent.

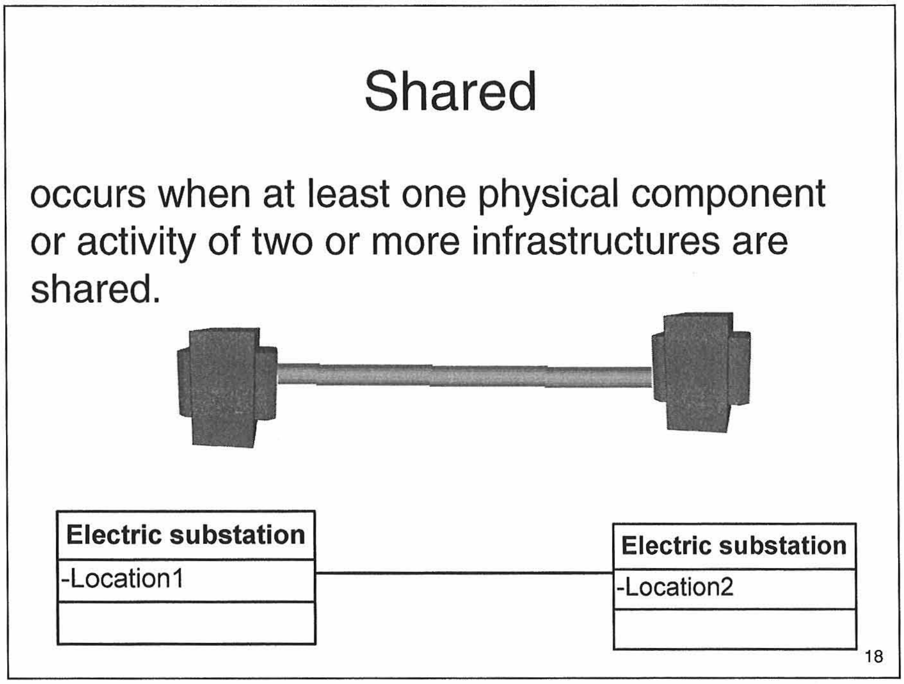


Figure A.18 Slide 18: Tutorial for visualizations of shared interdependency.

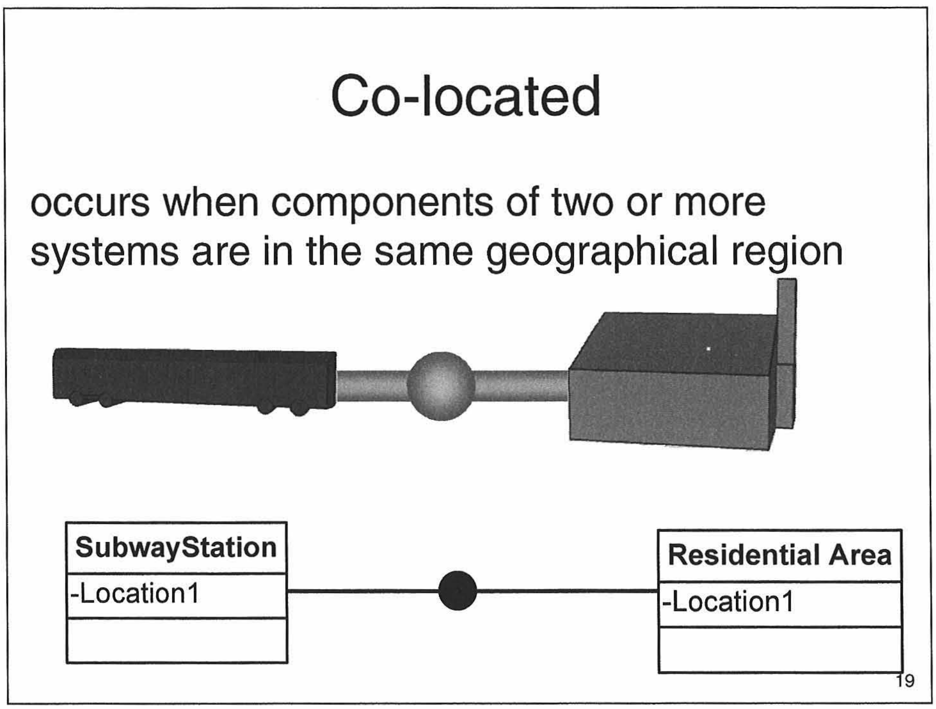


Figure A.19 Slide 19: Tutorial for visualizations of co-located interdependency.

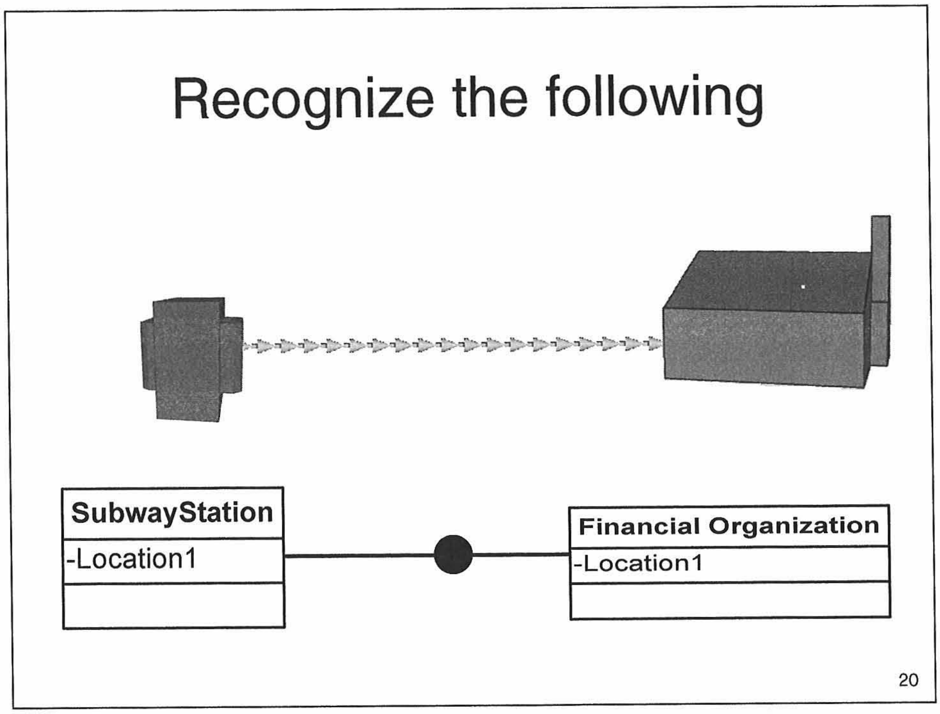


Figure A.20 Slide 20: Practice tasks to test participants' understanding of interdependencies.

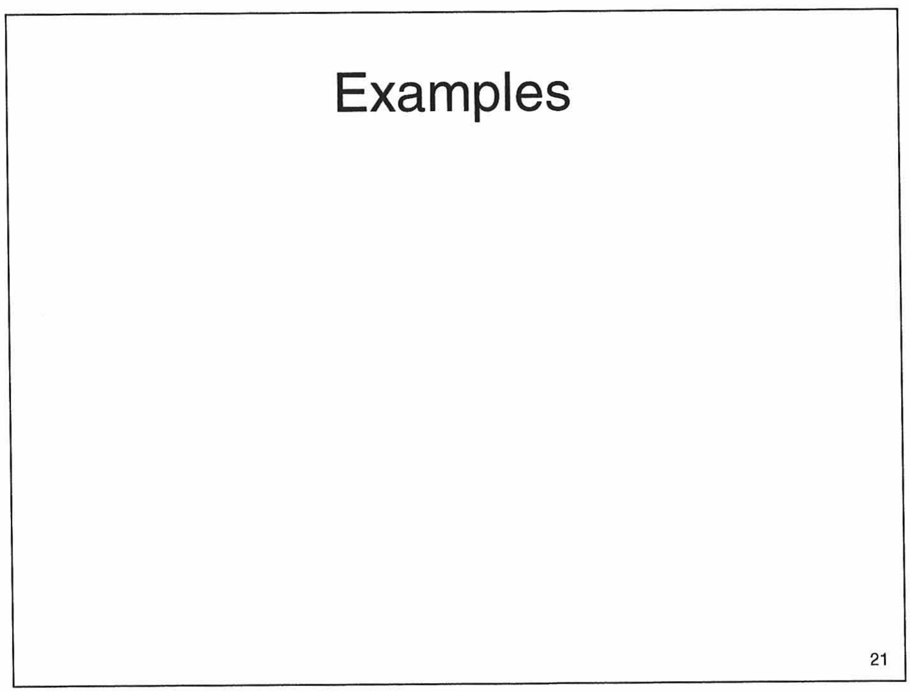


Figure A.21 Slide 21: Start of practice problem-solving tasks.

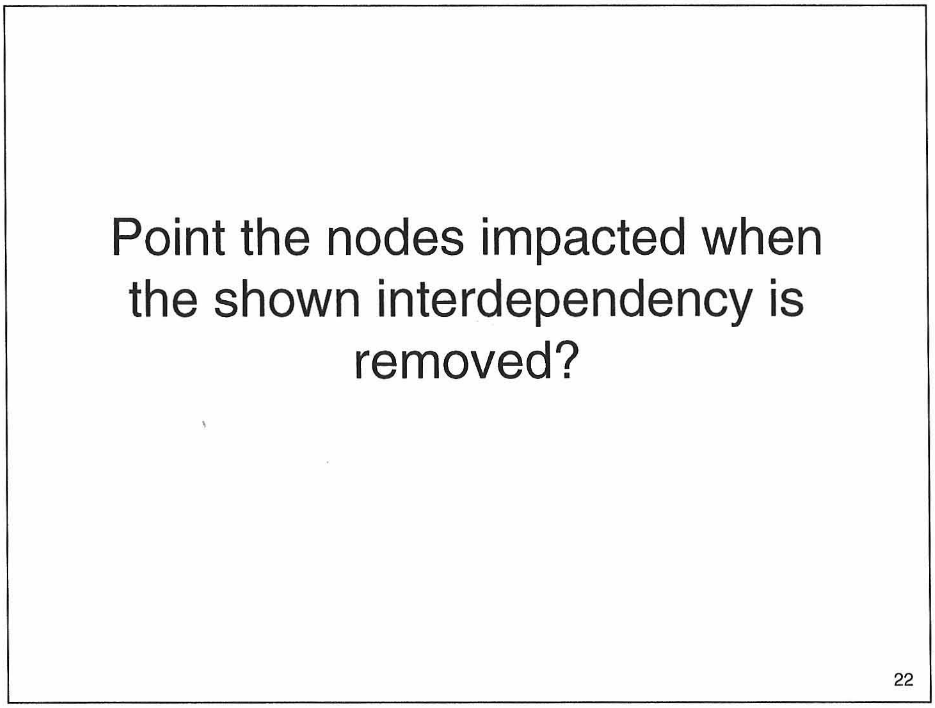


Figure A.22 Slide 22: Problem-solving task definition.

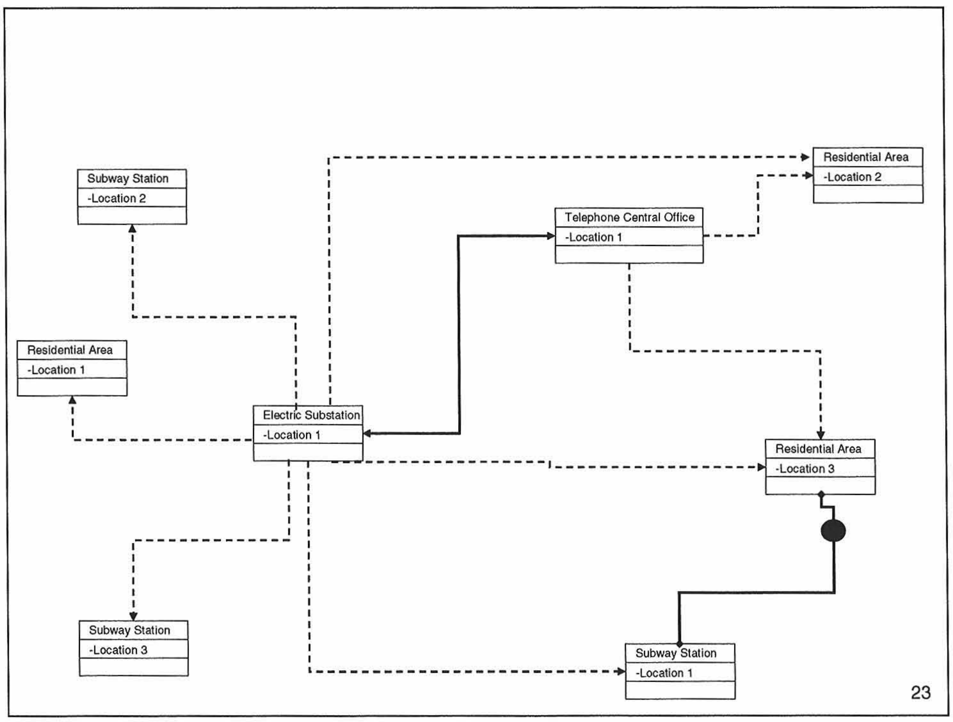


Figure A.23 Slide 23: Candidate visualization in simple UML for practice task.

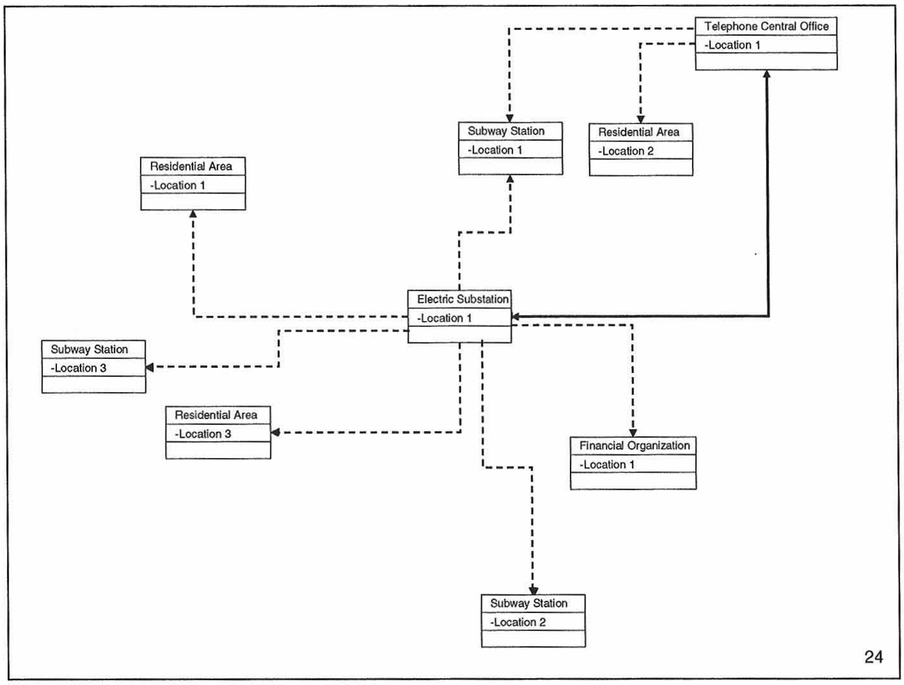


Figure A.24 Slide 24: Candidate visualization in simple UML for practice task.

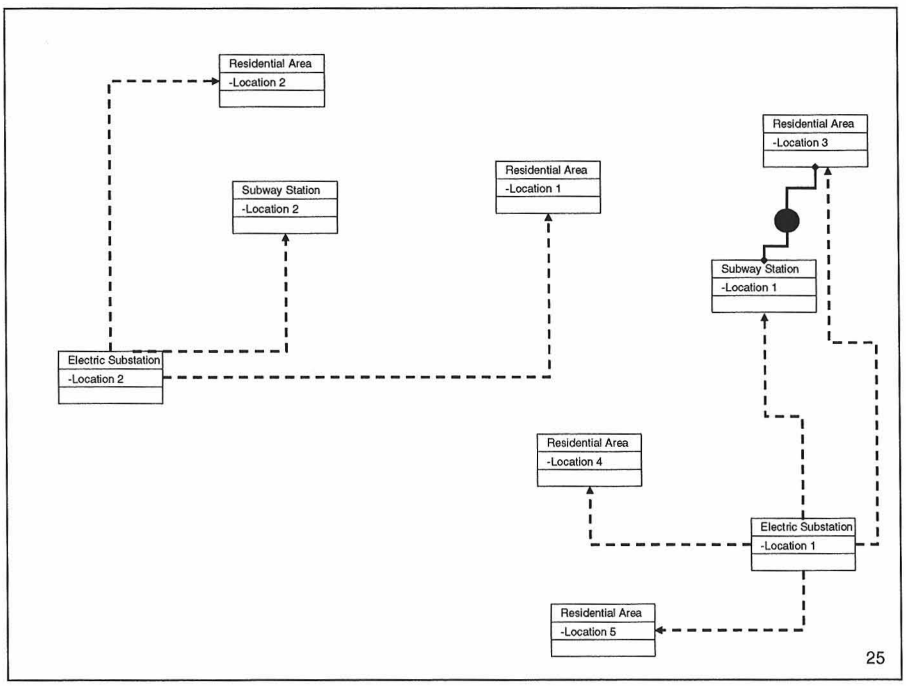


Figure A.25 Slide 25: Candidate visualization in simple UML for practice task.

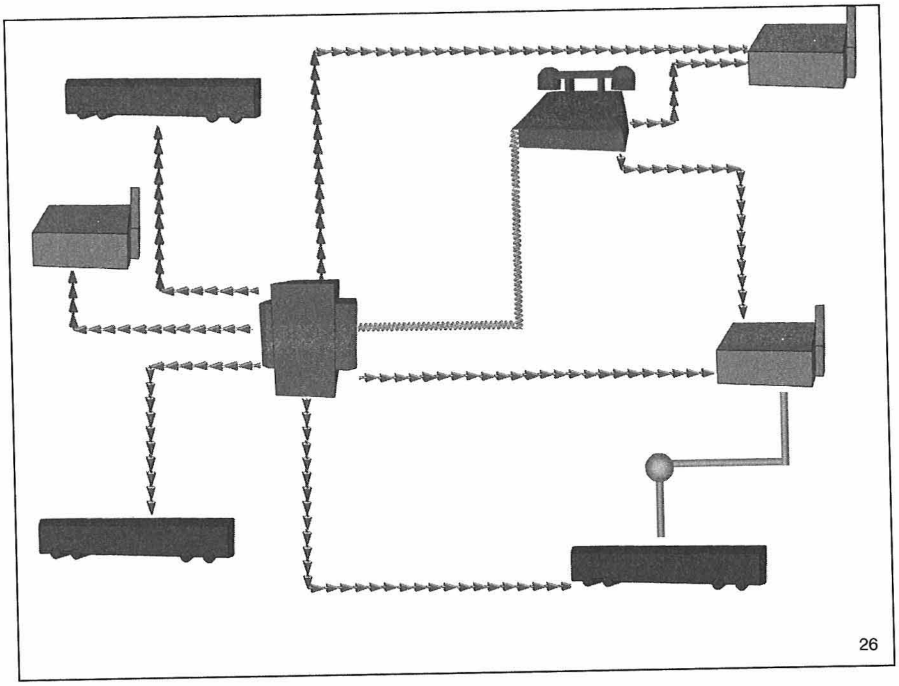


Figure A.26 Slide 26: Candidate visualization in simple geon for practice task.

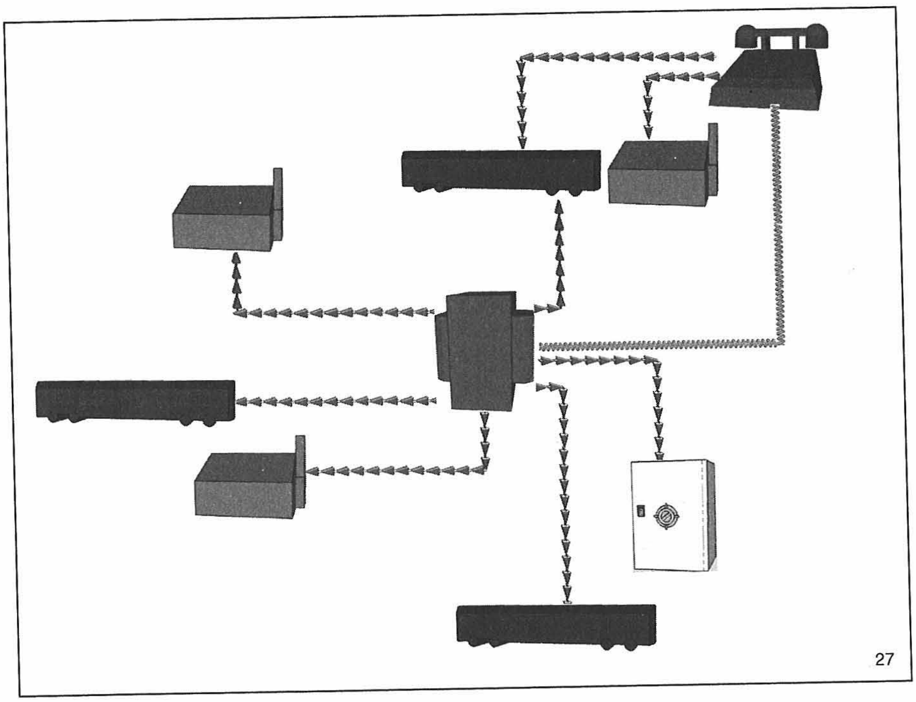


Figure A.27 Slide 27: Candidate visualization in simple geon for practice task.

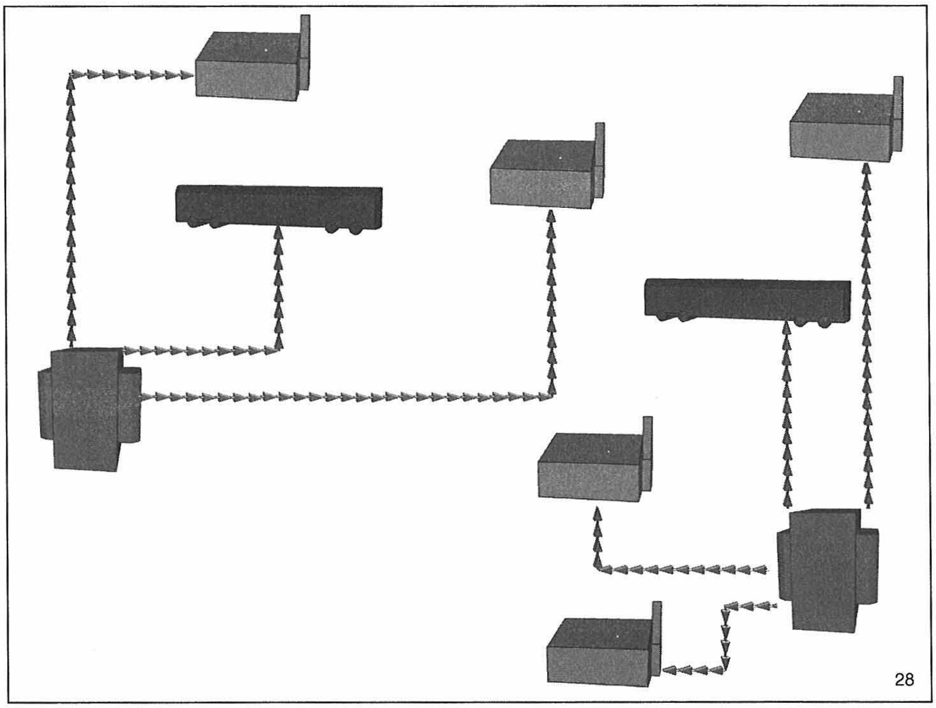


Figure A.28 Slide 28: Candidate visualization in simple geon for practice task.

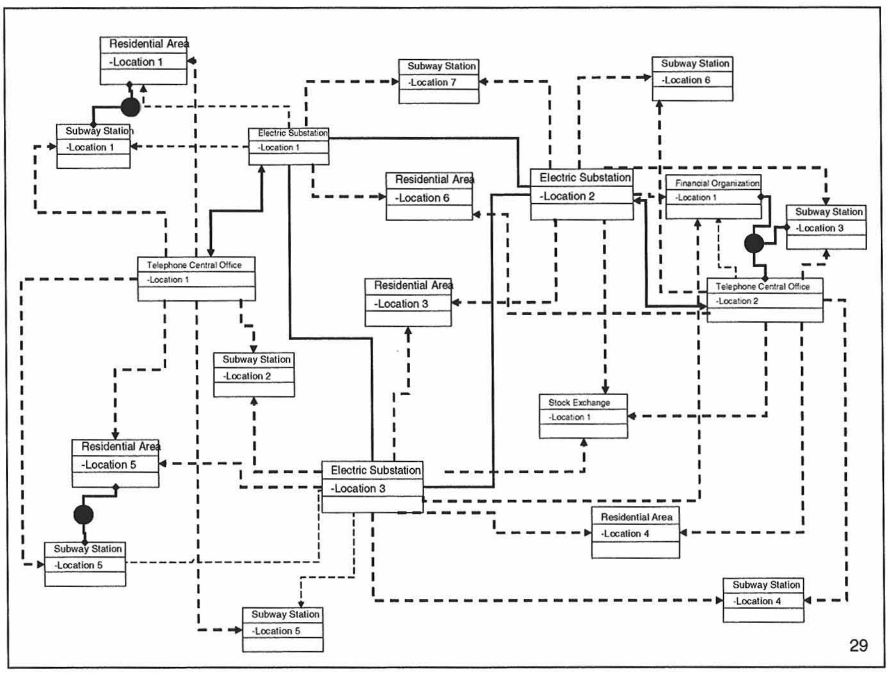


Figure A.29 Slide 29: Candidate visualization in complex UML for practice task.

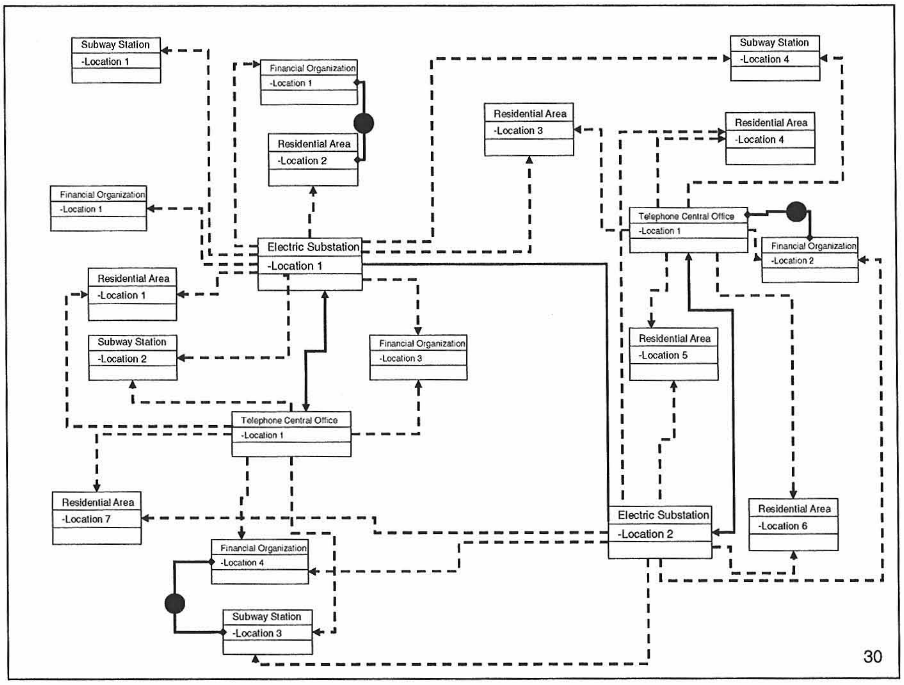


Figure A.30 Slide 30: Candidate visualization in complex UML for practice task.

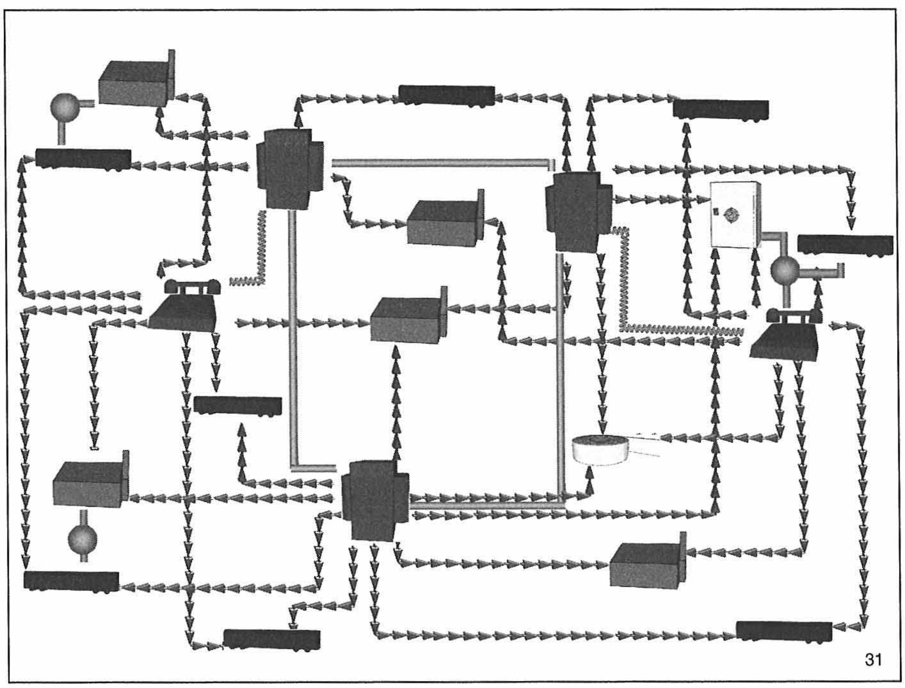


Figure A.31 Slide 31: Candidate visualization in complex geon for practice task.

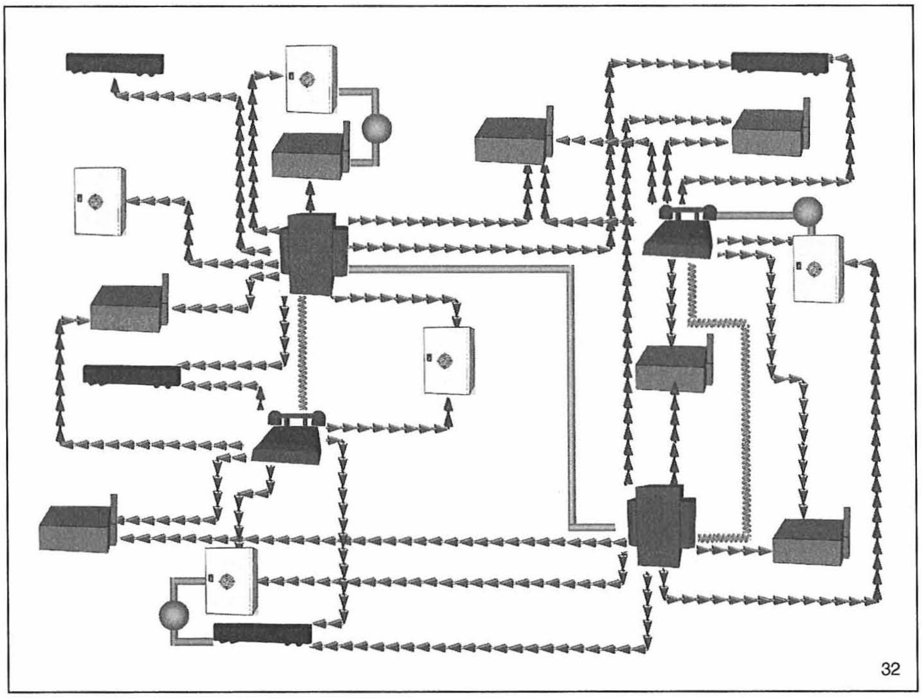


Figure A.32 Slide 32: Candidate visualization in complex geon for practice task.

Study tasks

You will now be shown 20 diagrams and asked to complete the same task.

Point the nodes impacted when the shown interdependency is removed?

Please talk aloud

33

Figure A.33 Slide 33: Overview of experimental task.

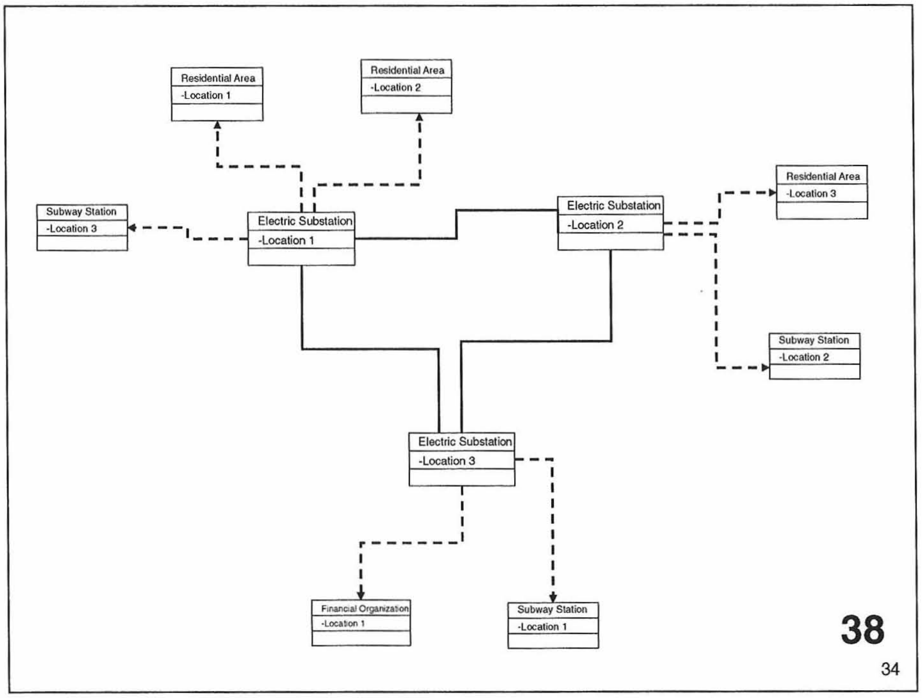


Figure A.34 Slide 34: Candidate visualization in simple UML for experiment.

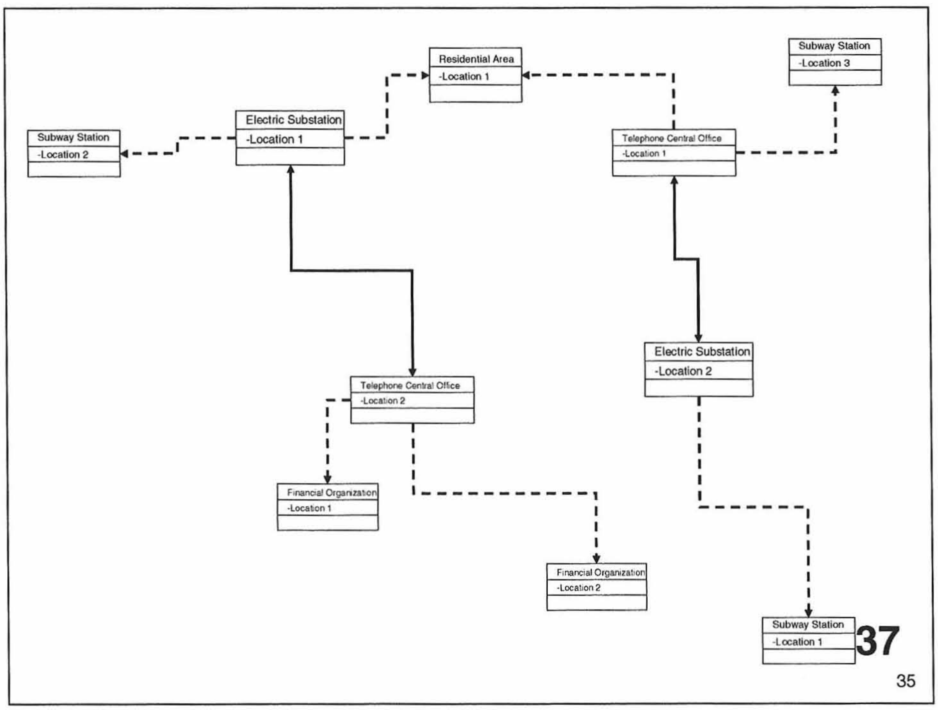


Figure A.35 Slide 35: Candidate visualization in simple UML for experiment.

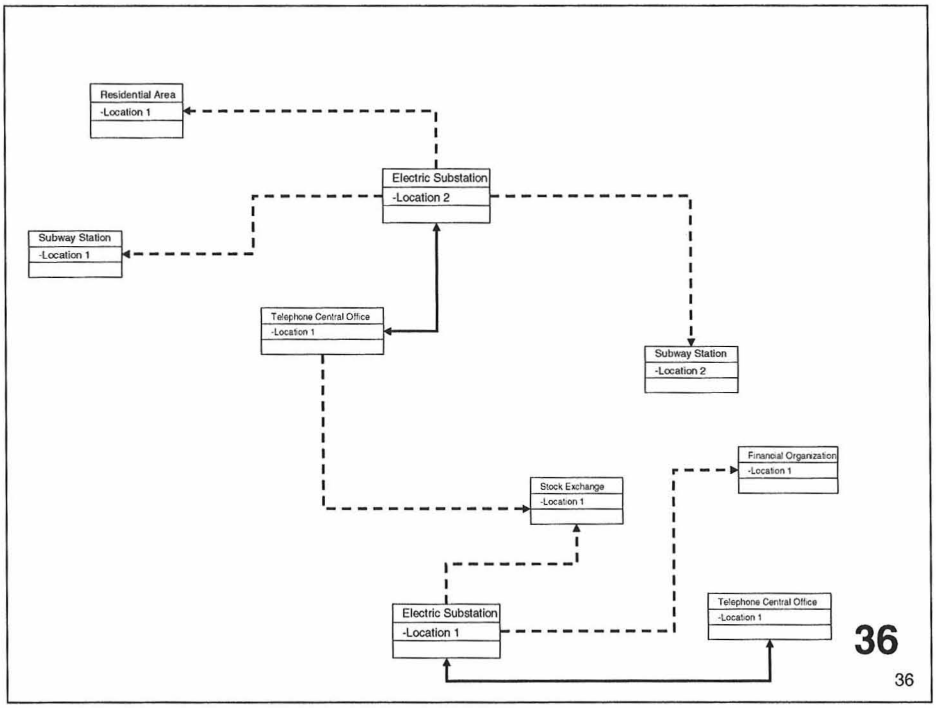


Figure A.36 Slide 36: Candidate visualization in simple UML for experiment.

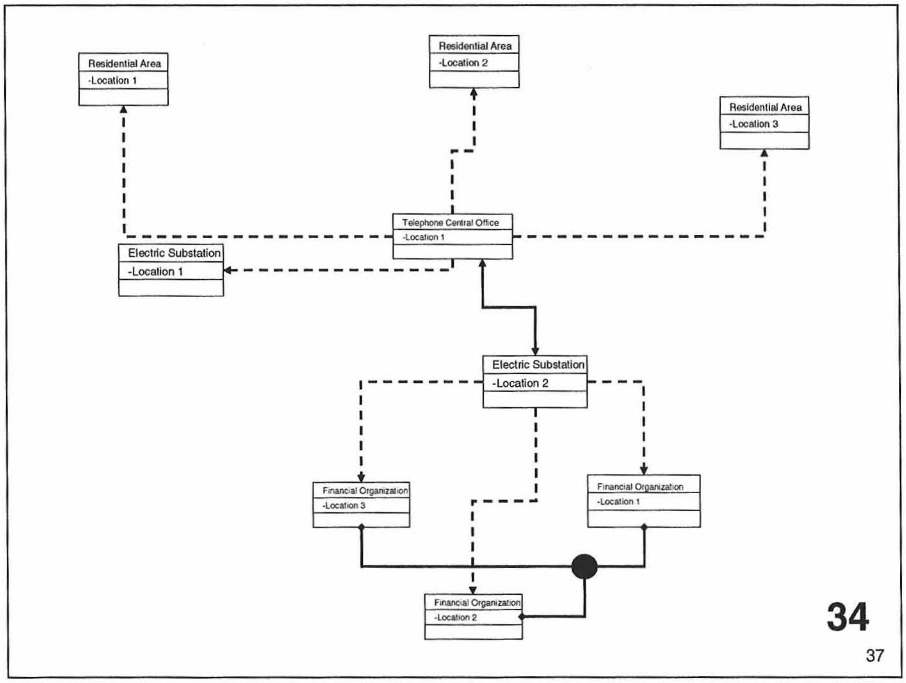


Figure A.37 Slide 37: Candidate visualization in simple UML for experiment.

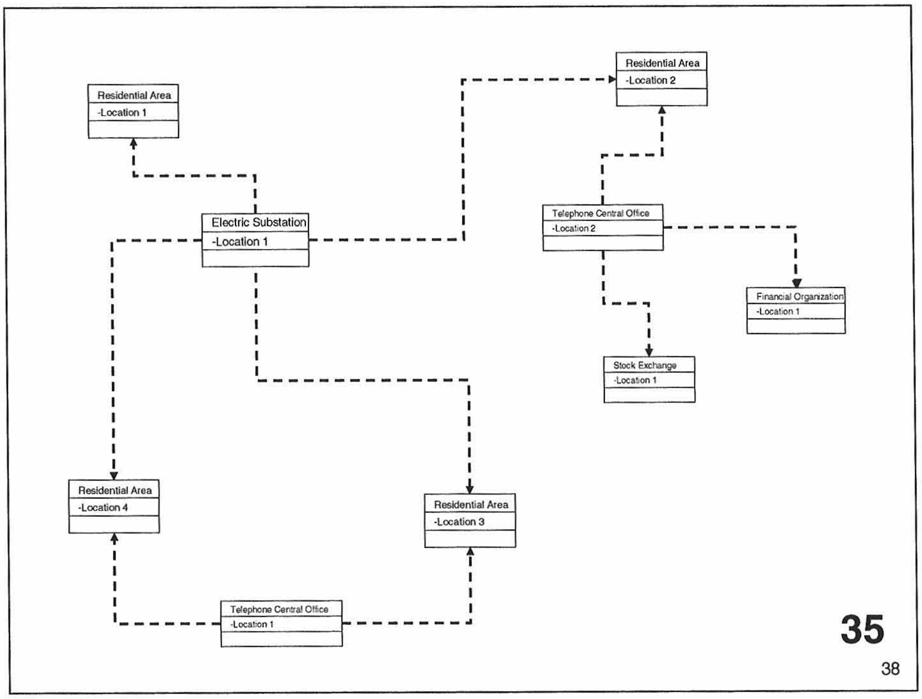


Figure A.38 Slide 38: Candidate visualization in simple UML for experiment.

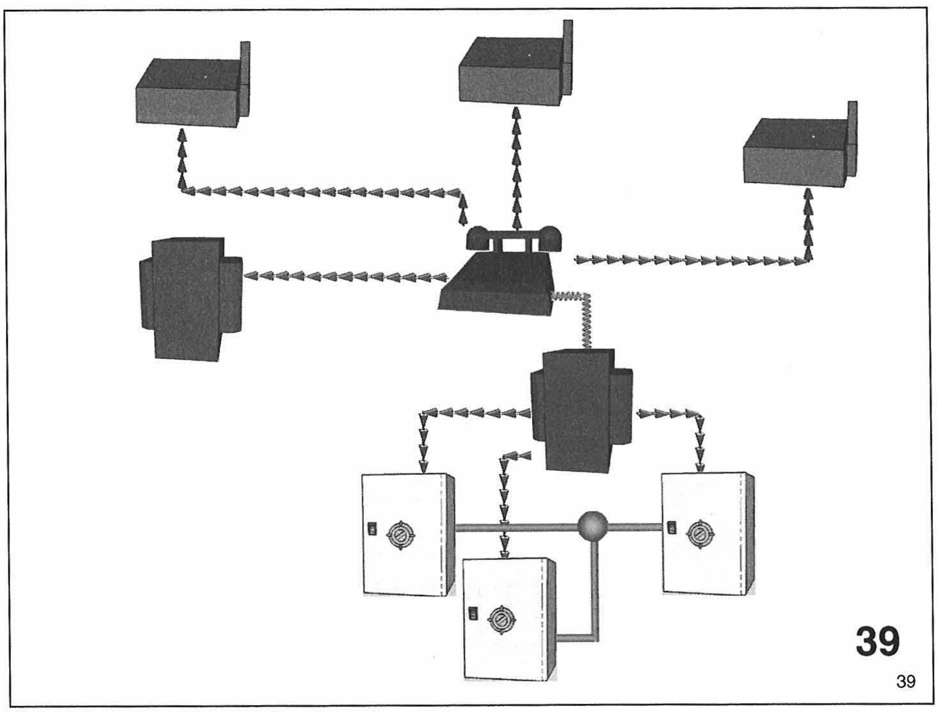


Figure A.39 Slide 39: Candidate visualization in simple geon for experiment.

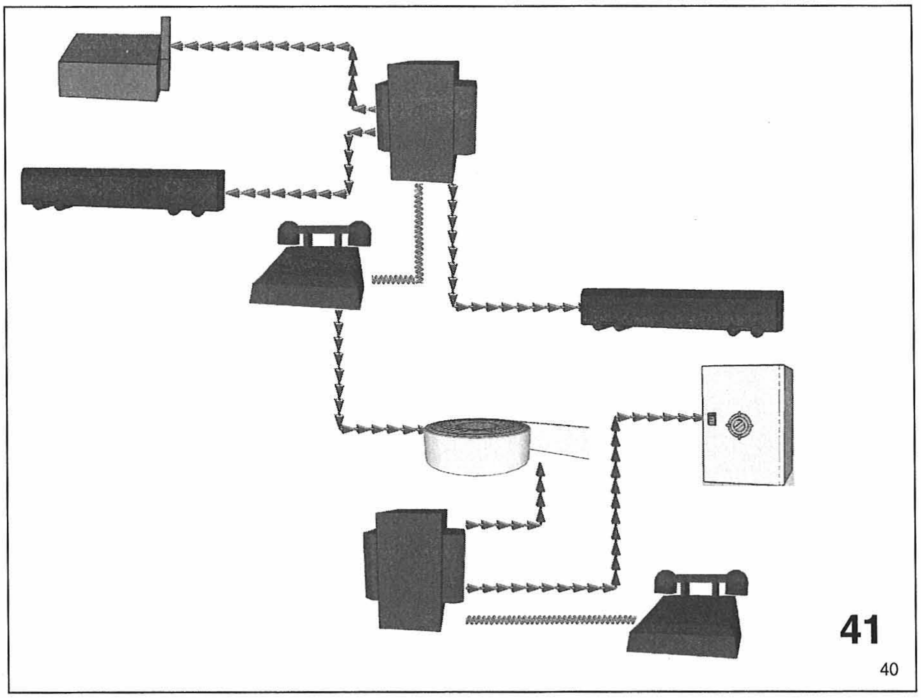


Figure A.40 Slide 40: Candidate visualization in simple geon for experiment.

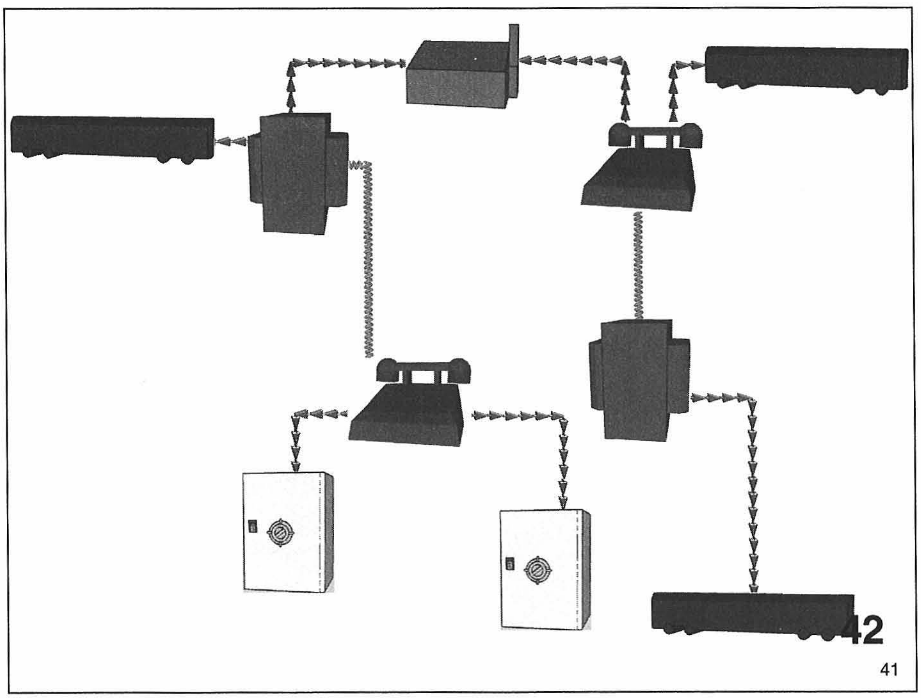


Figure A.41 Slide 41: Candidate visualization in simple geon for experiment.

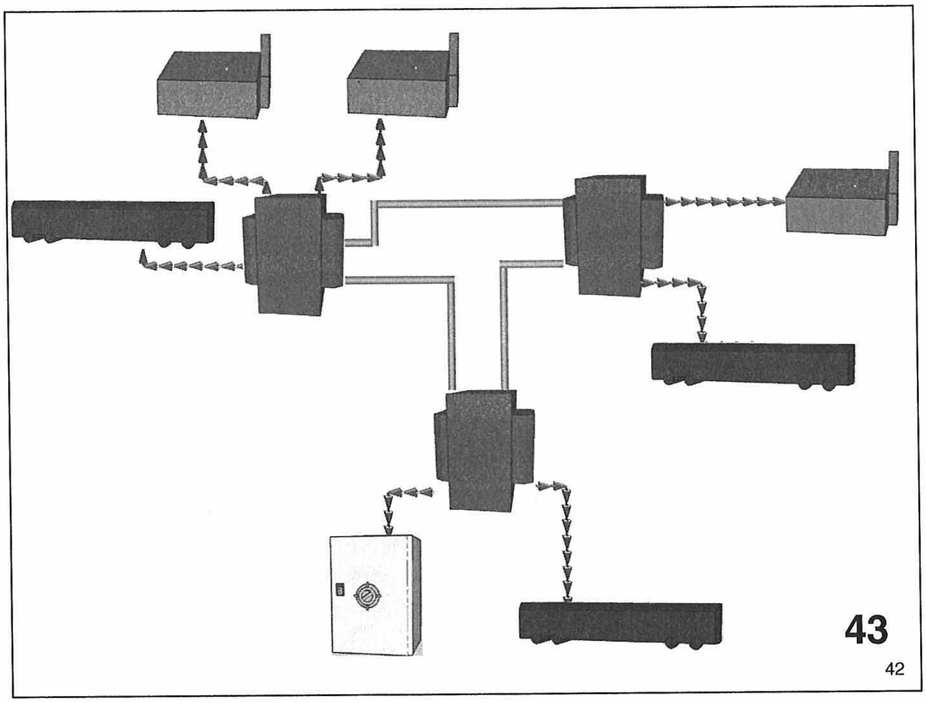


Figure A.42 Slide 42: Candidate visualization in simple geon for experiment.

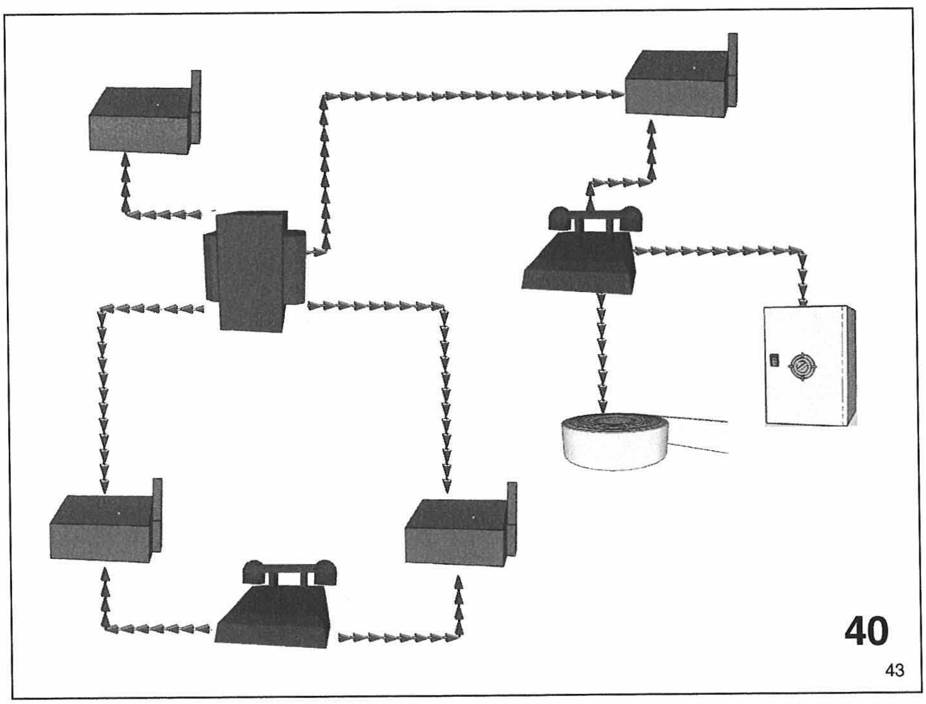


Figure A.43 Slide 43: Candidate visualization in simple geon for experiment.

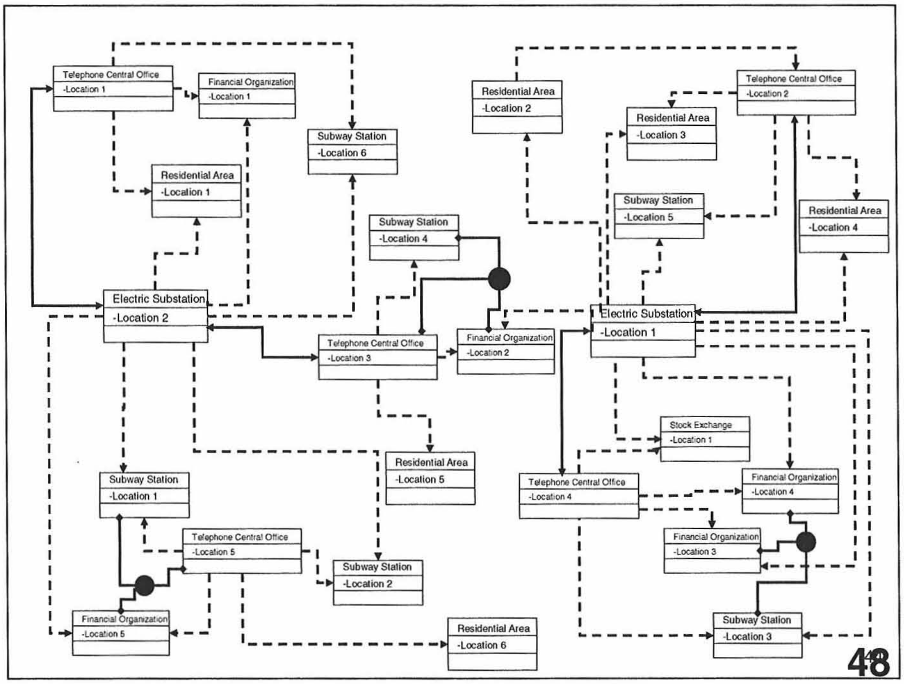


Figure A.44 Slide 44: Candidate visualization in complex UML for experiment.

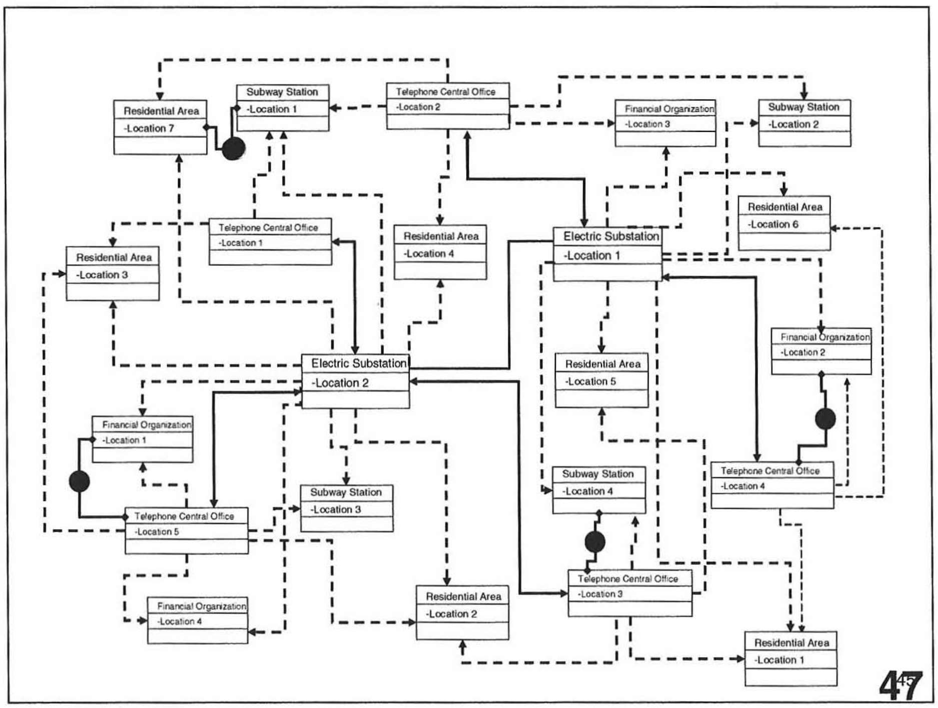


Figure A.45 Slide 45: Candidate visualization in complex UML for experiment.

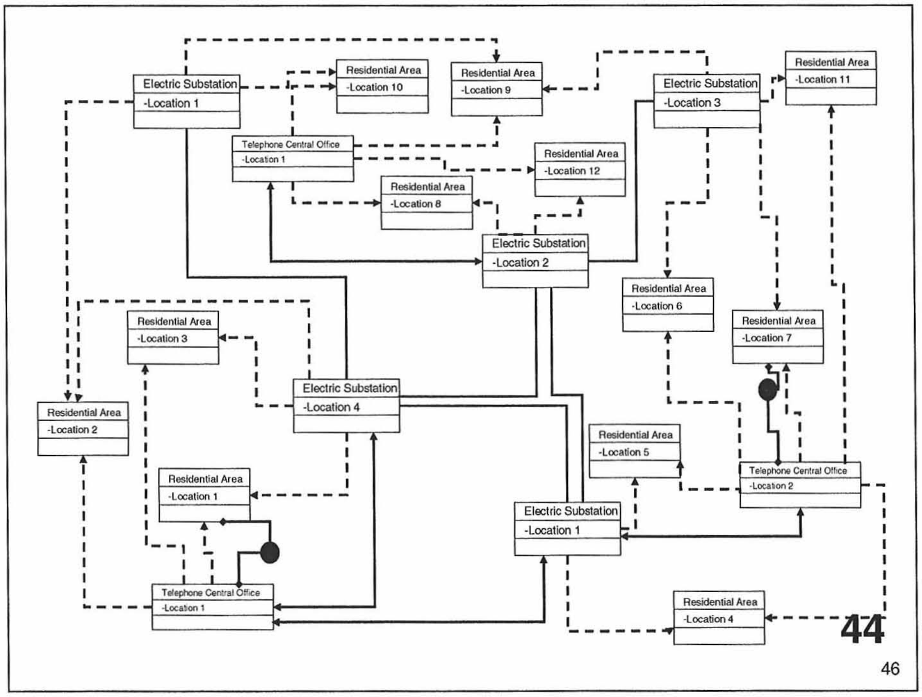


Figure A.46 Slide 46: Candidate visualization in complex UML for experiment.

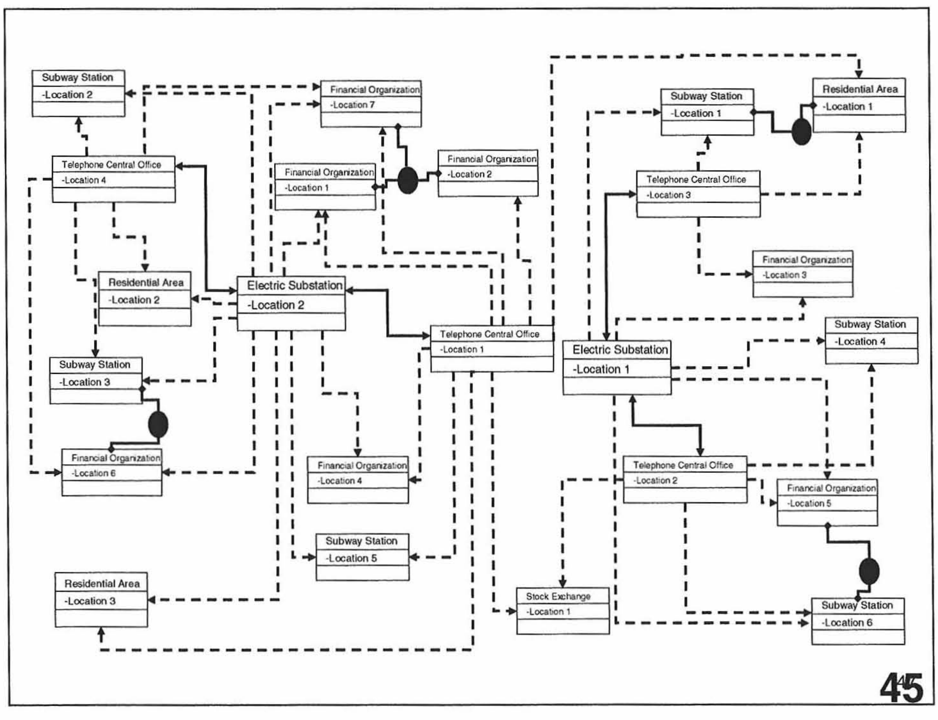


Figure A.47 Slide 47: Candidate visualization in complex UML for experiment.

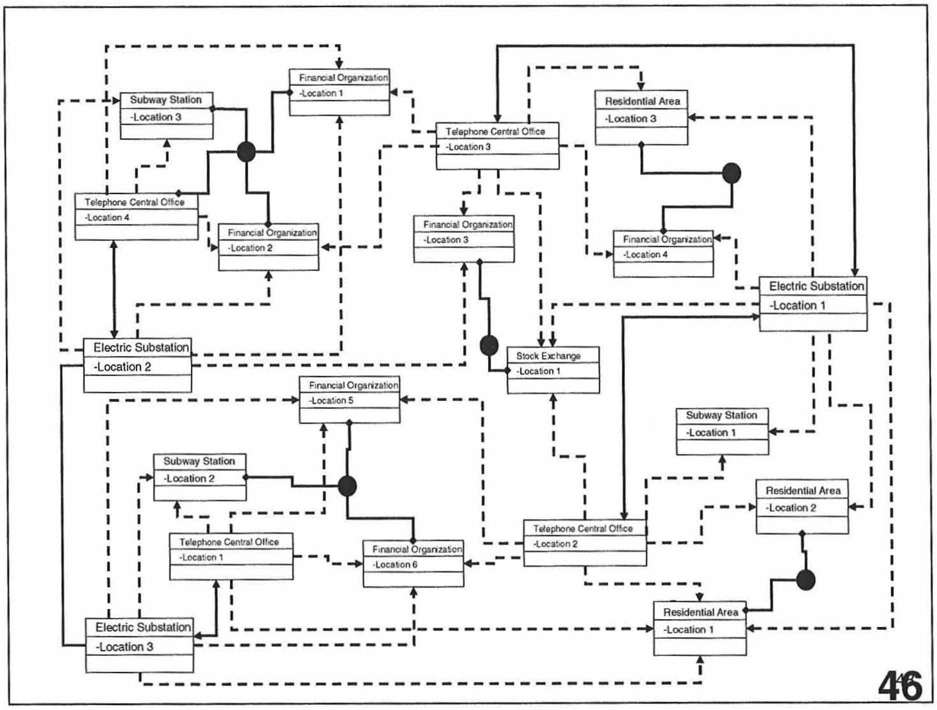


Figure A.48 Slide 48: Candidate visualization in complex UML for experiment.

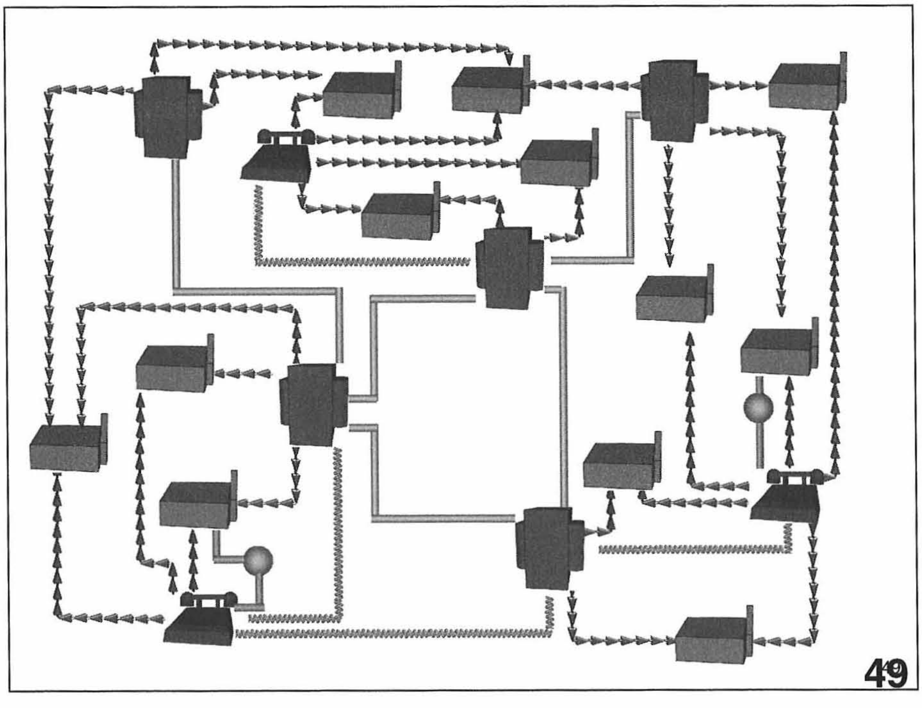


Figure A.49 Slide 49: Candidate visualization in complex geon for experiment.

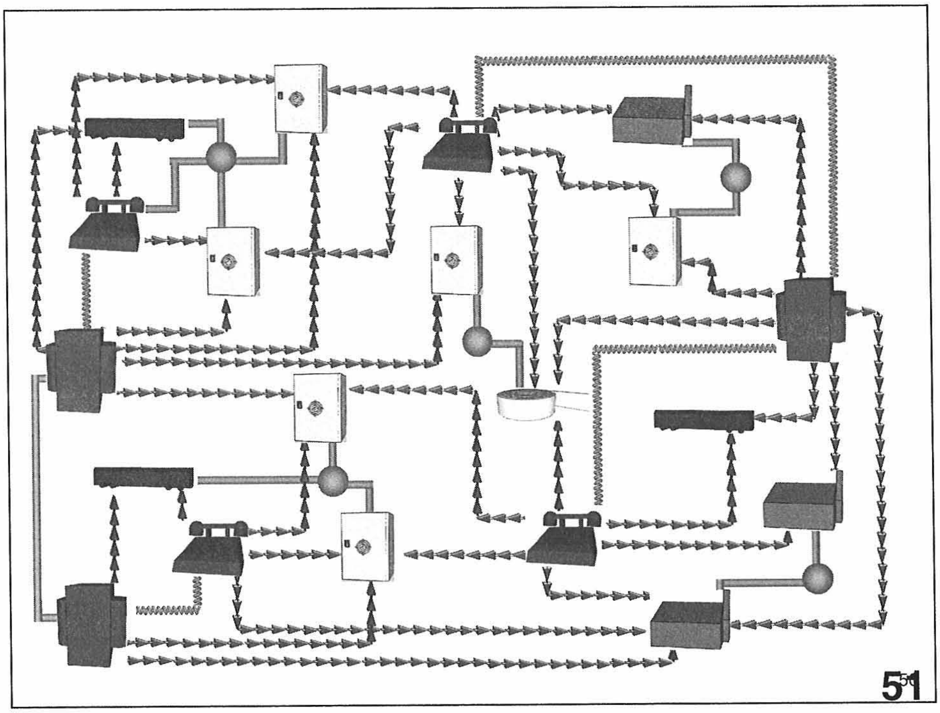


Figure A.50 Slide 50: Candidate visualization in complex geon for experiment.

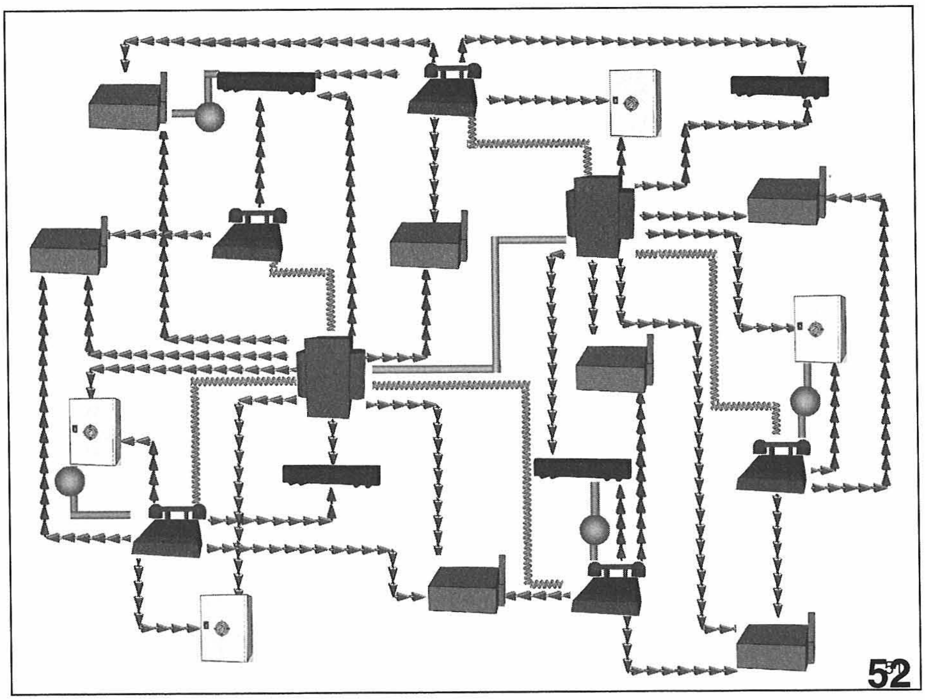


Figure A.51 Slide 51: Candidate visualization in complex geon for experiment.

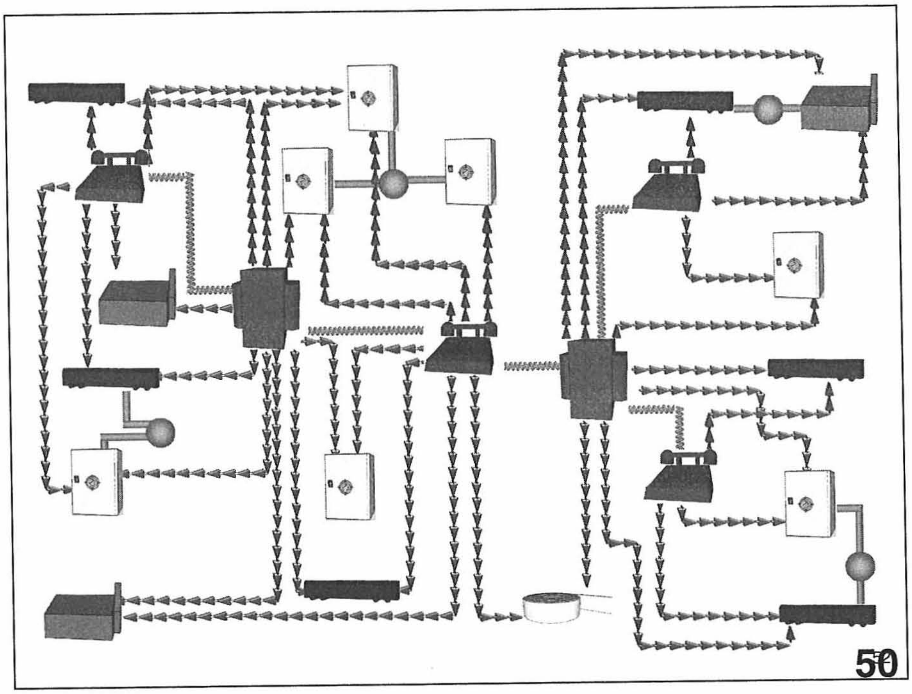


Figure A.52 Slide 52: Candidate visualization in complex geon for experiment.

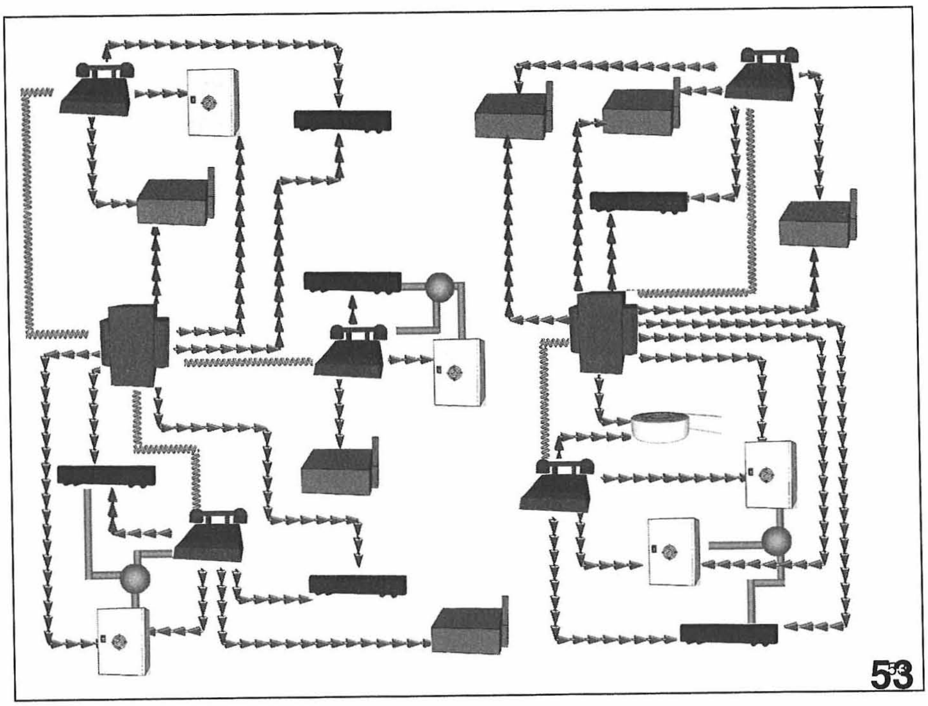


Figure A.53 Slide53: Candidate visualization in complex geon for experiment.

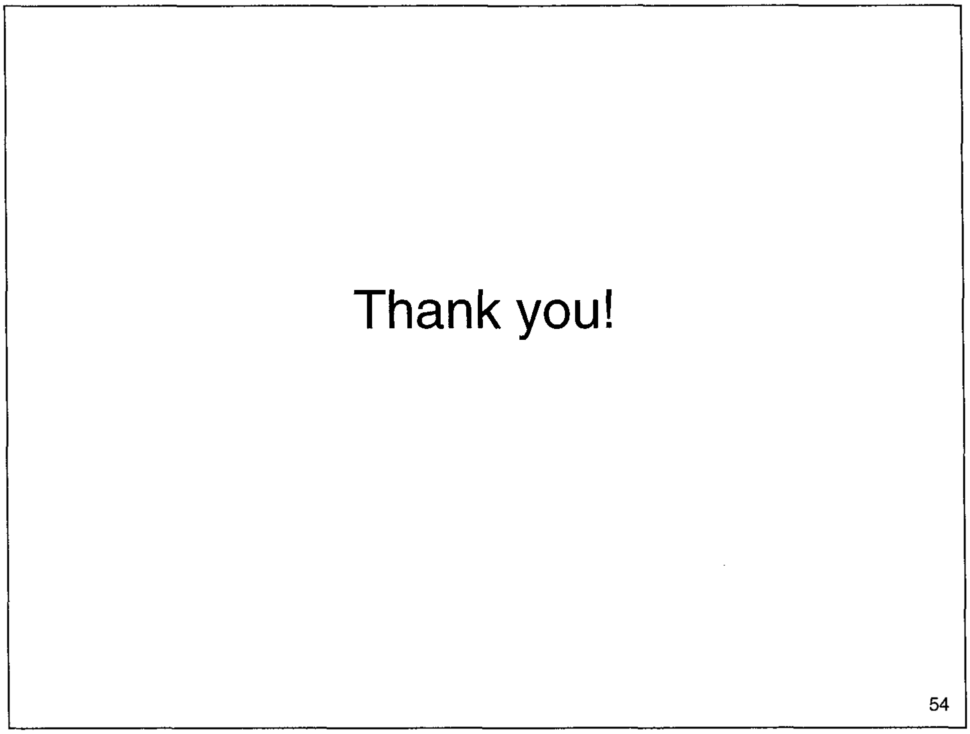


Figure A.54 Slide 54: Thanking the participant and debriefing.

APPENDIX B

CONSENT FORM

NEW JERSEY INSTITUTE OF TECHNOLOGY
323 MARTIN LUTHER KING BLVD.
NEWARK, NJ 07102

<u>CONSENT TO PARTICIPATE IN A RESEARCH STUDY</u>

TITLE OF STUDY: Understanding cognitive differences in solving visual problems using informationally equivalent but visually different representations

RESEARCH STUDY:
I, ______________________________, have been asked to participate in a research study under the direction of Dr. David Mendonça. Other professional persons who work with them as study staff may assist to act for them.

PURPOSE:
The purpose of this study is to improve understanding of human problem solving using visual representations.

DURATION:
My participation in this study will last for 30 minutes.

PROCEDURES:
I have been told that, during the course of this study, the following will occur:

I will be shown two different visual representations for the same set of elements and their relationships and given a task to complete. The task will be to look for a set of elements in the given visual representation. As I am completing the task, I will have to speak aloud about the actions I take to complete the task. I will be video and audio taped as I complete the task. The task will take about 30 minutes to complete.

PARTICIPANTS:
I will be one of about 50 participants in this study.

EXCLUSIONS:
You must be 18 years of age or older and read/write English to participate. You also must be able to read the information projected on the screen. Please let the researchers know immediately if you do not meet these criteria.

RISKS/DISCOMFORTS:
There may be risks and discomforts that are not yet known.

I fully recognize that there are risks that I may be exposed to by volunteering in this study which are inherent in participating in any study; I understand that I am not covered by NJIT's insurance policy for any injury or loss I might sustain in the course of participating in the study.

Approved by the NJIT IRB on 5/3/07.
Modifications may not be made to this consent form without NJIT IRB approval.

CONFIDENTIALITY:
I understand confidential is not the same as anonymous. Confidential means that my name will not be disclosed if there exists a documented linkage between my identity and my responses as recorded in the research records. Every effort will be made to maintain the confidentiality of my study records. If the findings from the study are published, I will not be identified by name. My identity will remain confidential unless disclosure is required by law.

VIDEOTAPING/AUDIOTAPING:
I understand that I will be video and audio taped during the course of this study. Video and audio tapes will be stored for 2 years after the end of this project (31st December 2007). After that time, the tapes will be erased by recording over my recorded sessions.

The tapes will be stored in a locked office at NJIT and will not be made available to anyone except Dr. David Mendonça and Madhavi M. Chakrabarty who are involved in this research.

PAYMENT FOR PARTICIPATION:
I have been told that I will receive no compensation for my participation in this study.

RIGHT TO REFUSE OR WITHDRAW:
I understand that my participation is voluntary and I may refuse to participate, or may discontinue my participation at any time with no adverse consequence. I also understand that the investigator has the right to withdraw me from the study at any time.

INDIVIDUAL TO CONTACT:
If I have any questions about my treatment or research procedures, I understand that I should contact the principal investigator David Mendonça at:

Information Systems Dept., GITC 4106
College of Computing Sciences
New Jersey Institute of Technology
323 Martin Luther King, Jr. Blvd
Newark, NJ 07102
Phone: 973 596 5212
Email: mendonca@njit.edu

If I have any addition questions about my rights as a research subject, I may contact:

Dawn Hall Apgar, PhD, IRB Chair
New Jersey Institute of Technology
323 Martin Luther King Boulevard
Newark, NJ 07102
(973) 642-7616
dawn.apgar@njit.edu

NJIT

Approved by the NJIT IRB on 5/5/07.
Modifications may not be made to this consent form without NJIT IRB approval.

SIGNATURE OF PARTICIPANT

I have read this entire form, or it has been read to me, and I understand it completely. All of my questions regarding this form or this study have been answered to my complete satisfaction. I agree to participate in this research study.

Subject Name:____

Signature:____

Date:______________________

NJIT

APPENDIX C

BACKGROUND QUESTIONNAIRE FOR PARTICIPANTS

Email id: ____________________________

Date: ________________________________

BACKGROUND QUESTIONNAIRE

Demographic:

1) Your gender:
   ___Male
   ___Female

2) Your age:
   ___16-25
   ___26-35
   ___36-45
   ___46-55
   ___56 and Over

3) Current degree program:
   ___Undergraduate
   ___Master
   ___ Ph.D.
   ___Post Graduate

4) Your major: ____________________________

5) English language proficiency
   ___native English speaker
   ___non-native English speaker
   ___English as second language

6) Your expertise in using UML (Unified Modeling Language) design
   ___Use extensively
   ___Have used at least once
   ___Had a course which included it
   ___Have some idea about it
   ____ No clue

7) Number of Computers at Home:
   ___None
   ___One
   ___Two or more

Thank You Very Much! ☺

APPENDIX D

INSTRUCTIONS FOR CODERS TO CODE PARTICIPANT VERBALIZATION

D.1 Coding the Protocols for Search Path

For each transcript, start reading at the beginning. As you read the text, for each quotation,

- If there is a reference to a node like **residential areas, subway station, electric substation, telephone central office, financial organization, stock market**, code it as N
- If there is a reference to a link like **shared, input, mutually dependent, co-located or connection,** code it as L.
- If there is a reference to a group of nodes and links like (this **whole cluster, this set of elements, the whole diagram, this area, these two, these three , all these** etc), code it as S

If you have any notes or comments for any quotation, make a note of it for discussing during our next meeting. Hand over the transcript(s) and the coding back to the investigator after completing the task.

Thank you!

D.2 Coding the Protocols for Search-Steps

For each transcript, start reading at the beginning. As you read the text, for each quotation, code it as follows:

- *Initiate* (I) – If a segment has an opening phrase like "*The visualization* ...", or pointing at a part of the display screen and/or starting a new problem with "*This diagram...*", then it is coded as *initiate.* This is usually the introductory statement made by the participant during the experiment.

- *Locate* (L) – If a segment includes phrases like – *"this is", "I can see*", then it is coded as *locate.* Participants use key words like *"this", these elements here" "this area"* or other demonstrative pronouns, when they are trying to locate a node or substructure for evaluation. These fragments signify that the participant is looking for particular nodes in the problem visualization. In the experimental setup, the participant could be locating a node, a link, a substructure or the whole search substructure.

- *Evaluate* (E) – If a segment includes a phrase like "*because of", "Is this the one*", it is coded as *evaluate.* Sometimes, participants use phrase like "*This is different"* to denote their evaluation of a node or link in the problem visualization. The participant may evaluate a node, a link connected to the node, a set of nodes and links or the substructure as a whole.

- *Decide* (D) – If a segment includes a phrase like "*this is affected", "this is not affected", "yes, I have completed*" or "*this is it*", it is coded as *decide.* If the participant does not say anything explicitly, then the end of the task marks the end of the search-steps. This action specifies that the participant has made the final decision regarding the visual problem and is ready to proceed to the next task or end the experiment as the case may be.

- Clarify (C) – There may be sections of participants' verbalization where the participant is either asking for a clarification from the experimenter or is trying to figure out the working of the computer or mouse. These segments of the verbalization are coded as clarify. These segments are coded during the coding process but not used for analyzing the participants' search-steps.

After reading the complete text, the complete protocol must now be annotated with one of I, L, E, D or C. Verify that no portion of the text is left out. Enter any comment or notes in column 3. After the coding is complete, hand over the transcript(s) and the coding to the investigator.

Thank you for your effort.

APPENDIX E

MARKOV PROCESS GRAPHS OF SEARCH STEPS

Figures E.1 to E.4 show the graphs of the Markov process transformations for simple and complex UML and geon diagrams.

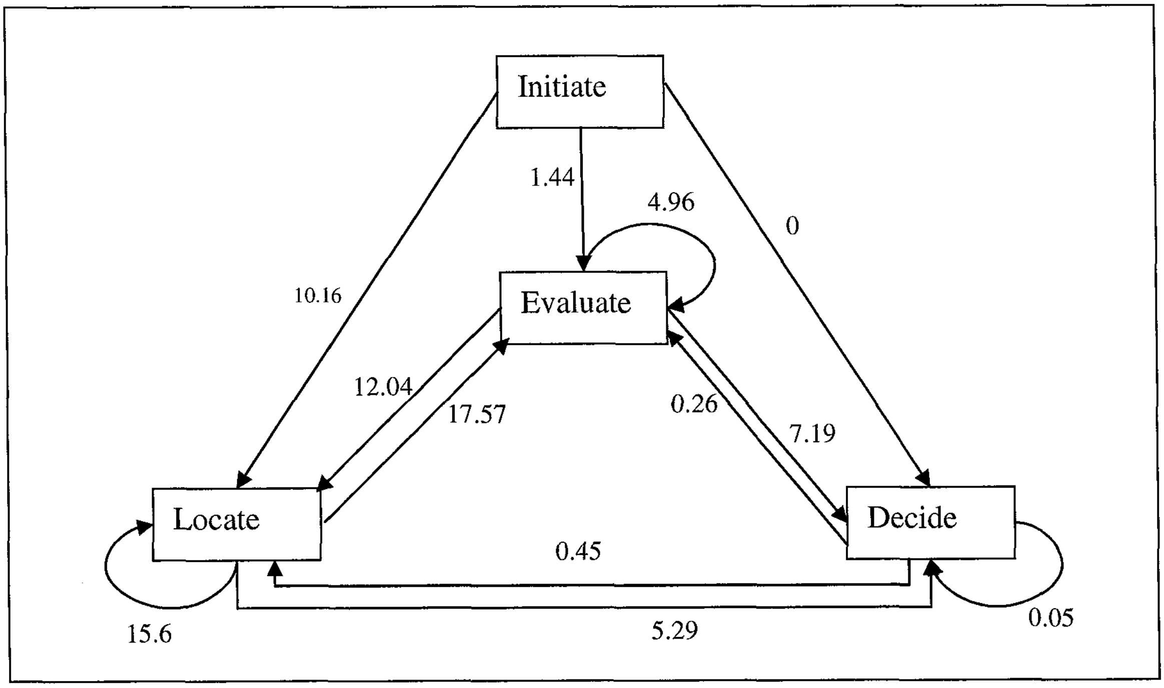


Figure E.1 Normalized transition for search-steps in simple UML diagrams.

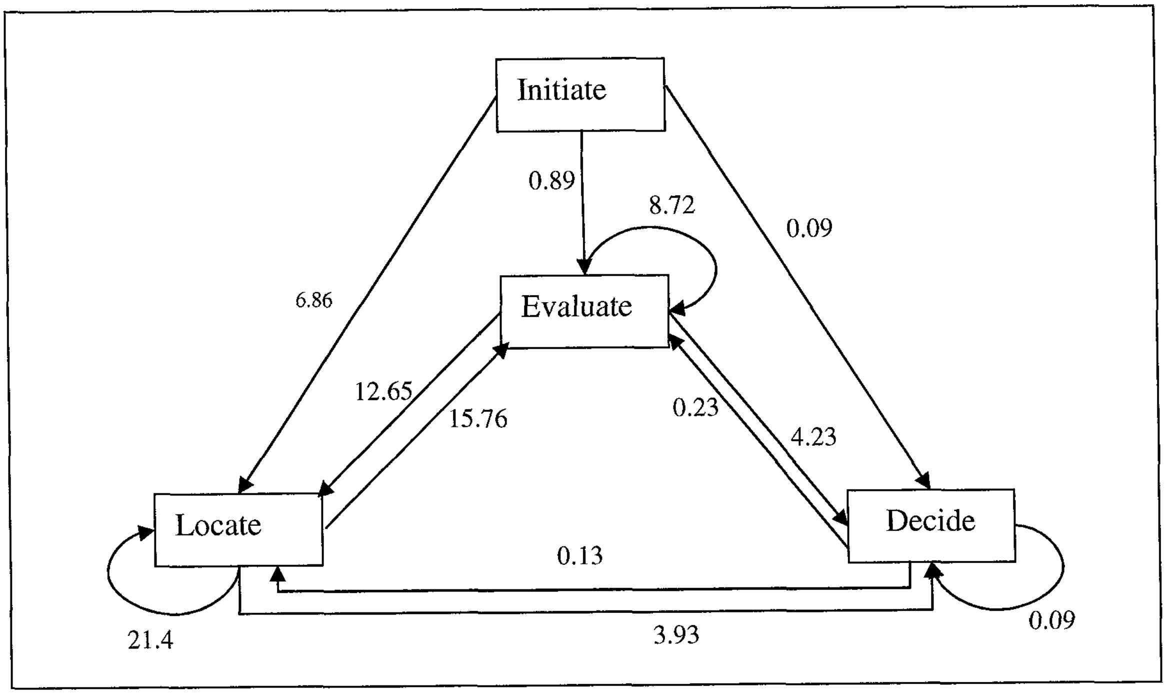


Figure E.2 Normalized transition for search-steps in complex UML diagrams.

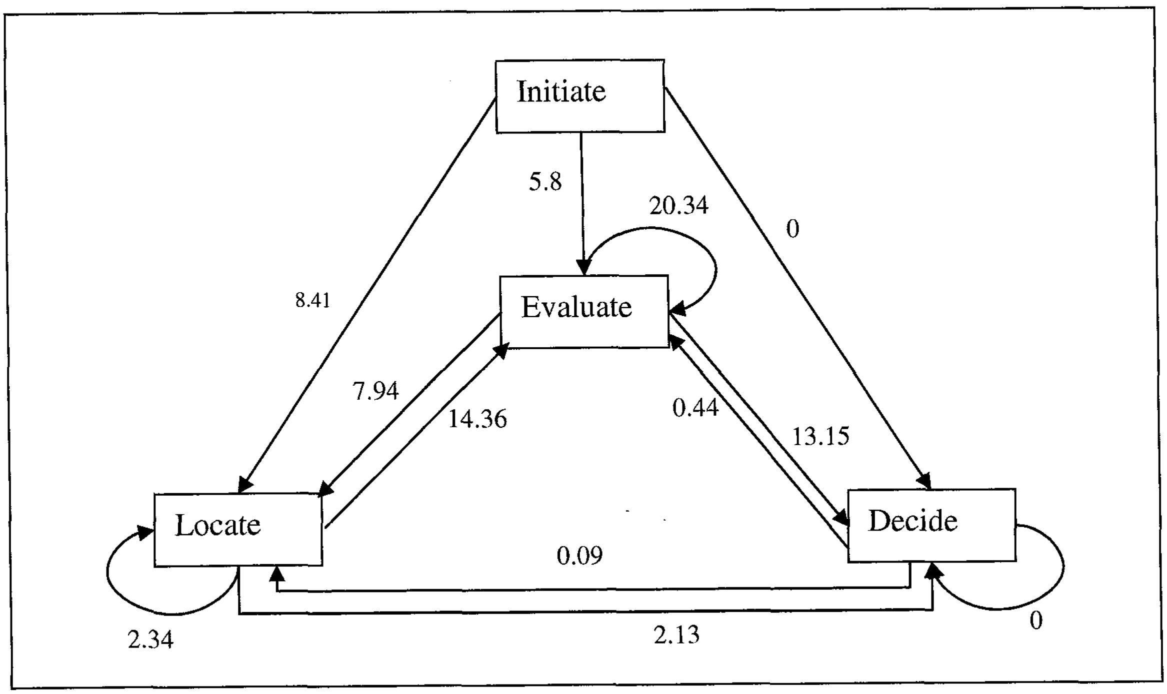


Figure E.3 Normalized transition for search-steps in simple geon diagrams.

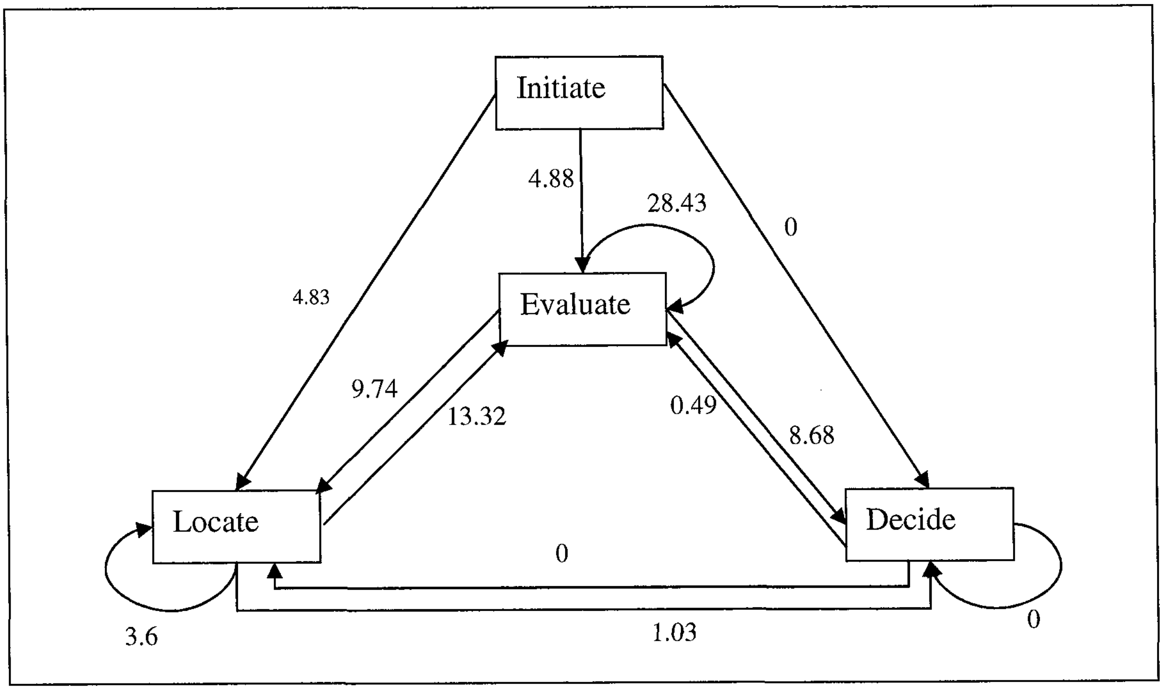


Figure E.4 Normalized transition for search-steps in complex geon diagrams.

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